11 Advances in Cognitive Neural Prosthesis: Recognition of Neural Data with an Information-Theoretic Objective

Zoran Nenadic
Department of Biomedical Engineering
University of California
Irvine, CA 92697

Daniel S. Rizzuto and Richard A. Andersen
Division of Biology
California Institute of Technology
Pasadena, CA 91125

Joel W. Burdick
Division of Engineering and Applied Science
California Institute of Technology
Pasadena, CA 91125

11.1 Abstract

We give an overview of recent advances in cognitive-based neural prostheses, and point out the major differences with respect to commonly used motor-based brain-machine interfaces. While encouraging results in neuroprosthetic research have demonstrated the proof of concept, the development of practical neural prostheses is still in the phase of infancy. To address complex issues arising in the development of practical neural prostheses we review several related studies ranging from the identification of new cognitive variables to the development of novel signal processing tools.

In the second part of this chapter, we discuss an information-theoretic approach to the extraction of low-dimensional features from high-dimensional neural data. We argue that this approach may be better suited for certain neuroprosthetic applications than the traditionally used features. An extensive analysis of electrical recordings from the human

brain demonstrates that processing data in this manner yields more informative features than off-the-shelf techniques such as linear discriminant analysis. Finally, we show that the feature extraction is not only a useful dimensionality reduction technique, but also that the recognition of neural data may improve in the feature domain.

11.2 Introduction

The prospect of assisting disabled individuals by using neural activity from the brain to control prosthetic devices has been a field of intense research activity in recent years. The nature of neuroprosthetic research is highly interdisciplinary, with the brain-machine interfaces (BMIs) playing the central role. Although the development of BMIs can be viewed largely as a technological solution for a specific practical application, it also represents a valuable resource for studying brain mechanisms and testing new hypotheses about brain function.

Up to date, the majority of neuroprosthetic research studies have focused on deriving hand trajectories by recording their neural correlates, primarily, but not exclusively, from the motor cortex (Wessberg et al. (2000); Serruya et al. (2002); Taylor et al. (2002); Carmena et al. (2003); Mussa-Ivaldi and Miller (2003)). The trajectory information contained in the action potentials of individual neurons is decoded and the information is used to drive a robotic manipulator or a cursor on a computer screen. We refer to this neuroprosthetic approach as "motor-based". Additionally, progress has been made in interfacing electroencephalographic (EEG) signals and assistive devices for communication and control (Wolpaw et al. (2002)). These noninvasive techniques are commonly termed brain-computer interfaces (BCIs) (Wolpaw and McFarland (2004); Pfurtscheller et al. (2003c)).

While remarkable success in the development of BMIs has been achieved over the past decade, practical neural prostheses are not yet feasible. Building a fully operational neuroprosthetic system presents many challenges ranging from long-term stability of recording implants to development of efficient neural signal processing algorithms. Since the full scope of prosthetic applications is still unknown and it is unlikely that a single BMI will be optimal for all plausible scenarios, it is important to introduce new ideas about the types of signals that can be used. It is also important to address the many technological challenges that are currently impeding the progress toward operational neural prostheses. To this end, the neuroprosthetic research effort of our group spans several related directions including cognitive-based BMIs, decoding from local field potentials (LFPs), identification of alternative cognitive control signals, electrophysiologic recording advances, and development of new decoding algorithms.

In section 11.3, we give a brief overview of these research efforts. More details can be found in the relevant literature cited. In section 11.4, we discuss novel information-theoretic tools for extraction of useful features from high-dimensional neural data. Experimental results with electrically recorded signals from the human brain are presented in section 11.5, and the advantages of our technique over traditional ones are discussed. Concluding remarks are given in section 11.6.

11.3 Advances in Cognitive Neural Prosthesis

The motor-based approach, although predominantly used, is certainly not the only way of using brain data for neuroprosthetic applications. Shenoy et al. (2003) argue that neural activity present before or even without natural arm movement provides an important source of control signals. In nonhuman primates, these types of neural signals can be found, among other areas, in parietal reach region (PRR) of the posterior parietal cortex (PPC). PPC is an area located at an early stage in the sensory-motor pathway (Andersen et al. (1997)), and is involved in transforming sensory inputs into plans for actions, so-called "sensory-motor integration". In particular, PRR was shown to exhibit directional selectivity with respect to planned reaching movements (Snyder et al. (1997)). Moreover, these plans are encoded in visual coordinates (also called retinal or eye-centered coordinates) relative to the current direction of gaze (Batista et al. (1999)), thus providing extrinsic spatial information and underscoring the cognitive nature of these signals. We refer to this approach to neural prostheses as "cognitive-based". The human homologue of PRR has recently been identified in functional-magnetic-resonance imaging experiments (Connolly et al. (2003)).

11.3.1 Cognitive-Based Brain-Machine Interfaces

The cognitive-based approach to neural prostheses does not require the execution of arm movements; its true potential lies in assisting paralyzed individuals who are unable to reach but who are capable of making reaching plans. It has been shown through a series of experiments (Musallam et al. (2004)) that monkeys easily learn to control the location of a computer cursor by merely thinking about movements. Briefly, the monkeys were shown a transient visual cue (target) at different screen locations over multiple trials. After the target disappeared, the monkeys were required to plan a reach movement to the target location without making any arm or eye movements. This stage of the experiment is referred to as the "delay" or "memory period". The action potentials (spike trains) of individual neurons from PRR were collected during the memory period and were decoded in real time to predict the target location. If the correct location was decoded, a feedback was provided to the animals by illuminating the target location and the animals were rewarded. The trials were aborted if the animals made eye or arm movements during the memory period. This ensured that only cognitive and not motor-related signals were used for decoding, thus underscoring the potential of the cognitive-based approach for severely paralyzed patients.

With vision being the main sensory modality of the posterior parietal cortex (Blatt et al. (1990); Johnson et al. (1996)), PRR is likely to continue receiving appropriate error signals after paralysis. In the absence of proprioceptive and somatosensory feedback (typically lost due to paralysis), visual error signals become essential in motor learning. Musallam et al. (2004) have shown that the performance of a PRR-operated prosthesis improved over the course of several weeks. Presumably, the visual feedback allowed the monkeys to learn how to compensate for decoding errors.

After reaching goals are decoded, trajectories can be computed from low-level trajectory instructions managed by smart output devices, such as robots, computers, or vehicles, using supervisory control systems (Sheridan (1992)). For example, given the Cartesian coordinates of an intended object for grasping, a robotic motion planner can determine the detailed joint trajectories that will transport a prosthetic hand to the desired location (Andersen et al. (2004a)). Sensors embedded in the mechanical arm can ensure that the commanded trajectories are followed and obstacles are avoided, thereby replacing, at least to some degree, the role of proprioceptive and somatosensory feedback.

11.3.2 Local Field Potentials

LFPs represent the composite extracellular potential from perhaps hundreds or thousands of neurons around the electrode tip. In general, LFPs are less sensitive to relative movement of recording electrodes and tissues; therefore, LFP recordings can be maintained for longer periods of time than single cell recordings (Andersen et al. (2004b)). However, LFPs have not been widely used in BMIs, perhaps because of the assumption that they do not correlate with movements or movement intentions as well as single cell activity. Recent experiments in monkey PPC, in particular the lateral intraparietal (LIP) area and PRR, have demonstrated that valuable information related to the animal's intentions can be uncovered from LFPs. For example, it has been shown that the direction of planned saccades in macaques can be decoded based on LFPs recorded from area LIP (Pesaran et al. (2002)). Moreover, the performances of decoders based on spike trains and LFPs were found to be comparable. Interestingly, the decoding of behavioral state (planning vs. execution of saccades) was more accurate with LFPs than with spike trains. Similar studies have been conducted in PRR. It was found that the decoding of the direction of planned reaches was only slightly inferior with LFPs than with spike trains (Scherberger et al. (2005)). As with LIP studies, it has also been shown that LFPs in this area provide better behavioral state (planning vs. execution of reaching) decoding than do spike trains.

While the decoding of a target position or a hand trajectory provides information on *where* to reach, the decoding of a behavioral state provides the information on *when* to reach. In current experiments, the time of reach is controlled with experimental protocol by supplying a "go signal." Practical neural prostheses cannot rely on external cues to initiate the movement; instead this information should be decoded from the brain, and future BMIs are likely to incorporate the behavioral state information. Therefore, it is expected that LFPs will play a more prominent role in the design of future neuroprosthetic devices.

11.3.3 Alternative Cognitive Control Signals

The potential benefits of a cognitive-based approach to neural prosthesis were demonstrated first through offline analysis (Shenoy et al. (2003)) and subsequently through closed loop (online) experiments (Musallam et al. (2004)). Motivated by previous findings of reward prediction based on neural activity in various brain areas (Platt and Glimcher (1999); Schultz (2004)), Musallam et al. (2004) have demonstrated that similar cognitive variables can be inferred from the activity in the macaques' PRR. In particular, they have found significant differences in cell activity depending on whether a preferred or nonpreferred reward was expected at the end of a trial. The experiments included various preferred versus nonpreferred reward paradigms such as citrus juice versus water, large amount versus small amount of reward, and high probability versus low probability of reward. On each day, the animal learned to associate one cue with the expectation of preferred reward and another cue with nonpreferred reward. The cues were randomly interleaved on a trial-by-trial basis. This study demonstrated that the performance of brain-operated cursor control increases under preferred reward conditions, and that both the reach goals and the reward type can be simultaneously decoded in real time.

The ability to decode expected values from brain data is potentially useful for future BMIs. The information regarding subjects' preferences, motivation level, and mood could be easily communicated to others in a manner similar to expressing these variables using body language. It is also conceivable that other types of cognitive variables, such as the patient's emotional state, could be inferred by recording activity from appropriate brain areas.

11.3.4 Neurophysiologic Recording Advances

One of the major challenges in the development of practical BMIs is to acquire meaningful data from many recording channels over a long period of time. This task is especially challenging if the spike trains of single neurons are used, since typically only a fraction of the electrodes in an implanted electrode array will record signals from well-isolated individual cells (Andersen et al. (2004b)). It is also hard to maintain the activity of isolated units in the face of inherent tissue and/or array drifts. Reactive gliosis (Turner et al. (1999)) and inadequate biocompatibility of the electrode's surface material (Edell et al. (1992)) may also contribute to the loss of an implant's function over time.

Fixed-geometry implants, routinely used for chronic recordings in BMIs, are not well suited for addressing the above issues. Motivated by these shortcomings, part of our research effort has been directed toward the development of autonomously movable electrodes that are capable of finding and maintaining optimal recording positions. Based on recorded signals and a suitably defined signal quality metric, an algorithm has been developed that decides when and where to move the recording electrode (Nenadic and Burdick (2006)). It should be emphasized that the developed control algorithm and associated signal processing steps (Nenadic and Burdick (2005)) are fully unsupervised, that is, free of any human involvement, and as such are suitable for future BMIs. Successful applications of the autonomously movable electrode algorithm using a meso-scale electrode testbed have recently been reported in Cham et al. (2005) and Branchaud et al. (2005).

The successful implementation of autonomously movable electrodes in BMIs will be beneficial for several reasons. For example, electrodes can be moved to target specific neural populations that are likely to be missed during implantation surgery. Optimal recording quality could be maintained and the effects of cell migration can be compensated for by moving the electrodes. Finally, movable electrodes could break through encapsulation and seek out new neurons, which is likely to improve the longevity of recording.

Clearly, the integration of movable electrodes with BMIs hinges upon the development of appropriate micro-electro-mechanical systems (MEMS) technology. Research efforts to develop MEMS devices for movable electrodes are under way (Pang et al. (2005a,b)).

11.3.5 Novel Decoding Algorithms

In mathematical terms, the goal of decoding algorithms is to build a map between neural patterns and corresponding motor behavior or cognitive processes. Because of the randomness inherent in the neuro-motor systems, the appropriate model of this map is probabilistic. In practical terms, decoding for cognitive-based BMIs entails the selection of the intended reach target from a discrete set of possible targets. Consequently, the decoder is designed as a classifier, where observed neural data is used for classifier training.

Recent advances in electrophysiologic recordings have enabled scientists to gather increasingly large volumes of data over relatively short time spans. While neural data ultimately is important for decoding, not all data samples carry useful information for the task at hand. Ideally, relevant data samples should be combined into meaningful features, while irrelevant data should be discarded as noise. For example, representing a finely sampled time segment of neural data with a (low-dimensional) vector of firing rates, can be viewed as an heuristic way of extracting features from the data. Another example is the use of the spectral power of EEG signals in various frequency bands, for example, μ-band or β-band (McFarland et al. (1997b); Pfurtscheller et al. (1997)), for neuroprosthetic applications such as BCIs.

In the next section, we cast the extraction of neural features within an information-theoretic framework and we show that this approach may be better suited for certain applications than the traditionally used heuristic features.

11.4 Feature Extraction

Feature extraction is a common tool in the analysis of multivariate statistical data. Typically, a low-dimensional representation of data is sought so that features have some desired properties. An obvious benefit of this dimensionality reduction is that data becomes computationally more manageable. More importantly, since the number of experimental trials is typically much smaller than the dimension of data (so-called small-sample-size problem (Fukunaga (1990))), the statistical parameters of data can be estimated more accurately using the low-dimensional representation.

Two major applications of feature extraction are representation and classification. Feature extraction for representation aims at finding a low-dimensional approximation of data, subject to certain criteria. These criteria assume that data are sampled from a common probability distribution, and so these methods are often referred to as blind or unsupervised. Principal component analysis (PCA) (Jolliffe (1986)) and independent component analysis (ICA) (Jutten and Herault (1991)) are the best-known representatives of these techniques. In feature extraction for classification, on the other hand, each data point's class membership is known, and thus the method is considered supervised. Low-dimensional features are found that maximally preserve class differences measured by suitably defined criteria. Linear discriminant analysis (LDA) (Duda et al. (2001)) is the best known representative of these techniques. Once the features are extracted, a classifier of choice can be designed in the feature domain.[1]

A common heuristic approach to feature extraction is to rank individual (scalar) features according to some class separability criterion. For example, informative neural features are those that exhibit stimulus-related tuning, that is, they take significantly different values when conditioned upon different stimuli. The feature vector is then constructed by concatenating the several most informative features. While seemingly reasonable, this strategy is completely ignorant of the joint statistical properties of the features and may produce highly suboptimal feature vectors. More elaborate algorithms exist for the selection of scalar features (Kittler (1978)), but they are combinatorially complex (Cover and Campenhout (1977)) and their practical applicability is limited.

Another popular strategy for analyzing spatiotemporal neural signals is to separate the processing in the spatial and temporal domain. Data are first processed spatially, typically by applying off-the-shelf tools such as the Laplacian filter (McFarland et al. (1997b); Wolpaw and McFarland (2004)), followed by temporal processing, such as autoregressive frequency analysis (Wolpaw and McFarland (2004); Pfurtscheller et al. (1997)). However, the assumption of space-time separability is not justified and may be responsible for suboptimal performance. In addition, while spectral power features have clear physical interpretation, there is no reason to assume that they are optimal features for decoding. Rizzuto et al. (2005) have recently demonstrated that decoding accuracy with spectral power features could be up to 20 percent lower than a straightforward time domain decoding.

In the next two subsections, we introduce a novel information-theoretic criterion for feature extraction conveniently called "information-theoretic discriminant analysis" (ITDA). We show that informative features can be extracted from data in a linear fashion, that is, through a matrix manipulation.[2] For spatiotemporal signals, the feature extraction matrix plays the role of a spatiotemporal filter and does not require an assumption about the separability of time and space. Moreover, the features are extracted using their joint statistical properties, thereby avoiding heuristic feature selection strategies and computationally expensive search algorithms.

11.4.1 Linear Supervised Feature Extraction

In general, linear feature extraction is a two-step procedure: (1) an objective function is defined and (2) a full-rank feature extraction matrix is found that maximizes such an objective. More formally, let $\mathsf{R} \in \mathbb{R}^n$ be a random data vector with the class-conditional probability density function (PDF) $f_{\mathsf{R}|\Omega}(\boldsymbol{r} \,|\, \omega_i)$, where the class random variable (RV) $\Omega = \{\omega_1, \omega_2, \cdots, \omega_c\}$ is drawn from a discrete distribution with the probability $P(\omega_i) \triangleq P(\Omega = \omega_i)$, $\forall i = 1, 2, \cdots, c$. For example, R could be a matrix of EEG data from an array of electrodes sampled in time and written in a vector form. The class variable could be the location of a visual target, or some cognitive task such as imagination of left and right hand movements (Pfurtscheller et al. (1997)). The features $\mathsf{F} \in \mathbb{R}^m$ are extracted as

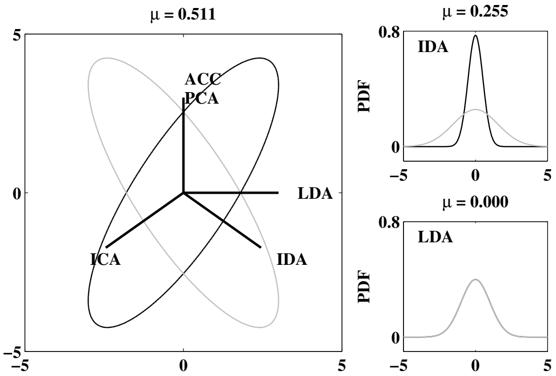

Figure 11.1 (Left) Two Gaussian class-conditional PDFs with $P(\omega_1) = P(\omega_2)$, represented by 3-Mahalanobis distance contours. The straight lines indicate optimal 1D subspace according to different feature extraction methods: PCA, ICA, LDA, ITDA and approximate Chernoff criterion (Loog and Duin (2004)) ACC. (Right) The PDFs of optimal 1D features extracted with ITDA and LDA.

$\mathsf{F} = \boldsymbol{T}\,\mathsf{R}$, where $\boldsymbol{T} \in \mathbb{R}^{m \times n}$ is a full-rank feature extraction matrix found by maximizing a suitably chosen class separability objective function $J(\boldsymbol{T})$.

Many objective functions have been used for supervised feature extraction purposes. In its most common form, LDA, also known as the Fisher criterion (Fisher (1936)) or canonical variate analysis, maximizes the generalized Rayleigh quotient (Duda et al. (2001)). Under fairly restrictive assumptions, it can be shown that LDA is an optimal[3] feature extraction method. In practice, however, these assumptions are known to be violated, and so the method suffers from suboptimal performance. A simple example where LDA fails completely is illustrated in figure 11.1. Another deficiency of LDA is that the dimension of the extracted subspace is at most $c - 1$, where c is the number of classes. This constraint may severely limit the practical applicability of LDA features, especially when the number of classes is relatively small.

Kumar and Andreou (1998) have developed a maximum-likelihood feature extraction method and showed that these features are better suited for speech recognition than the classical LDA features. Saon and Padmanabhan (2000) used both Kullback-Leibler (KL) and Bhattacharyya distance as an objective function. However, both of these metrics are defined pairwise, and their extension to multicategory cases is often heuristic. Loog and Duin (2004) have developed an approximation of the Chernoff distance, although their method seems to fail in some cases (see figure 11.1).

Mutual information is a natural measure of class separability. For a continuous RV R and a discrete RV Ω, the mutual information, denoted by $\mu I(\mathsf{R};\Omega)$, is defined as

$$\mu I(\mathsf{R};\Omega) \triangleq H(\mathsf{R}) - H(\mathsf{R}\,|\,\Omega) = H(\mathsf{R}) - \sum_{i=1}^{c} H(\mathsf{R}\,|\,\omega_i)\,P(\omega_i) \tag{11.1}$$

where $H(\mathsf{R}) \triangleq -\int f_{\mathsf{R}}(\boldsymbol{r}) \log(f_{\mathsf{R}}(\boldsymbol{r}))\, d\boldsymbol{r}$ is Shannon's entropy. Generally, higher mutual information implies better class separability and smaller probability of misclassification. In particular, it was shown in Hellman and Raviv (1970) that $\varepsilon_{\mathsf{R}} \leq 1/2\ [H(\Omega) - \mu I(\mathsf{R};\Omega)]$, where $H(\Omega)$ is the entropy of Ω and ε_{R} is the Bayes error. On the other hand, the practical applicability of the mutual information is limited by its computational complexity, also known as the curse of dimensionality, which for multivariate data requires numerical integrations in high-dimensional spaces. Principe et al. (2000) explored the alternative definitions of entropy (Renyi (1961)), which, when coupled with Parzen window density estimation, led to a computationally feasible mutual information alternative that was applicable to multivariate data. Motivated by these findings, Torkkola developed an information-theoretic feature extraction algorithm (Torkkola (2003)), although his method is computationally demanding and seems to be limited by the curse of dimensionality. Next, we introduce a feature extraction objective function that is based on the mutual information, yet is easily computable.

11.4.2 Information-Theoretic Objective Function

Throughout the rest of the article we assume, that the class-conditional densities are Gaussian, that is, $\mathsf{R}\,|\,\omega_i \sim \mathcal{N}(\boldsymbol{m}_i, \boldsymbol{\Sigma}_i)$, with positive definite covariance matrices. The entropy of a Gaussian random variable is easily computed as

$$H(\mathsf{R}\,|\,\omega_i) = \frac{1}{2}\log((2\pi e)^n|\boldsymbol{\Sigma}_i|)$$

where $|\,\Sigma\,|$ denotes for the determinant of the matrix Σ. To complete the calculations required by (11.1), we need to evaluate the entropy of the mixture PDF $f_{\mathsf{R}}(\boldsymbol{r}) \triangleq \sum_i f_{\mathsf{R}|\Omega}(\boldsymbol{r}\,|\,\omega_i)P(\omega_i)$. It is easy to establish that $\mathsf{R} \sim (\boldsymbol{m}, \boldsymbol{\Sigma})$, where

$$\boldsymbol{m} = \sum_{i=1}^{c} \boldsymbol{m}_i P(\omega_i) \quad \text{and} \quad \boldsymbol{\Sigma} = \sum_{i=1}^{c}\left[\boldsymbol{\Sigma}_i + (\boldsymbol{m}_i - \boldsymbol{m})(\boldsymbol{m}_i - \boldsymbol{m})^{\mathrm{T}}\right] P(\omega_i). \tag{11.2}$$

Note that unless the class-conditional PDFs are completely overlapped, the RV R is non-Gaussian. However, we propose a metric similar to (11.1) by replacing $H(\mathsf{R})$ with the entropy of a Gaussian RV with the same covariance matrix $\boldsymbol{\Sigma}$:

$$\mu(\mathsf{R};\Omega) \triangleq H_g(\mathsf{R}) - \sum_{i=1}^{c} H(\mathsf{R}\,|\,\omega_i)P(\omega_i) = \frac{1}{2}\left[\log(|\boldsymbol{\Sigma}|) - \sum_{i=1}^{c}\log(|\boldsymbol{\Sigma}_i|)P(\omega_i)\right] \tag{11.3}$$

where $H_g(\mathsf{R})$ is the Gaussian entropy. Throughout the rest of the article, we refer to this metric as a μ-metric.

We will explain briefly why the μ-metric is a valid class separability objective. For a thorough mathematical exposition, the reader is referred to Nenadic (2006). If the class-conditional PDFs are fully overlapped, that is, $\boldsymbol{m}_1 = \cdots = \boldsymbol{m}_c$ and $\boldsymbol{\Sigma}_1 = \cdots = \boldsymbol{\Sigma}_c$, it follows from (11.2) and (11.3) that $\mu(\mathsf{R};\Omega) = 0$. Also note that in this case $\mathsf{R} \sim \mathcal{N}(\boldsymbol{m}, \boldsymbol{\Sigma})$, thus $\mu(\mathsf{R};\Omega) = \mu I(\mathsf{R};\Omega)$. On the other hand, if the class-conditional PDFs are different, R deviates from the Gaussian RV, so the μ-metric $\mu(\mathsf{R};\Omega)$ can be viewed as a biased version of $\mu I(\mathsf{R};\Omega)$, where $\mu(\mathsf{R};\Omega) \geq \mu I(\mathsf{R};\Omega) \geq 0$ because for a fixed covariance matrix, Gaussian distribution maximizes the entropy $[H_g(\mathsf{R}) \geq H(\mathsf{R})]$. As the classes are more separated, the deviation of R from a Gaussian RV increases, and the μ-metric gets bigger. It turns out that this bias is precisely the negentropy defined as $\bar{H}(\mathsf{R}) \triangleq H_g(\mathsf{R}) - H(\mathsf{R})$, which has been used as an objective function for ICA applications (see Hyvärinen (1999) for survey). Therefore, ITDA can be viewed as a supervised version of ICA. Figure 11.1 confirms that ICA produces essentially the same result as our method (note the symmetry of the example), although the two methods are fundamentally different (unsupervised vs. supervised). Figure 11.1 also shows the μ-metric in the original space and subspaces extracted by ITDA and LDA.

The μ-metric has some interesting properties, many of which are reminiscent of the Bayes error ε_{R} and the mutual information (11.1). We give a brief overview of these properties next. For a detailed discussion, refer to Nenadic (2006). First, if the class-conditional covariances are equal, the μ-metric takes the form of the generalized Rayleigh quotient; therefore, under these so-called homoscedastic conditions, ITDA reduces to the classical LDA method. Second, for a two-class case with overlapping class-conditional means and equal class probabilities (e.g., figure 11.1), the μ-metric reduces to the well known Bhattacharyya distance. Like many other discriminant metrics, the μ-metric is independent of the choice of a coordinate system for data representation. Moreover, the search for the full-rank feature extraction matrix $\boldsymbol{T}$ can be restricted to the subspace of orthonormal projection matrices without compromising the objective function. Finally, the μ-metric of any subspace of the original data space is bounded above by the μ-metric of the original space. These properties guarantee that the following optimization problem is well posed. Given the response samples $\mathsf{R} \in \mathbb{R}^n$ and the dimension of the feature space m, we find an orthonormal matrix $\boldsymbol{T} \in \mathbb{R}^{m \times n}$ such that the μ–metric $\mu(\mathsf{F};\Omega)$ is maximized

$$\boldsymbol{T}^* = \arg \max_{\boldsymbol{T} \in \mathbb{R}^{m \times n}} \{\mu(\mathsf{F};\Omega) \, : \, \mathsf{F} = \boldsymbol{T}\mathsf{R}\} \quad \text{subject to} \quad \boldsymbol{T}\boldsymbol{T}^{\mathrm{T}} = \boldsymbol{I}. \tag{11.4}$$

Based on our discussion in section 11.4.2, it follows that such a transformation would find an m-dimensional subspace, where the class separability is maximal. Interestingly, both the gradient $\partial\mu(\mathsf{F};\Omega)/\partial\boldsymbol{T}$ and the Hessian $\partial^2\mu(\mathsf{F};\Omega)/\partial\boldsymbol{T}^2$ can be found analytically (Nenadic (2006)), so the problem (11.4) is amenable to Newton's optimization method.

11.5 Experimental Results

In this section, we compare the performances of LDA and ITDA on a dataset adopted from Rizzuto et al. (2005). The data represents intracranial encephalographic (iEEG) recordings from the human brain during a standard memory reach task (see figure 11.2). It should be noted that iEEG signals are essentially local field potentials (see section 11.3.2). At the start of each trial, a fixation stimulus is presented in the middle of a touchscreen and the participant initiates the trial by placing his right hand on the stimulus. After a short fixation period, a target is flashed on the screen, followed by a memory period. After the memory period, the fixation stimulus is extinguished, which signals the participant to reach to the

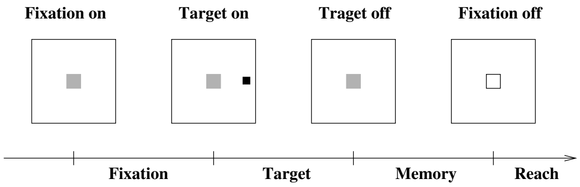

Figure 11.2 The timeline of experimental protocol.

memorized location (formerly indicated by the target). The duration of fixation, target, and memory periods varied uniformly between 1 and 1.3 s. The subject had 8 electrodes implanted into each of the following target brain areas: orbital frontal cortex (OF), amygdala (A), hippocampus (H), anterior cingulate cortex (AC), supplementary motor cortex (SM), and parietal cortex (P). The total number of electrodes in both hemispheres was 96. The targets were presented at 6 different locations: 0^o, 60^o, 120^o, 180^o, 240^o, 300^o; these locations respectively correspond to right, top right, top left, left, bottom left, and bottom right position with respect to the fixation stimulus. The number of trials per stimulus varied between 69 and 82, yielding a total of 438 trials. The electrode signals were amplified, sampled at 200 Hz and bandpass filtered. Only a few electrodes over a few brain areas showed stimulus-related tuning according to the location of the target. The goal of our analysis is to decode the target location and the behavioral state based on the brain data. Such a method could be used to decode a person's motor intentions in real time, supporting neuroprosthetic applications. All decoding results are based on a linear, quadratic, and support vector machine (SVM) classifier (Collobert and Bengio (2001)) with a Gaussian kernel.

11.5.1 Decoding the Target Position

To decode the target position, we focused on a subset of data involving only two target positions: left and right. While it is possible to decode all six target positions, the results are rather poor, partly because certain directions were consistently confused. The decoding was performed during the target, memory and reach periods (see figure 11.2). All decoding results are based on selected subsegments of data within 1 s of the stimulus that marks the beginning of the period. figure. 11.3 shows that only a couple of electrodes in both left and right parietal cortex exhibit directional tuning, mostly around 200 ms after the onset of the target stimulus. In addition, there is some tuning in the SM and OF regions. Similar plots (not shown) are used for the decoding during memory and reach periods.

For smoothing purposes and to further reduce the dimensionality of the problem, the electrode signals were binned using a 30 to 70 ms window. The performance (% error) of the classifier in the feature domain was evaluated through a leave-one-out cross-validation; the results are summarized in table 11.1. Note that the chance error is 50 percent for this particular task. For a given classifier, the performance of the better feature extraction method is shown in boldface, and the asterisk denotes the best performance per classification task. Except for a few cases (mostly with the quadratic classifier), the performance of the ITDA method is superior to that of LDA, regardless of the choice of classifier. More

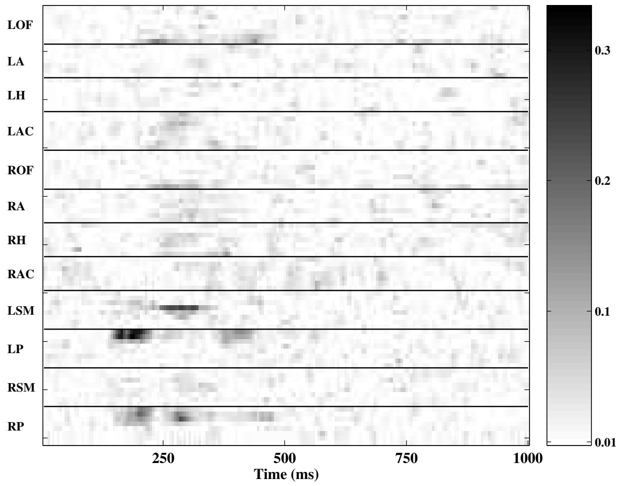

Figure 11.3 The distribution of the μ-metric over individual electrodes during the target period. The results are for two-class recognition task, and are based on 162 trials (82 left and 80 right). Different brain areas are: orbital frontal (OF), amygdala (A), hippocampus (H), anterior cingulate (AC), supplementary motor (SM), and parietal (P), with the prefixes L and R denoting the left and right hemisphere.

importantly, ITDA provides the lowest error rates in all but one case (target, SM), where the two methods are tied for the best performance. We note that all the error rates are significantly smaller ($p < 0.001$) than the chance error, including those during the memory period, which was not demonstrated previously (Rizzuto et al. (2005)). Also note that, in general, the SVM classifier is better combined with both ITDA and LDA features than are the linear and quadratic classifiers.

11.5.2 Decoding the Behavioral State

As discussed in section 11.3.2, for fully autonomous neuroprosthetic applications it is not only important to know *where* to reach, but also *when* to reach. Therefore, the goal is to decode what experimental state (fixation, target, memory, reach) the subject is experiencing, based on the brain data. To this end, we pooled the data for all six directions, with 438 trials per state, for a total of 1,752 trials. As with the target decoding, all the decoding results are based on selected subsegments of data within 1 s of the stimulus that marks the beginning of the period. Figure 11.4 shows that only a subset of electrodes exhibits state tuning (mostly the electrodes in the SM area during the second part of the trial state period). In addition, there is some tuning in the AC, H, and P areas. The data were further smoothed by applying a 40 to 50 ms window. The performance (% error) of the classifier in the feature space was evaluated through a stratified twenty-fold cross-validation (Kohavi (1995)), and the results are summarized in table 11.2.

Table 11.1 The average decoding errors and their standard deviations during the target, memory and reach periods. The columns represent the brain area, the number of electrodes N_e, the period (ms) used for decoding, the bin size (ms), the size of the data space (n), the type of the classifier (L-linear, Q-quadratic, S-SVM). The size of the optimal subspace (m) is given in the parentheses. Note that LDA is constrained to $m = 1$.

Period	Area	N_e	Time	Bin	n	Class.	LDA		(m)	ITDA		(m)
target	OF	4	160–510	70	20	L	6.17	$\pm$ 0.24	(1)	$\mathbf{4.94}^*$	$\pm$ 0.22	(1)
						Q	**6.17**	$\pm$ 0.24	(1)	8.02	$\pm$ 0.27	(1)
						S	6.17	$\pm$ 0.25	(1)	$\mathbf{4.94}^*$	$\pm$ 0.22	(1)
	P	2	150–450	50	12	L	7.41	$\pm$ 0.26	(1)	$\mathbf{6.79}^*$	$\pm$ 0.25	(1)
						Q	8.02	$\pm$ 0.27	(1)	**7.41**	$\pm$ 0.26	(1)
						S	7.41	$\pm$ 0.26	(1)	$\mathbf{6.79}^*$	$\pm$ 0.25	(2)
	SM	2	100–450	70	10	L	14.20	$\pm$ 0.35	(1)	$\mathbf{13.58}^*$	$\pm$ 0.34	(3)
						Q	14.20	$\pm$ 0.35	(1)	$\mathbf{13.58}^*$	$\pm$ 0.34	(2)
						S	$\mathbf{13.58}^*$	$\pm$ 0.34	(1)	$\mathbf{13.58}^*$	$\pm$ 0.34	(3)
	SM,P	2	120–520	40	20	L	5.56	$\pm$ 0.23	(1)	$\mathbf{4.32}^*$	$\pm$ 0.20	(1)
						Q	**5.56**	$\pm$ 0.23	(1)	**5.56**	$\pm$ 0.23	(1)
						S	4.94	$\pm$ 0.22	(1)	$\mathbf{4.32}^*$	$\pm$ 0.20	(1)
memory	OF	3	240–330	30	6	L	29.63	$\pm$ 0.46	(1)	$\mathbf{28.40}^*$	$\pm$ 0.45	(1)
						Q	30.25	$\pm$ 0.46	(1)	$\mathbf{28.40}^*$	$\pm$ 0.45	(2)
						S	31.48	$\pm$ 0.47	(1)	**29.01**	$\pm$ 0.46	(1)
	P	4	610–730	30	16	L	33.95	$\pm$ 0.48	(1)	**32.72**	$\pm$ 0.47	(1)
						Q	**33.33**	$\pm$ 0.47	(1)	35.80	$\pm$ 0.48	(1)
						S	31.48	$\pm$ 0.47	(1)	$\mathbf{29.63}^*$	$\pm$ 0.46	(4)
	SM	2	250–370	30	8	L	29.63	$\pm$ 0.45	(1)	**29.01**	$\pm$ 0.46	(6)
						Q	29.63	$\pm$ 0.46	(1)	**25.93**	$\pm$ 0.44	(3)
						S	29.63	$\pm$ 0.46	(1)	$\mathbf{24.69}^*$	$\pm$ 0.43	(4)
	SM, P,A	3	620–680	30	6	L	28.40	$\pm$ 0.45	(1)	$\mathbf{26.54}^*$	$\pm$ 0.44	(1)
						Q	**27.16**	$\pm$ 0.45	(1)	28.40	$\pm$ 0.45	(1)
						S	27.16	$\pm$ 0.45	(1)	$\mathbf{26.54}^*$	$\pm$ 0.44	(1)
reach	OF	2	270–420	50	6	L	10.49	$\pm$ 0.31	(1)	**9.26**	$\pm$ 0.29	(1)
						Q	10.49	$\pm$ 0.31	(1)	**9.88**	$\pm$ 0.30	(1)
						S	9.88	$\pm$ 0.30	(1)	$\mathbf{8.64}^*$	$\pm$ 0.28	(1)
	OF	4	250–550	50	24	L	6.79	$\pm$ 0.25	(1)	**6.17**	$\pm$ 0.24	(1)
						Q	**6.79**	$\pm$ 0.25	(1)	**6.79**	$\pm$ 0.25	(1)
						S	6.17	$\pm$ 0.24	(1)	$\mathbf{4.94}^*$	$\pm$ 0.22	(22)

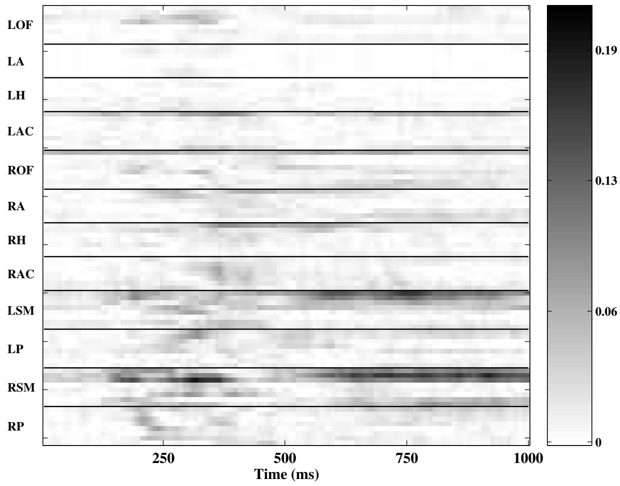

Figure 11.4 The distribution of the μ-metric over individual electrodes. The results are for four-class recognition task based on 1,752 trials (438 trials per state).

Table 11.2 The average behavioral state decoding errors and their standard deviations with pooled data (6 directions, 4 trial states). Note that LDA is constrained to $m \leq 3$.

Area	N_e	Time	Bin	n	Class.	LDA		(m)	ITDA		(m)
SM	4	500–1000	50	40	L	24.70	±0.04	(3)	**24.17**	±0.04	(4)
					Q	24.82	±0.04	(3)	**24.58**	±0.04	(5)
					S	24.76	±0.04	(3)	$\mathbf{23.99}^*$	±0.04	(4)
SM	3	120–400	40	21	L	35.36	±0.06	(3)	**35.06**	±0.05	(9)
					Q	36.25	±0.05	(3)	$\mathbf{31.31}^*$	±0.05	(12)
					S	35.42	±0.06	(3)	**31.43**	±0.06	(14)
SM, AC,H	4	250–500	50	20	L	29.23	±0.06	(3)	**28.75**	±0.06	(3)
					Q	28.99	±0.06	(3)	$\mathbf{27.74}^*$	±0.06	(5)
					S	28.93	±0.06	(3)	$\mathbf{27.74}^*$	±0.06	(5)
P	4	200–350	50	12	L	48.69	±0.06	(3)	**47.86**	±0.05	(10)
					Q	**48.99**	±0.07	(3)	50.89	±0.05	(10)
					S	49.70	±0.05	(3)	$\mathbf{47.68}^*$	±0.04	(10)

Note that the chance error is 75 percent for this particular task. Except for one case, the classification accuracy with ITDA features is superior to LDA features, regardless of the classifier choice. Additionally, the best single performance always is achieved with the ITDA method. Note that the best decoding results are obtained from the SM area in the interval [500–1000] ms. Interestingly, we were able to decode the trial states from the parietal area, although the accuracy was considerably lower (just above 50 percent).

11.5.3 Discussion

Based on the analyzed data, we conclude that the classification with ITDA features is more accurate than the classification with LDA features, with an improvement as high as 5 percent. In rare cases where LDA provides better performance, the quadratic classifier was used. This could mean that LDA features fit the quadratic classifier assumptions (Gaussian classes, different covariance matrices) better than do ITDA features. Nevertheless, ITDA features are in general better coupled to the quadratic classifier than are LDA features. The advantages are even more apparent when ITDA is used in conjunction with the linear and SVM classifier. Similar behavior was observed when ITDA was tested on a variety of data sets from the UCI machine learning repository (Hettich et al. (1998)). Details can be found in Nenadic (2006).

In all cases, the best performance is achieved in a subspace of considerably lower dimension than the dimension of the original data space, n. Therefore, not only is the classification easier to implement in the feature space, but the overall classification accuracy is improved. While theoretical analysis shows that dimensionality reduction cannot improve classification accuracy (Duda et al. (2001)), the exact opposite effect is often seen in dealing with finitely sampled data.

Like many other second-order techniques, for example, LDA or ACC, ITDA assumes that the class-conditional data distribution is Gaussian. Although this assumption is likely to be violated in practice, it seems that the ITDA method performs reasonably well. For example, the performance in the original space with the SVM classifier is Gaussian-assumption free, yet it is inferior to the SVM classifier performance in the ITDA feature space. Likewise, it was found in Nenadic (2006) that unless data is coarsely discretized and the Gaussian assumption is severely violated, the performance of ITDA does not critically depend on the Gaussian assumption.

11.6 Summary

We have reviewed recent advances in cognitive-based neural prosthesis. The major differences between the cognitive-based and the more common motor-based approach to BMIs have been discussed. To maximize information encoded by neurons, better understanding of multiple brain areas and the types of signals the brain uses are needed. Part of our research effort is to identify sources of information potentially useful for neuroprosthetic applications. Other research efforts are focused on technological issues such as the stability of recording, the development of unsupervised signal analysis tools, or the design of complex decoding algorithms.

The decoding of neural signals in cognitive-based BMIs reduces to the problem of classification. High-dimensional neural data typically contains relatively low-dimensional useful signals (features) embedded in noise. To meet computational constraints associated with BMIs, it may be beneficial to implement the classifier in the feature domain. We have applied a novel information-theoretic method to uncover useful low-dimensional features in neural data. We have demonstrated that this problem can be posed within an optimization framework, thereby avoiding unjustified assumptions and heuristic feature selection strategies. Experimental results using iEEG signals from the human brain show that our method may be better suited for certain applications than are the traditional feature extraction tools. The study also demonstrates that iEEG signals may be a valuable alternative to spike trains commonly used in neuroprosthetic research.

Notes

E-mail for correspondence: znenadic@uci.edu

(1) Consistent with engineering literature (Fukunaga (1990)), we consider the feature extraction as a preprocessing step for classification. Some authors, especially those using artificial neural networks, consider feature extraction an integral part of classification.

(2) Recently, a couple of nonlinear feature extraction methods have been proposed (Roweis and Saul (2000); Tenenbaum et al. (2000)) where features reside on a low-dimensional manifold embedded in the original data space. However, linear feature extraction methods continue to play an important role in many applications, primarily due to their computational effectiveness.

(3) Optimality is in the sense of Bayes.

References

Altschuller, E. L., A. Vankov, E. M. Hubbard, E. Roberts, V. S. Ramachandran, and J. A. Pineda. 2000. Mu wave blocking by observation of movement and its possible use as a tool to study theory of other minds. *Society of Neuroscience Abstracts* 26(68).

Andersen, R. A., J. W. Burdick, S. Musallam, B. Pesaran, and J. G. Cham. 2004a. Cognitive neural prosthetics. *Trends in Cognitive Sciences* 8(11):486–493.

Andersen, R. A., J. W. Burdick, S. Musallam, H. Scherberger, B. Pesaran, D. Meeker, B. D. Corneil, I. Fineman, Z. Nenadic, E. Branchaud, J. G. Cham, B. Greger, Y. C. Tai, and M. M. Mojarradi. 2004b. Recording advances for neural prosthetics. In *Proceedings of the 26th International Conference of the Engineering in Medicine and Biology Society* vol. 7: 5352–5355. IEEE.

Andersen, R. A., L. H. Snyder, D. C. Bradley, and J. Xing. 1997. Multimodal representation of space in the posterior parietal cortex and its use in planning movements. *Annual Review of Neuroscience* 20(303–330):591–596.

Anderson, C. 2005. Taxonomy of feature extraction and translation methods for bci (Web page). http://www.cs.colostate.edu/eeg/taxonomy.html.

Anderson, C. W. 1997. Effects of variations in neural network topology and output averaging on the discrimination of mental tasks from spontaneous EEG. *Journal of Intelligent Systems* 7:165–190.

Anderson, C. W. and M. J. Kirby. 2003. EEG subspace representations and feature selection for brain-computer interfaces. In *Proceedings of the 1st IEEE Workshop on Computer Vision and Pattern Recognition for Human Computer Interaction (CVPRHCI)*, Madison, Wis.

Anderson, C. W., J. N. Knight, T. O'Connor, M. J. Kirby, and A. Sokolov. 2006. Geometric subspace methods and time-delay embedding for EEG artifact removal and classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2): 142–146.

Annett, J. 1995. Motor imagery: perception or action? *Neuropsychologia* 33(11):1395–1417.

Arkin, R. C. 1998. Behavior-based robotics. MIT Press.

Ashe, J. 1997. Force and the motor cortex. *Behavioural Brain Research* 87(2):255–269.

Babiloni, C., A. Brancucci, L. Arendt-Nielsen, F. Babiloni, P. Capotosto, F. Carducci, F. Cincotti, L. Romano, A. C. Chen, and P. M. Rossini. 2004. Alpha event-related desynchronization preceding a go/no-go task: a high-resolution eeg study. *Neuropsychology* 18(4):719–728.

Babiloni, C., F. Carducci, F. Cincotti, P. M. Rossini, C. Neuper, G. Pfurtscheller, and F. Babiloni. 1999. Human movement-related potentials vs. desynchronization of EEG alpha rhythm: a high-resolution EEG study. *NeuroImage* 10(6):658–665.

Babiloni, F., F. Cincotti, L. Bianchi, G. Pirri, J. d. R. Millán, J. Mouriño, S. Salinari, and M. G. Marciani. 2001. Recognition of imagined hand movements with low resolution surface Laplacian and linear classifiers. *Medical Engineering & Physics* 23(5):323–328.

Babiloni, F., F. Cincotti, L. Lazzarini, J. d. R. Millán, J. Mouriño, M. Varsta, J. Heikkonen, L. Bianchi, and M. G. Marciani. 2000. Linear classification of low-resolution EEG patterns produced by imagined hand movements. *IEEE Transactions on Rehabilitation Engineering* 8:186–188.

Baillet, S., J. C. Mosher, and R. M. Leahy. 2001. Electromagnetic brain mapping. *IEEE Signal Processing Magazine* 18(6):14–30.

Balbale, U. H., J. E. Huggins, S. L. BeMent, and S. P. Levine. 1999. Multi-channel analysis of human event-related cortical potentials for the development of a direct brain interface. In *Proceedings of the First Joint BMES/EMBS Conference. IEEE Engineering in Medicine and Biology* vol. 1.

Barnett, V. and T. Lewis. 1994. Outliers in statistical data. New York: Wiley, 3rd edition.

Bashashati, A., R. K. Ward, and G. E. Birch. 2005. A new design of the asynchronous brain computer interface using the knowledge of the path of features. In *2nd International IEEE-EMBS Conference on Neural Engineering*. IEEE-EMBS.

Batista, A. P., C. A. Buneo, L. H. Snyder, and R. A. Andersen. 1999. Reach plans in eye-centered coordinates. *Science* 285(5425):257–260.

Bauer, G., F. Gerstenbrand, and E. Rumpl. 1979. Varieties of the locked-in syndrome. *Journal of Neurology* 221(2):77–91.

Bayliss, J. D. 2003. Use of the evoked potential P3 component for control in a virtual apartment. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11 (2):113–116.

Bayliss, J. D. and D. H. Ballard. 2000. A virtual reality testbed for brain-computer interface research. *IEEE Transactions on Rehabilitation Engineering* 8(2):188–190.

Bayliss, J. D., S. A. Inverso, and A. Tentler. 2004. Changing the P300 brain computer interface. *Cyberpsychology & Behavior: The Impact of the Internet, Multimedia and Virtual Reality on Behavior and Society* 7(6):694–704.

BCI Competition III. 2005. Available from http://ida.first.fhg.de/projects/bci/competition_iii/results/.

BCI Competition III. 2005a. Data set IIIa of the BCI competition. Available from http://ida.first.fhg.de/projects/bci/competition_iii/results/#graz1.

BCI Competition III. 2005b. Data set IIIb of the BCI competition. Available from http://ida.first.fhg.de/projects/bci/competition_iii/results/#graz2.

Beck, D. M. and N. Lavie. 2005. Look here but ignore what you see: Effects of distractors at fixation. *Journal of Experimental Psychology: Human Perception and Performance* 31(3):592–607.

Bell, A. J. and T. J. Sejnowski. 1995. An information-maximization approach to blind separation and blind deconvolution. *Neural Computation* 7(6):1129–1159.

Belouchrani, A., K. A. Meraim, J.-F. Cardoso, and E. Moulines. 1997. A blind source separation technique based on second order statistics. *IEEE Transactions on Signal Processing* 45(2):434–444.

Benabid, A. L., P. Pollak, C. Gervason, D. Hoffmann, D. M. Gao, M. Hommel, J. E. Perret, and J. de Rougemont. 1991. Long-term suppression of tremor by chronic stimulation of the ventral intermediate thalamic nucleus. *Lancet* 337(8738):403–406.

Bennett, K. P. and O. L. Mangasarian. 1992. Robust linear programming discrimination of two linearly inseparable sets. *Optimization Methods and Software* 1:23–34.

Berger, T. W. and D. L. Glanzman, editors. 2005. Toward replacement parts for the brain: Implantable biomimetic electronics as neural prostheses. Cambridge, Mass.: MIT Press.

Birbaumer, N. 2005. Nur das Denken bleibt. Neuroethik des Eingeschlossen-Seins. In *Neurowissenschaften und Menschenbild*, edited by E. Engels and E. Hildt. Paderborn: Mentis-Verlag.

Birbaumer, N. 2006a. Breaking the silence: brain-computer interfaces (BCI) for communication and motor control. *Psychophysiology* 43(6):517–532.

Birbaumer, N. 2006b. Brain-computer-interface research: coming of age. *Clinical Neurophysiology* 117(3):479–483.

Birbaumer, N. and L. Cohen. 2005. A brain-computer-interface (BCI) for chronic stroke. In *35th Annual Meeting of the Society for Neuroscience*, Washington, DC.

Birbaumer, N., T. Elbert, A. G. Canavan, and B. Rockstroh. 1990. Slow potentials of the cerebral cortex and behavior. *Physiological Review* 70(1):1–41.

Birbaumer, N., N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kübler, J. Perelmouter, E. Taub, and H. Flor. 1999. A spelling device for the paralysed. *Nature* 398:297–298.

Birbaumer, N., T. Hinterberger, A. Kübler, and N. Neumann. 2003. The thought translation device (TTD): neurobehavioral mechanisms and clinical outcome. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):120–123.

Birbaumer, N., A. Kübler, N. Ghanayim, T. Hinterberger, J. Perelmouter, J. Kaiser, I. Iversen, B. Kotchoubey, N. Neumann, and H. Flor. 2000. The thought translation device (TTD) for completly paralyzed patients. *IEEE Transactions on Rehabilitation Engineering* 8(2):190–193.

Birbaumer, N. and R. F. Schmid. 2006. Biologische psychologie, chapter Methoden der Biologischen Psychologie, 483–511. Berlin: Springer, 6 edition.

Birbaumer, N., R. Veit, M. Lotze, M. Erb, C. Hermann, W. Grodd, and H. Flor. 2005. Deficient fear conditioning in psychopathy: a functional magnetic resonance imaging study. *Archives of General Psychiatry* 62(7):799–805.

Birch, G. E., Z. Bozorgzadeh, and S. G. Mason. 2002. Initial on-line evaluations of the LF-ASD brain-computer interface with able-bodied and spinal-cord subjects using imagined voluntary motor potentials. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 10(4):219–224.

Birch, G. E., P. D. Lawrence, and R. D. Hare. 1993. Single-trial processing of event-related potentials using outlier information. *IEEE Transactions on Biomedical Engineering* 40 (1):59–73.

Birch, G. E., S. G. Mason, and J. F. Borisoff. 2003. Current trends in brain-computer interface research at the Neil Squire Foundation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):123–126.

Birch, G. E., J. R. Watzke, and C. Bolduc. 1995. Research and development of adaptive equipment for persons with significant disabilities and the elderly; activities conducted by the Neil Squire Foundation. *Technology and Disability* 4:169–173.

Bishop, C. M. 1995. Neural networks for pattern recognition. Oxford, UK: Clarendon Press.

Blanchard, G. and B. Blankertz. 2004. BCI competition 2003 – data set IIa: Spatial patterns of self-controlled brain rhythm modulations. *IEEE Transactions on Biomedical Engineering* 51(6):1062–1066.

Blanchard, G., M. Sugiyama, M. Kawanabe, V. Spokoiny, and K.-R. Müller. 2006. In search of non-Gaussian components of a high-dimensional distribution. *Journal of Machine Learning Research* 7:247–282.

Blankertz, B. 2003. BCI Competition 2003 results (Web page). http://ida.first.fhg.de/projects/bci/competition_ii/results/.

Blankertz, B. 2005a. BCI Competition III results (Web page). http://ida.first.fhg.de/projects/bci/competition_iii/results/.

Blankertz, B. 2005b. BCI Competitions. Web page. http://ida.first.fhg.de/projects/bci/competitions/.

Blankertz, B., G. Curio, and K.-R. Müller. 2002. Classifying single trial EEG: towards brain computer interfacing. In *Advances in Neural Information Processing Systems (NIPS 01)*, edited by T. G. Diettrich, S. Becker, and Z. Ghahramani vol. 14: 157–164, Cambridge, Mass. The MIT Press.

Blankertz, B., G. Dornhege, M. Krauledat, K.-R. Müller, and G. Curio. 2005. The Berlin Brain-Computer Interface: report from the feedback sessions. Technical Report 1, Fraunhofer FIRST.

Blankertz, B., G. Dornhege, M. Krauledat, K.-R. Müller, V. Kunzmann, F. Losch, and G. Curio. 2006a. The Berlin Brain-Computer Interface: EEG-based communication without subject training. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):147–152.

Blankertz, B., G. Dornhege, S. Lemm, M. Krauledat, G. Curio, and K.-R. Müller. 2006b. The Berlin Brain-Computer Interface: Machine learning based detection of user specific brain states. *Journal of Universal Computer Science* 12(6):581–607.

Blankertz, B., G. Dornhege, C. Schäfer, R. Krepki, J. Kohlmorgen, K.-R. Müller, V. Kunzmann, F. Losch, and G. Curio. 2003. Boosting bit rates and error detection for the classification of fast-paced motor commands based on single-trial EEG analysis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):127–131.

Blankertz, B., K. R. Müller, G. Curio, T. M. Vaughan, G. Schalk, J. R. Wolpaw, A. Schlögl, C. Neuper, G. Pfurtscheller, T. Hinterberger, M. Schröder, and N. Birbaumer. 2004. The BCI Competition 2003: progress and perspectives in detection and discrimination of EEG single trials. *IEEE Transactions on Biomedical Engineering* 51(6):1044–1051.

Blankertz, B., K. R. Müller, D. Krusienski, J. R. Wolpaw, A. Schlögl, G. Pfurtscheller, J. d. R. Millán, M. Schröder, and N. Birbaumer. 2006c. The BCI competition III: Validating alternative approaches to actual BCI problems. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):153–159.

Blatt, G. J., R. A. Andersen, and G. R. Stoner. 1990. Visual receptive-field organization and cortico-cortical connections of the lateral intraparietal area (area LIP) in the macaque. *The Journal of Comparative Neurology* 299(4):421–445.

Bock, O., S. Schneider, and J. Bloomberg. 2001. Conditions for interference versus facilitation during sequential sensorimotor adaptation. *Experimental Brain Research* 138(3):359–365.

Borisoff, J. F., S. G. Mason, A. Bashashati, and G. E. Birch. 2004. Brain-computer interface design for asynchronous control applications: improvements to the LF-ASD asynchronous brain switch. *IEEE Transactions on Biomedical Engineering* 51(6):985–992.

Bortz, H. and G. A. Lienert. 1998. Kurzgefasste statistik für die klassische forschung, chapter 6: Übereinstimmungsmaße für subjektive Merkmalsurteile, 265–270. Berlin Heidelberg: Springer.

Boser, B. E., I. M. Guyon, and V. N. Vapnik. 1992. A training algorithm for optimal margin classifiers. In *Proceedings of the 5th Annual ACM Workshop on Computational Learning Theory*, edited by D. Haussler: 144–152.

Brain-Computer Interface Technology: Theory and Practice—First International Meeting Program and Papers. 1999. Wadsworth Center Brain-Computer Interface Project.

Brain-Computer Interface Technology: Third International Meeting. 2005. Rensselaerville, New York. June 14-19.

Branchaud, E., J. G. Cham, Z. Nenadic, R. A. Andersen, and J. W. Burdick. 2005. A miniature robot for autonomous single neuron recordings. In *Proceedings of the 2005 IEEE International Conference on Robotics and Automation* vol. 2: 5352–5355 Vol. 7. IEEE.

Braun, C., R. Schweizer, T. Elbert, N. Birbaumer, and E. Taub. 2000. Differential activation in somatosensory cortex for different discrimination tasks. *Journal of Neuroscience* 20 (1):446–450.

Braun, C., M. Staudt, C. Schmitt, H. Preissl, N. Birbaumer, and C. Gerloff. submitted. Crossed cortico-spinal motor control after capsular stroke. *Journal of Neurophysiology*.

Breiman, L., J. Friedman, J. Olshen, and C. Stone. 1984. Classification and regression trees. Wadsworth.

Britten, K. H., W. T. Newsome, M. N. Shadlen, S. Celebrini, and J. A. Movshon. 1996. A relationship between behavioral choice and visual responses of neurons in macaque MT. *Visual Neuroscience* 13(1):87–100.

Britten, K. H., M. N. Shadlen, W. T. Newsome, and J. A. Movshon. 1992. The analysis of visual motion: a comparison of neuronal and psychophysical performance. *Journal of Neuroscience* 12(12):4745–4765.

Brockwell, A. E., A. L. Rojas, and R. E. Kass. 2004. Recursive Bayesian decoding of motor cortical signals by particle filtering. *Journal of Neurophysiology* 91(4):1899–1907.

Bronstein, M. M., A. M. Bronstein, M. Zibulevsky, and Y. Y. Zeevi. 2005. Blind deconvolution of images using optimal sparse representations. *IEEE Trans Image Process* 14(6):726–736.

Brookings, J. B., G. F. Wilson, and C. R. Swain. 1996. Psychophysiological responses to changes in workload during simulated air traffic control. *Biological Psychology* 42(3): 361–377.

Brunner, C., B. Graimann, J. E. Huggins, S. P. Levine, and G. Pfurtscheller. 2005. Phase relationships between different subdural electrode recordings in man. *Neuroscience Letters* 375(2):69–74.

Brunner, C., R. Scherer, B. Graimann, G. Supp, and G. Pfurtscheller. In revision. Online control of a brain-computer interface using phase synchronization. *IEEE Transactions on Biomedical Engineering*.

Bunce, S. C., M. Izzetoglu, K. Izzetoglu, B. Onaral, and K. Pourrezaei. 2006. Functional near-infrared spectroscopy. *IEEE Engineering in Medicine and Biology Magazine* 25 (4):54–62.

Burges, C. J. C. 1998. A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery* 2(2):121–167.

Buttfield, A., P. W. Ferrez, and J. d. R. Millán. 2006. Towards a robust BCI: error recognition and online learning. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):164–168.

Cacace, A. T. and D. J. McFarland. 2003. Spectral dynamics of electroencephalographic activity during auditory information processing. *Hearing Research* 176(1–2):25–41.

Caminiti, R., P. B. Johnson, and A. Urbano. 1990. Making arm movements within different parts of space: dynamic aspects in the primary motor cortex. *Journal of Neuroscience* 10(7):2039–2058.

Campbell, C. and K.P. Bennett. 2001. A linear programming approach to novelty detection. In *Advances in Neural Information Processing Systems (NIPS 00)*, edited by T.K. Leen, T.G. Dietterich, and V. Tresp vol. 13: 395–401, Cambridge, Mass. The MIT Press.

Cardoso, J.-F. and A. Souloumiac. 1993. Blind beamforming for non gaussian signals. *IEE Proceedings-F.* 140(46):362–370.

Carmena, J. M., M. A. Lebedev, R. E. Crist, J. E. O'Doherty, D. M. Santucci, D. F. Dimitrov, P. G. Patil, C. S. Henriquez, and M. A. Nicolelis. 2003. Learning to control a brain-machine interface for reaching and grasping by primates. *PLoS Biology* 1(2):E42.

Carter, C. S., T. S. Braver, D. M. Barch, M. M. Botvinick, D. Noll, and J. D. Cohen. 1998. Anterior cingulate cortex, error detection, and the online monitoring of performance. *Science* 280(5364):747–749.

Cham, J. G., E. A. Branchaud, Z. Nenadic, B. Greger, R. A. Andersen, and J. W. Burdick. 2005. Semi-chronic motorized microdrive and control algorithm for autonomously isolating and maintaining optimal extracellular action potentials. *Journal of Neurophysiology* 93(1):570–579.

Chapelle, O., P. Haffner, and V. Vapnik. 1999. Support vector machines for histogram based image classification. *IEEE Transactions on Neural Networks* 10(5):1055–1064.

Chapin, J. K. 2006. Talk presented at IEEE 2006 International Conference of the Engineering in Medicine and Biology Society, New York City, USA.

Chapin, J. K., K. A. Moxon, R. S. Markowitz, and M. A. Nicolelis. 1999. Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex. *Nature Neuroscience* 2(7):664–670.

Chen, W. and S. Ogawa. 2000. Principles of BOLD functional MRI. In *Functional MRI*, edited by C. Moonen and P. Bandettini. Berlin Heidelberg: Springer.

Cheng, M., X. Gao, S. Gao, and D. Xu. 2002. Design and implementation of a brain-computer interface with high transfer rates. *IEEE Transactions on Biomedical Engineering* 49(10):1181–1186.

Cohen, J. 1960. A coefficient of agreement for nominal scales. *Educational and Psychological Measurement* 20:37–46.

Cohen, J. and J. Polich. 1997. On the number of trials needed for P300. *International Journal of Psychophysiology* 25(3):249–255.

Coin3D. High-level 3d graphics toolkit for developing cross-platform real-time 3d visualization and visual simulation software. Available from http://www.coin3d.org.

Collobert, R. and S. Bengio. 2001. SVMTorch: support vector machines for large-scale regression problems. *Journal of Machine Learning Research* 1(2):143–160.

Connolly, J. D., R. A. Andersen, and M. A. Goodale. 2003. FMRI evidence for a "parietal reach region" in the human brain. *Experimental Brain Research* 153(2):140–145.

Cover, T. M. 1969. Learning in pattern recognition. In *Methodologies of Pattern Recognition*, edited by Satoshi Watanabe. New York: Academic Press.

Cover, T. M. and J. M. Van Campenhout. 1977. On the possible ordering in the measurement selection problem. *IEEE transactions on systems, man, and cybernetics* SMC-7: 657–661.

Coyle, S., T. Ward, C. Markham, and G. McDarby. 2004. On the suitability of near-infrared (NIR) systems for next-generation brain-computer interfaces. *Physiological Measurement* 25(4):815–822.

Crammer, K. and Y. Singer. 2001. On the algorithmic implementation of multiclass kernel-based vector machines. *Journal of Machine Learning Research* 2(2):265–292.

Creasey, G. H., C. H. Ho, R. J. Triolo, D. R. Gater, A. F. DiMarco, K. M. Bogie, and M. W. Keith. 2004. Clinical applications of electrical stimulation after spinal cord injury. *The Journal of Spinal Cord Medicine* 27(4):365–375.

Crochiere, R. E. 1980. A weighted overlap-add method of short-time fourier analysis/synthesis. *IEEE Transactions on Acoustics, Speech, & Signal Processing* ASSP-28 (1):99–102.

Cruz-Neira, C., D. J. Sandin, and T. A. DeFanti. 1993. Surround-screen projection-based virtual reality: the design and implementation of the CAVE. In *Proceedings of the 20th annual conference on Computer graphics and interactive techniques*: 135–142.

Cui, R. Q., D. Huter, W. Lang, and L. Deecke. 1999. Neuroimage of voluntary movement: topography of the Bereitschaftspotential, a 64-channel DC current source density study. *Neuroimage* 9(1):124–134.

Cunnigham, H. A. and R. B. Welch. 1994. Multiple concurrent visual-motor mappings: implication for models of adaptation. *Journal of Experimental Psychology. Human Perception and Performance* 20(5):987–999.

Curran, E. A. and M. J. Stokes. 2003. Learning to control brain activity: A review of the production and control of EEG components for driving brain-computer interface (BCI) systems. *Brain and cognition* 51(3):326–336.

Dakin, S. C., R. F. Hess, T. Ledgeway, and R. L. Achtman. 2002. What causes non-monotonic tuning of fMRI response to noisy images? *Current Biology* 12(14):R476–477.

Davidson, R. J., D. Pizzagalli, J. B. Nitschke, and K. Putnam. 2002. Depression: perspectives from affective neuroscience. *Annual Review of Psychology* 53:545–574.

Decety, J., D. Perani, M. Jeannerod, V. Bettinardi, B. Tadary, R. Woods, J. C. Mazziotta, and F. Fazio. 1994. Mapping motor representations with positron emission tomography. *Nature* 371(6498):600–602.

DeCharms, R. C., K. Christoff, G. H. Glover, J. M. Pauly, S. Whitfield, and J. D. Gabrieli. 2004. Learned regulation of spatially localized brain activation using real-time fMRI. *Neuroimage* 21(1):436–443.

DeCharms, R. C., F. Maeda, G. H. Glover, D. Ludlow, J. M. Pauly, D. Soneji, J. D. Gabrieli, and S. C. Mackey. 2005. Control over brain activation and pain learned by using real-time functional MRI. *Proceedings of the National Academy of Sciences of the United States of America* 102(51):18626–18631.

Delorme, A. and S. Makeig. 2003. EEG changes accompanying learned regulation of 12-Hz EEG activity. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):133–137.

Delorme, A. and S. Makeig. 2004. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods* 134(1):9–21.

Donchin, E., K. M. Spencer, and R. Wijesinghe. 2000. The mental prosthesis: assessing the speed of a P300-based brain-computer interface. *IEEE Transactions on Rehabilitation Engineering* 8(2):174–179.

Donoghue, J. 2002. Connecting cortex to machines: Recent advances in brain interfaces. *Nature Neuroscience* 5:1085–1088.

Dornhege, G. 2006. Increasing information transfer rates for brain-computer interfacing. PhD thesis, University of Potsdam.

Dornhege, G., B. Blankertz, and G. Curio. 2003a. Speeding up classification of multi-channel brain-computer interfaces: common spatial patterns for slow cortical potentials. In *Proceedings of the 1st International IEEE EMBS Conference on Neural Engineering. Capri 2003*: 595–598.

Dornhege, G., B. Blankertz, G. Curio, and K. R. Müller. 2003b. Combining features for BCI. In *Advances in Neural Information Processing Systems (NIPS 02)*, edited by S. Becker, S. Thrun, and K. Obermayer vol. 15: 1115–1122, Cambridge, Mass. The MIT Press.

Dornhege, G., B. Blankertz, G. Curio, and K. R. Müller. 2004a. Boosting bit rates in noninvasive EEG single-trial classifications by feature combination and multi-class paradigms. *IEEE Transactions on Biomedical Engineering* 51(6):993–1002.

Dornhege, G., B. Blankertz, G. Curio, and K. R. Müller. 2004b. Increase information transfer rates in BCI by CSP extension to multi-class. In *Advances in Neural Information Processing Systems (NIPS 03)*, edited by S. Thrun, L. Saul, and B. Schölkopf, vol. 16. Cambridge, Mass.: The MIT Press.

Dornhege, G., B. Blankertz, M. Krauledat, F. Losch, and G. and K. R. Müller. 2006a. Combined optimization of spatial and temporal filters for improving brain-computer interfacing. *IEEE Transactions on Biomedical Engineering* 53(11):2274–2281.

Dornhege, G., B. Blankertz, M. Krauledat, F. Losch, G. Curio, and K.-R. Müller. 2006b. Optimizing spatio-temporal filters for improving brain-computer interfacing. In *Advances in Neural Information Processing Systems (NIPS 05)* vol. 18: 315–322, Cambridge, Mass. The MIT Press.

Drake, K. L., K. D. Wise, J. Farraye, D. J. Anderson, and S. L. BeMent. 1988. Performance of planar multisite microprobes in recording extracellular single-unit intracortical activity. *IEEE Transactions on Biomedical Engineering* 35(9):719–732.

Duda, R. O., P. E. Hart, and D. G. Stork. 2001. Pattern classification. New York: John Wiley and Sons Publishing Company, 2nd edition.

Duncan-Johnson, C. C. and E. Donchin. 1977. On quantifying surprise: the variation of event-related potentials with subjective probability. *Psychophysiology* 14(5):456–467.

Duque, J., F. Hummel, P. Celnik, N. Murase, R. Mazzocchio, and L. G. Cohen. 2005. Transcallosal inhibition in chronic subcortical stroke. *Neuroimage* 28(4):940–946.

Dworkin, B. R. and N. E. Miller. 1986. Failure to replicate visceral learning in the acute curarized rat preparation. *Behavioral neuroscience* 100(3):299–314.

Eaton, J. W. Octave. Available at http://www.octave.org/.

Eckmiller, R. 1997. Learning retina implants with epiretinal contacts. *Ophthalmic research* 29(5):281–289.

Edell, D. J., V. V. Toi, V. M. McNeil, and L. D. Clark. 1992. Factors influencing the biocompatibility of insertable silicon microshafts in cerebral cortex. *IEEE Transactions on Biomedical Engineering* 39(6):635–643.

Eichhorn, J., A. Tolias, A. Zien, M. Kuss, C. E. Rasmussen, J. Weston, N. Logothetis, and B. Schölkopf. 2004. Prediction on spike data using kernel algorithms. In *Advances in Neural Information Processing Systems (NIPS 03)*, edited by S. Thrun, L. Saul, and B. Schölkopf vol. 16, Cambridge, MA. The MIT Press.

Elbert, T., B. Rockstroh, W. Lutzenberger, and N. Birbaumer. 1980. Biofeedback of slow cortical potentials. I. *Electroencephalography and Clinical Neurophysiology* 48(3):293–301.

EMEGS. Electromagnetic encaphalography software. Available at http://134.34.43.26/˜emegs/modules/news/.

Evarts, E. V. 1968. Relation of pyramidal tract activity to force exerted during voluntary movement. *Journal of Neurophysiology* 31(1):14–27.

Fabiani, G. E., D. J. McFarland, J. R. Wolpaw, and G. Pfurtscheller. 2004. Conversion of EEG activity into cursor movement by a brain computer interface (BCI). *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 12(3):331–338.

Fabiani, M., G. Gratton, D. Karis, and E. Donchin. 1987. Definition, identification, and reliability of measurement of the P300 component of the event-related brain potential. *Advances in Psychophysiology* 2:1–78.

Falkenstein, M., J. Hoormann, S. Christ, and J. Hohnsbein. 2000. ERP components on reaction errors and their functional significance: a tutorial. *Biological Psychology* 51 (2–3):87–107.

Farwell, L. A. and E. Donchin. 1988. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and Clinical Neurophysiology* 70(6):510–523.

Felton, E. A., J. A. Wilson, R. G. Radwin, J. C. Williams, and P. C. Garell. 2005. Electrocorticogram-controlled brain-computer interfaces with patients with temporary subdural electrode implants. *Neurosurgery* 57(2).

Ferrez, P. W. and J. d. R. Millán. 2005. You are wrong!—Automatic detection of interaction errors from brain waves. In *19th International Joint Conference on Artificial Intelligence*.

FES. The cleveland functional electrical stimulation center. Available at http://fescenter.case.edu.

Fessler, J. A., S. Y. Chun, J. E. Huggins, and S. P. Levine. 2005. Detection of event-related spectral changes in electrocorticograms. In *Proceedings IEEE EMBS Conference on Neural Engineering*: 269–272.

FieldTrip. Available at http://www2.ru.nl/fcdonders/fieldtrip/1020.html.

Fisher, R. A. 1936. The use of multiple measurements in taxonomic problems. *Annals of Eugenics* 7:179–188.

Flach, P. A. 2004. The many faces of ROC analysis in machine learning. Tutorial presented at the 21st International Conference on Machine Learning. Available from http://www.cs.bris.ac.uk/˜flach/ICML04tutorial/.

Flament, D. and J. Hore. 1988. Relations of motor cortex neural discharge to kinematics of passive and active elbow movements in the monkey. *Journal of Neurophysiology* 60 (4):1268–1284.

Fleiss, J. L. 1981. Statistical methods for rates and proportions. New York: John Wiley and Sons Publishing Company, 2nd edition.

Flotzinger, D., G. Pfurtscheller, C. Neuper, J. Berger, and W. Mohl. 1994. Classification of non-averaged EEG data by learning vector quantisation and the influence of signal preprocessing. *Medical & Biological Engineering & Computing* 32(5):571–576.

Foffani, G., A. M. Bianchi, A. Priori, and G. Baselli. 2004. Adaptive autoregressive identification with spectral power decomposition for studying movement-related activity in scalp EEG signals and basal ganglia local field potentials. *Journal of Neural Engineering* 1(3):165–173.

Franceschini, M. A., S. Fantini, J. H. Thompson, J. P. Culver, and D. A. Boas. 2003. Hemodynamic evoked response of the sensorimotor cortex measured noninvasively with near-infrared optical imaging. *Psychophysiology* 40(4):548–560.

Frecon, E., G. Smith, A. Steed, M. Stenius, and O. Stahl. 2001. An overview of the COVEN platform. *Presence-Teleoperators and Virtual Environments* 10(1):109–127.

Friedman, J. H. 1988. Fitting functions to noisy data in high dimensions. In *Computing Science and Statistics: Proceedings of the 20th Symposium on the Interface*, edited by E. Wegman, D. Gantz, and J. Miller: 13–43, Alexandria, Va. American Statistical Association.

Friedman, J. H. 1989. Regularized discriminant analysis. *Journal of the American Statistical Association* 84(405):165–175.

Friedman, J. H. 1991. Multivariate adaptive regression splines. *Annals of Statistics* 19(1): 1–141.

Fu, Q. G., D. Flament, J. D. Coltz, and T. J. Ebner. 1995. Temporal coding of movement kinematics in the discharge of primate primary motor and premotor neurons. *Journal of Neurophysiology* 73(2):836–854.

Fukunaga, K. 1990. Inroduction to statistical pattern recognition. San Diego: Academic Press, 2nd edition.

Gandolfo, F., C. S. R. Li, B. J. Benda, C. P. Schioppa, and E. Bizzi. 2000. Cortical correlates of learning in monkeys adapting to a new dynamical environment. *Proceedings of the National Academy of Sciences of the United States of America* 97(5):2259–2263.

Gao, X., D. Xu, M. Cheng, and S. Gao. 2003a. A BCI-based environmental controller for the motion-disabled. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):137–140.

Gao, Y., M. J. Black, E. Bienenstock, S. Shoham, and J. P. Donoghue. 2002. Probabilistic inference of hand motion from neural activity in motor cortex. In *Advances in Neural Information Processing Systems (NIPS 01)*, edited by T. G. Dietterich, S. Becker, and Z. Ghahramani vol. 14: 213–220, Cambridge, Mass. The MIT Press.

Gao, Y., M. J. Black, E. Bienenstock, W. Wu, and J. P. Donoghue. 2003b. A quantitative comparison of linear and non-linear models of motor cortical activity for the encoding and decoding of arm motions. In *First International IEEE EMBS Conference on Neural Engineering*: 189–192.

Garrett, D., D. A. Peterson, C. W. Anderson, and M. H. Thaut. 2003. Comparison of linear, nonlinear, and feature selection methods for EEG signal classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):141–144.

Gehring, W., M. Coles, D. Meyer, and E. Donchin. 1990. The error-related negativity: An event-related brain potential accompanying errors. *Psychophysiology* 27:34.

Georgopoulos, A. P., J. F. Kalaska, R. Caminiti, and J. T. Massey. 1982. On the relations between the direction of two-dimensional arm movements and cell discharge in primate motor cortex. *Journal of Neuroscience* 2(11):1527–1537.

Georgopoulos, A. P., J. F. Kalaska, and J. T. Massey. 1983. Spatial coding of movements: A hypothesis concerning the coding of movement direction by motor cortical populations. *Experimental Brain Research* 7:327–336.

Georgopoulos, A. P., R. E. Kettner, and A. B. Schwartz. 1988. Primate motor cortex and free arm movements to visual targets in three-dimensional space. II. Coding of the direction of movement by a neuronal population. *Journal of Neuroscience* 8(8):2928–2937.

Georgopoulos, A. P., A. B. Schwartz, and R. E. Kettner. 1986. Neural population coding of movement direction. *Science* 233(4771):1416–1419.

Gerson, A. D., L. C. Parra, and P. Sajda. 2005. Cortical origins of response time variability during rapid discrimination of visual objects. *Neuroimage* 28(2):342–353.

Gevins, A., M. E. Smith, H. Leong, L. McEvoy, S. Whitfield, R. Du, and G. Rush. 1998. Monitoring working memory load during computer-based tasks with EEG pattern recognition methods. *Human Factors* 40(1):79–91.

Gevins, A., M. E. Smith, L. McEvoy, and D. Yu. 1997. High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. *Cerebral Cortex* 7(4):374–385.

Girone, M., G. Burdea, M. Bouzit, V. Popescu, and J. E. Deutsch. 2000. Orthopedic rehabilitation using the “Rutgers ankle” interface. *Studies in Health Technology and*

Informatics 70:89–95.

glib. GTK+ team: *General-purpose utility library*. Available at http://www.gtk.org.

Goncharova, I. I., D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw. 2003. EMG contamination of EEG: spectral and topographical characteristics. *Clinical Neurophysiology* 114(9):1580–1593.

Gonsalvez, C. L. and J. Polich. 2002. P300 amplitude is determined by target-to-target interval. *Psychophysiology* 39(3):388–396.

GPL. Free Software Foundation: *The GNU General Public License*. Available at http://www.gnu.org/licenses/licenses.html.

Graimann, B., J. E. Huggins, S. P. Levine, and G. Pfurtscheller. 2002. Visualization of significant ERD/ERS patterns in multichannel EEG and ECoG data. *Clinical Neurophysiology* 113(1):43–47.

Graimann, B., J. E. Huggins, S. P. Levine, and G. Pfurtscheller. 2004. Towards a direct brain interface based on human subdural recordings and wavelet-packet analysis. *IEEE Transactions on Biomedical Engineering* 51(6):954–962.

Graimann, B., J. E. Huggins, A. Schlögl, S. P. Levine, and G. Pfurtscheller. 2003. Detection of movement-related desynchronization patterns in ongoing single-channel electrocorticogram. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(3): 276–281.

Graimann, B., G. Townsend, J. E. Huggins, A. Schlögl, S. P. Levine, and G. Pfurtscheller. 2005. A comparison between using ECoG and EEG for direct brain communication. In *Proceedings of the EMBEC05*.

Grave de Peralta Menendez, R., S. Gonzalez Andino, A. Khateb, A. Pegna, G. Thut, and T. Landis. 2005a. About the information content of local field potentials non-invasively estimated from the EEG. In *16th Meeting of the International Society for Brain Electromagnetic Topography*.

Grave de Peralta Menendez, R., S. Gonzalez Andino, L. Perez, P. W. Ferrez, and J. d. R. Millán. 2005b. Non-invasive estimation of local field potentials for neuroprosthesis control. *Cognitive Processing* 6:59–64.

Grave de Peralta Menendez, R. and S. L. Gonzalez Andino. 1998. A critical analysis of linear inverse solutions to the neuroelectromagnetic inverse problem. *IEEE Transactions on Biomedical Engineering* 45(4):440–448.

Grave de Peralta Menendez, R., S. L. Gonzalez Andino, S. Morand, C. M. Michel, and T. Landis. 2000. Imaging the electrical activity of the brain: ELECTRA. *Human Brain Mapping* 9(1):1–12.

Grave de Peralta Menendez, R., M. M. Murray, C. M. Michel, R. Martuzzi, and S. L. Gonzalez Andino. 2004. Electrical neuroimaging based on biophysical constraints. *Neuroimage* 21(2):527–539.

Green, D. M. and J. A. Swets. 1966. Signal detection theory and psychophysics. New York: Wiley.

Gruzelier, J. and T. Egner. 2005. Critical validation studies of neurofeedback. *Child and Adolescent Psychiatric Clinics of North America* 14(1):83–104.

g.tec. g.tec Guger Technologies. Available at http.//www.gtec.at.

GTK. GTK+ team: *The GIMP Toolkit*. Available at http://www.gtk.org.

Guger, C., G. Edlinger, W. Harkam, I. Niedermayer, and G. Pfurtscheller. 2003. How many people are able to operate an EEG-based brain-computer interface (BCI)? *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):145–147.

Guger, C., W. Harkam, C. Hertnaes, and G. Pfurtscheller. 1999. Prosthetic control by an EEG-based brain-computer interface (BCI). In *Proceedings if the 5th European Conference for the Advancement of Assistive Technology (AAATE)*, Düsseldorf, Germany.

Guger, C., H. Ramoser, and G. Pfurtscheller. 2000. Real-time EEG analysis with subject-specific spatial patterns for a brain computer interface (BCI). *IEEE Transactions on Rehabilitation Engineering* 8(4):447–456.

Guger, C., A. Schlögl, C. Neuper, D. Walterspacher, T. Strein, and G. Pfurtscheller. 2001. Rapid prototyping of an EEG-based brain-computer interface (BCI). *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 9(1):49–58.

Guyon, I., S. Gunn, M. Nikravesh, and L. Zadeh, editors. 2006a. Feature extraction, foundations and applications, chapter Filter Methods. Springer.

Guyon, I., S. Gunn, M. Nikravesh, and L. A. Zadeh, editors. 2006b. Feature extraction: Foundations and applications. Springer.

Guyon, I., J. Weston, S. Barnhill, and V. Vapnik. 2002. Gene selection for cancer classification using support vector machines. *Machine Learning* 46(1–3):389–422.

Gysels, E. and P. Celka. 2004. Phase synchronization for the recognition of mental tasks in a brain computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 12(4):406–415.

Halgren, E., T. Raij, K. Marinkovic, V. Jousmaki, and R. Hari. 2000. Cognitive response profile of the human fusiform face area as determined by MEG. *Cerebral Cortex* 10(1): 69–81.

Hamalainen, M. S. and R. J. Ilmoniemi. 1994. Interpreting magnetic fields of the brain: minimum norm estimates. *Medical & Biological Engineering & Computing* 32(1):35–42.

Hampel, F. R., E. M. Rochetti, P. J. Rousseeuw, and W. A. Stahel. 1986. Robust statistics. New York: Wiley.

Hanagasi, H. A., I. H. Gurvit, N. Ermutlu, G. Kaptanoglu, S. Karamursel, H. A. Idrisoglu, M. Emre, and T. Demiralp. 2002. Cognitive impairment in amyotrophic lateral sclerosis: evidence from neuropsychological investigation and event-related potentials. *Brain Research. Cognitive Brain Research* 14(2):234–244.

Hancock, K. M., A. R. Craig, H. G. Dickson, E. Chang, and J. Martin. 1993. Anxiety and depression over the first year of spinal cord injury: a longitudinal study. *Paraplegia* 31 (6):349–357.

Hankins, T. C. and G. F. Wilson. 1998. A comparison of heart rate, eye activity, EEG and subjective measures of pilot mental workload during flight. *Aviation, Space, and Environmental Medicine* 69(4):360–367.

Harland, C. J., T. D. Clark, and R. J. Prance. 2002. Remote detection of human eleectroencephalograms using ultrahigh input impedance electric potential sensors. *Applied Physics Letters* 81(17):3284–3286.

Harmeling, S. 2005. Independent component analysis and beyond. PhD thesis, University of Potsdam, Potsdam.

Harmeling, S., G. Dornhege, D. Tax, F. Meinecke, and K. R. Müller. 2006. From outliers to prototypes: ordering data. *Neurocomputing* 69(13–15).

Harmeling, S., A. Ziehe, M. Kawanabe, and K.-R. Müller. 2002. Kernel feature spaces and nonlinear blind source separation. In *Advances in Neural Information Processing Systems (NIPS 01)*, edited by T.G. Dietterich, S. Becker, and Z. Ghahramani vol. 14, Cambridge, Mass. The MIT Press.

Harmeling, S., A. Ziehe, M. Kawanabe, and K.-R. Müller. 2003. Kernel-based nonlinear blind source separation. *Neural Computation* 15:1089–1124.

Harris, F. J. 1978. On the Use of Windows for Harmonic Analysis with Discrete Fourier Transform. *Proceedings of the IEEE* 66:51–83.

Hasson, U., I. Levy, M. Behrmann, T. Hendler, and R. Malach. 2002. Eccentricity bias as an organization principle for human high-order object areas. *Neuron* 34(3):479–490.

Hastie, T., R. Tibshirani, and J. Friedman. 2001. The elements of statistical learning: data mining, inference, and prediction. New York: Springer-Verlag.

Hauser, A., P. E. Sottas, and J. d. R. Millán. 2002. Temporal processing of brain activity for the recognition of EEG patterns. In *Proceedings 12th International Conference on Artificial Neural Networks*.

Haynes, J. D. and G. Rees. 2006. Decoding mental states from brain activity in humans. *Nature Reviews Neuroscience* 7(7):523–534.

He, B., J. Lian, K. M. Spencer, J. Dien, and E. Donchin. 2001. A cortical potential imaging analysis of the P300 and novelty P3 components. *Human Brain Mapping* 12(2):120–130.

Heekeren, H. R., S. Marrett, P. A. Bandettini, and L. G. Ungerleider. 2004. A general mechanism for perceptual decision-making in human brain. *Nature* 431(7010):859–862.

Hellman, M. E. and J. Raviv. 1970. Probability of error, equivocation, and the Chernoff bound. *IEEE Transactions on Information Theory* IT-16(4):368–372.

Hernandez, A., A. Zainos, and R. Romo. 2000. Neuronal correlates of sensory discrimination in the somatosensory cortex. *Proceedings of the National Academy of Sciences of the United States of America* 97(11):6191–6196.

Hettich, S., C. L. Blake, and C. J. Merz. 1998. UCI repository of machine learning databases. http://www.ics.uci.edu/∼mlearn/MLRepository.html. University of California, Irvine, Department of Information and Computer Sciences.

Hill, N. J., T. N. Lal, K. Bierig, N. Birbaumer, and B. Schölkopf. 2005. An auditory paradigm for brain–computer interfaces. In *Advances in Neural Information Processing Systems 17*, edited by L. K. Saul, Y. Weiss, and L. Bottou: 569–576, Cambridge, Mass., USA. The MIT Press.

Hill, N. J., T. N. Lal, M. Schröder M, T. Hinterberger, B. Wilhelm, F. Nijboer, U. Mochty, G. Widman, C. Elger, B.Schölkopf, A. Kübler, and N. Birbaumer. 2006. Classifying EEG and ECoG signals without subject training for fast BCI implementation: comparison of nonparalyzed and completely paralyzed subjects. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):183–186.

Hinterberger, T., N. Birbaumer, and H. Flor. 2005a. Assessment of cognitive function and communication ability in a completely locked-in patient. *Neurology* 64(7):1307–1308.

Hinterberger, T., J. Kaiser, A. Kübler, N. Neumann, and N. Birbaumer. 2001. The Thought Translation Device and its applications to the completely paralyzed. In *Sciences of the Interfaces*, edited by H. Diebner, T. Druckrey, and P. Weibel. Genista-Verlag Tübingen.

Hinterberger, T., A. Kübler, J. Kaiser, N. Neumann, and N. Birbaumer. 2003a. A brain-computer interface (BCI) for the locked-in: comparison of different EEG classifications for the thought translation device. *Clinical Neurophysiology* 114(3):416–425.

Hinterberger, T., J. Mellinger, and N. Birbaumer. 2003b. The Thought Translation Device: Structure of a multimodal brain-computer communication system. In *Proceedings of the 1st International IEEE EMBS Conference on Neural Engineering*: 603–606, Capri Island, Italy.

Hinterberger, T., N. Neumann, M. Pham, A. Kübler, A. Grether, N. Hofmayer, B. Wilhelm, H. Flor, and N. Birbaumer. 2004a. A multimodal brain-based feedback and communication system. *Experimental Brain Research* 154(4):521–526.

Hinterberger, T., S. Schmidt, N. Neumann, J. Mellinger, B. Blankertz, G. Curio, and N. Birbaumer. 2004b. Brain-computer communication and slow cortical potentials. *IEEE Transactions on Biomedical Engineering* 51(6):1011–1018.

Hinterberger, T., R. Veit, U. Strehl, T. Trevorrow, M. Erb, B. Kotchoubey, H. Flor, and N. Birbaumer. 2003c. Brain areas activated in fMRI during self-regulation of slow cortical potentials (SCPs). *Experimental Brain Research* 152(1):113–122.

Hinterberger, T., R. Veit, B. Wilhelm, N. Weiskopf, J. J. Vatine, and N. Birbaumer. 2005b. Neural mechanisms underlying control of a brain-computer-interface. *The European Journal of Neuroscience* 21(11):3169–3181.

Hinterberger, T., N. Weiskopf, R. Veit, B. Wilhelm, E. Betta, and N. Birbaumer. 2004c. An EEG-driven brain-computer interface combined with functional magnetic resonance imaging MRI. *IEEE Transactions on Biomedical Engineering* 51(6):971–974.

Hinterberger, T., B. Wilhelm, J. Mellinger, B. Kotchoubey, and N. Birbaumer. 2005c. A device for the detection of cognitive brain functions in completely paralyzed or unresponsive patients. *IEEE Transactions on Biomedical Engineering* 52(2):211–220.

Hjorth, B. 1970. EEG analysis based on time domain properties. *Electroencephalography and Clinical Neurophysiology* 29(3):306–310.

Hochberg, L. R., M. D. Serruya, G. M. Friehs, J. A. Mukand, M. Saleh, A. H. Caplan, A. Branner, D. Chen, R. D. Penn, and J. P. Donoghue. 2006. Neuronal ensemble control of prosthetic devices by a human with tetraplegia. *Nature* 442(7099):164–171.

Hochberg, L. R., M. D. Serruya, J. A. Mukand, G. M. Polykoff, G. M. Friehs, and J. P. Donoghue. 2005. Braingate neuromotor prosthesis: Nature and use of neural control signals. In *Society for Neuroscience*, Washington.

Hoel, P., S. Port, and C. Stone. 1971. Introduction to statistical theory. Boston: Houghton Mifflin.

Holden, M. K. 2005. Virtual environments for motor rehabilitation: review. *Cyberpsychology & Behavior: the Impact of the Internet, Multimedia and Virtual Reality on Behavior and Society* 8(3):187–211. discussion 212–219.

Holroyd, C. B. and M. G. Coles. 2002. The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity. *Psychological Review* 109(4):679–709.

Howard, M. W., D. S. Rizzuto, J. B. Caplan, J. R. Madsen, J. Lisman, R. Aschenbrenner-Scheibe, A. Schulze-Bonhage, and M. J. Kahana. 2003. Gamma oscillations correlate with working memory load in humans. *Cerebral Cortex* 13(12):1369–1374.

Huan, N.-J. and R. Palaniappan. 2004. Neural network classification of autoregressive features from electroencephalogram signals for brain computer interface design. *Journal of Neural Engineering* 1(3):142–150.

Huber, H. 2005. Der Einsatz virtueller Realitäten in der psychologischen Behandlung [the use of virtual realties in psychological threatment]. *Psychologie in Österreich* 25(1): 13–200.

Huber, P. J. 1981. Robust statistics. New York: John Wiley and Sons.

Huggins, J. E., S. P. Levine, S. L. BeMent, R. K. Kushwaha, L. A. Schuh, E. A. Passaro, M. M. Rohde, D. A. Ross, K. V. Elisevich, and B. J. Smith. 1999. Detection of event-related potentials for development of a direct brain interface. *Journal of Clinical Neurophysiology* 16(5):448–455.

Hundley, D. R., M. J. Kirby, and M. Anderle. 2002. Blind source separation using the maximum signal fraction approach. *Signal Processing* 82(10):1505–1508.

Hwang, E. J., O. Donchin, M. A. Smith, and R. Shadmehr. 2003. A gain-field encoding of limb position and velocity in the internal model of arm dynamics. *Public Library of Science: Biology* 1(2):E25.

Hyvärinen, A. 1999. Survey on independent component analysis. *Neural Computing Surveys* 2:94–128.

Hyvarinen, A., J. Karhunen, and E. Oja. 2001. Independent component analysis. New York: Wiley.

IEEE754. IEEE Standard for Binary Floating-Point Arithmetic (ANSI/IEEE Std 754-1985). It is also known as IEC 60559:1989, Binary floating-point arithmetic for microprocessor systems (originally the reference number was IEC 559:1989).

Ilmoniemi, R. J. 1993. Models of source currents in the brain. *Brain Topography* 5(4): 331–336.

Isaacs, R. E., D. J. Weber, and A. B. Schwartz. 2000. Work toward real-time control of a cortical neural prothesis. *IEEE Transactions on Rehabilitation Engineering* 8(2): 196–198.

Jack, D., R. Boian, A. S. Merians, M. Tremaine, G. C. Burdea, S. V. Adamovich, M. Recce, and H. Poizner. 2001. Virtual reality-enhanced stroke rehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 9(3):308–318.

Jacob, R. J. K. 1990. What you look at is what you get: eye movement-based interaction techniques. In *Proceedings CHI'90*: 11–18.

James, W. 1983. The principles of psychology. New York: Holt. reprint: Cambridge, Mass.: Harvard University Press.

Jasper, H. H. 1958. Report of the committee on methods of clinical investigation of EEG. Appendix: The ten twenty electrode system of the international federation. *Electroencephalography and Clinical Neurophysiology* 10:371–375.

Jeannerod, M. and V. Frak. 1999. Mental imaging of motor activity in humans. *Current Opinion in Neurobiolology* 9(6):735–739.

Jeffreys, D. A. 1996. Evoked studies of face and object processing. *Visual Cognition* 3(1): 1–38.

Joachims, T. 1998. Text categorization with support vector machines: Learning with many relevant features. In *Proceedings of the European Conference on Machine Learning*, edited by Claire Nédellec and Céline Rouveirol: 137–142, Berlin. Springer.

Johnson, J. S. and B. A. Olshausen. 2003. Timecourse of neural signatures of object recognition. *Journal of Vision* 3(7):499–512.

Johnson, P. B., S. Ferraina, L. Bianchi, and R. Caminiti. 1996. Cortical networks for visual reaching: physiological and anatomical organization of frontal and parietal lobe arm regions. *Cerebral Cortex* 6(2):102–119.

Johnson, R. Jr. and E. Donchin. 1978. On how P300 amplitude varies with the utility of the eliciting stimuli. *Electroencephalography and Clinical Neurophysiology* 44(4): 424–437.

Jolliffe, I. T. 1986. Principal component analysis. New York: Springer Verlag.

Jurkiewicz, M. T., A. P. Crawley, M. C. Verrier, M. G. Fehlings, and D. J. Mikulis. 2006. Somatosensory cortical atrophy after spinal cord injury: a voxel-based morphometry study. *Neurology* 66(5):762–764.

Jutten, C. and J. Herault. 1991. Blind separation of sources, part I: An adaptive algorithm based on neuromimetic architecture. *Signal Processing* 24(1):1–10.

Kagerer, F. A., J. L. Contreras-Vidal, and G. E. Stelmach. 1997. Adaptation to gradual as compared with sudden visuo-motor distortions. *Experimental Brain Research* 115(3): 557–561.

Kaiser, J., J. Perelmouter, I. H. Iversen, N. Neumann, N. Ghanayim, T. Hinterberger, A. Kübler, B. Kotchoubey, and N. Birbaumer. 2001. Self-initiation of EEG-based communication in paralyzed patients. *Clinical Neurophysiology* 112(3):551–554.

Kalcher, J., D. Flotzinger, C. Neuper, S. Gölly, and G. Pfurtscheller. 1996. Graz brain-computer interface II: towards communication between man and computer based on on-line classification of three different EEG patterns. *Medical & Biological Engineering & Computing* 34(5):382–388.

Kalman, R. E. 1960. A new approach to linear filtering and prediction problems. *Trans. ASME, Journal of Basic Engineering* 82:35–45.

Kamitani, Y. and F. Tong. 2005. Decoding the visual and subjective contents of the human brain. *Nature Neuroscience* 8(5):679–685.

Kammer, T., L. Lehr, and K. Kirschfeld. 1999. Cortical visual processing is temporally dispersed by luminance in human subjects. *Neuroscience Letters* 263(2–3):133–136.

Kaper, M., P. Meinicke, U. Grossekathoefer, T. Lingner, and H. Ritter. 2004. BCI Competition 2003–Data set IIb: support vector machines for the P300 speller paradigm. *IEEE Transactions on Biomedical Engineering* 51(6):1073–1076.

Kaper, M., A. Saalbach, A. Finke, H. M. Mueller, S. Weiss, and H. Ritter. 2005. Exploratory data analysis of EEG coherence using self-organizing maps. In *Proceedings of the International Conference on Neural Information Processing (ICONIP)*.

Karim, A. A., T. Hinterberger, J. Richter, J. Mellinger, N. Neumann, A. Kübler, M. Bensch, M. Schröder, H. Flor, and N. Birbaumer. Submitted. Neural internet: Web surfing with brain potentials for the completely paralysed. *Neurorehabilitation and Neural Repair*.

Kassubek, J., A. Unrath, H. J. Huppertz, D. Lule, T. Ethofer, A. D. Sperfeld, and A. C. Ludolph. 2005. Global brain atrophy and corticospinal tract alterations in ALS, as investigated by voxel-based morphometry of 3-D MRI. *Amyotrophic Lateral Sclerosis and other Motor Neuron Disorders* 6(4):213–220.

Katz, R. T., A. J. Haig, B. B. Clark, and R. J. DiPaola. 1992. Long-term survival, prognosis, and life-care planning for 29 patients with chronic locked-in syndrome. *Archives of Physical Medicine and Rehabilitation* 73(5):403–408.

Kauhanen, K., T. Nykopp, J. Lehtonen, P. Jylanki, J. Heikkonen, P. Rantanen, H. Alaranta, and M. Sams. 2006. EEG and MEG brain-computer interface for tetraplegic patients. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):190–193.

Kauhanen, L., P. Rantanen, J. A. Lehtonen, I. Tarnanen, H. Alaranta, and M. Sams. 2004. Sensorimotor cortical activity of tetraplegics during attempted finger movements. *Biomedizinische Technik* 49(1):59–60.

Kay, S. M. 1988. Modern spectral estimation. New York: Prentice-Hall.

Keirn, Z. A. and J. I. Aunon. 1990. A new mode of communication between man and his surroundings. *IEEE Transactions on Biomedical Engineering* 37(12):1209–1214.

Keith, M. W., P. H. Peckham, G. B. Thrope, K. C. Stroh, B. Smith, J. R. Buckett, K. L. Kilgore, and J. W. Jatich. 1989. Implantable functional neuromuscular stimulation in the tetraplegic hand. *The Journal of Hand Surgery* 14(3):524–530.

Kelly, S. P., E. C. Lalor, R. B. Reilly, and J. J. Foxe. 2005. Visual spatial attention tracking using high-density SSVEP data for independent brain-computer communication. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 13(2):172–178.

Kennedy, P. R. and R. A. Bakay. 1998. Restoration of neural output from a paralyzed patient by a direct brain connection. *Neuroreport* 9(8):1707–1711.

Kennedy, P. R., R. A. Bakay, M. M. Moore, K. Adams, and J. Goldwaithe. 2000. Direct control of a computer from the human central nervous system. *IEEE Transactions on Rehabilitation Engineering* 8(2):198–202.

Kennedy, P. R., M. T. Kirby, M. M. Moore, B. King, and A. Mallory. 2004. Computer control using human intracortical local field potentials. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 12(3):339–344.

Kettner, R. E., A. B. Schwartz, and A. P. Georgopoulos. 1988. Primate motor cortex and free arm movements to visual targets in three-dimensional space. III. Positional gradients and population coding of movement direction from various movement origins. *Journal of Neuroscience* 8(8):2938–2947.

Kew, J. J., P. N. Leigh, E. D. Playford, R. E. Passingham, L. H. Goldstein, R. S. Frackowiak, and D. J. Brooks. 1993. Cortical function in amyotrophic lateral sclerosis. A positron emission tomography study. *Brain* 116(3):655–680.

Keysers, C., D.-K. Xiao, P. Foldiak, and D. I. Perrett. 2001. The speed of sight. *Journal of Cognitive Neuroscience* 13(1):90–101.

Kilgore, K. L. and R. F. Kirsch. 2004. Upper and lower extremity motor prosthesis. In *Neuroprosthetics Theory and Practice*, edited by K. W. Horch and G. S. Dhillon. New York: World Scientific Publishing Co.

Kim, J. N. and M. N. Shadlen. 1999. Neural correlates of decision making in the dorsolateral prefrontal cortex of the macaque. *Nature Neuroscience* 2(2):176–185.

Kim, S-.P., J. C. Sanchez, Y. N. Rao, D. Erdogmus, J. M. Carmena, M. A. Lebedev, M. A. L. Nicolelis, and J. C. Principe. 2006. A comparison of optimal MIMO linear and nonlinear models for brain-machine interfaces. *Journal of Neural Engineering* 3(2): 145–161.

Kipke, D. R., R. J. Vetter, J. C. Williams, and J. F. Hetke. 2003. Silicon-substrate intracortical microelectrode arrays for long-term recording of neuronal spike activity in cerebral cortex. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):151–155.

Kira, K. and L. A. Rendell. 1992. The feature selection problem: traditional methods and a new algorithm. In *10th National Conference on Artificial Intelligence*: 129–134.

Kirby, M. and C. Anderson. 2003. Geometric analysis for the characterization of non-stationary time-series. In *Springer Applied Mathematical Sciences Series Celebratory Volume for the Occasion of the 70th Birthday of Larry Sirovich*, edited by E. Kaplan, J. Marsden, and K. R. Katepalli Sreenivasan. Springer-Verlag.

Kirby, M., F. Weisser, and G. Dangelmayr. 1993. A model problem in the representation of digital image sequences. *Pattern Recognition* 26(1):63–73.

Kittler, J. 1978. Feature set search algorithms. In *Pattern Recognition and Signal Processing*, edited by C. H. Chen. Alphen aan den Rijn, The Netherlands: Sijthoff and Noordhoff, 2nd edition.

Kivinen, J. and M. K. Warmuth. 1995. Additive versus exponentiated gradient updates for linear prediction. In *Proceedings 27th Annual ACM Symposium Theory Computing*: 209–218.

Klassen, J., C. Tong, and J. R. Flanagan. 2005. Learning and recall of incremental kinematic and dynamic sensorimotor transformations. *Experimental Brain Research* 164(2):250–259.

Knight, J. N. 2003. Signal fraction analysis and artifact removal in EEG. Master's thesis, Department of Computer Science, Colorado State University. Available at http://www.cs.colostate.edu/eeg/publications/natethesis.pdf.

Kohavi, R. 1995. A study of cross-validation and bootstrap for accuracy estimation and model selection. In *IJCAI 95. Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence*, edited by C. S. Mellish vol. 2: 1137–1145.

Kohonen, T. 1997. Self-organizing maps. Berlin, Germany: Springer-Verlag, 2nd edition.

Koles, Z. J., M. S. Lazar, and S. Z. Zhou. 1990. Spatial patterns underlying population differences in the background EEG. *Brain Topography* 2(4):275–284.

Koles, Z. J. and A. C. K. Soong. 1998. EEG source localization: implementing the spatio-temporal decomposition approach. *Electroencephalography and Clinical Neurophysiology* 107(5):343–352.

Kornhuber, H. H. and L. Deecke. 1965. Hirnpotentialänderungen bei Willkürbewegungen und passiven Bewegungen des Menschen: Bereitschaftspotential und reafferente Potentiale. *Pflügers Archiv* 284:1–17.

Kotchoubey, B. 2005. Apallic syndrome is not apallic: is vegetative state vegetative? *Neuropsychological Rehabilitation* 15:333–356.

Kotchoubey, B., S. Lang, V. Bostanov, and N. Birbaumer. 2002. Is there a mind? Electrophysiology of unconscious patients. *News in Physiological Sciences* 1–17:38–42.

Kotchoubey, B., S. Lang, G. Mezger, D. Schmalohr, M. Schneck, A. Semmler, V. Bostanov, and N. Birbaumer. 2005. Information processing in severe disorders of consciousness: vegetative state and minimally conscious state. *Clinical Neurophysiology* 116(10):2441–2453.

Kotchoubey, B., H. Schleichert, W. Lutzenberger, and N. Birbaumer. 1997. A new method for self-regulation of slow cortical potentials in a timed paradigm. *Applied Psychophysiology and Biofeedback* 22(2):77–93.

Kotchoubey, B., D. Schneider, H. Schleichert, U. Strehl, C. Uhlmann, V. Blankenhorn, W. Fröscher, and N. Birbaumer. 1996. Self-regulation of slow cortical potentials in epilepsy: a retrial with analysis of influencing factors. *Epilepsy Research* 25(3):269–276.

Kraemer, H. C. 1982. Kappa coefficient. In *Encyclopedia of Statistical Sciences*, edited by S. Kotz and N. L. Johnson. New York: John Wiley & Sons.

Krauledat, M., G. Dornhege, B. Blankertz, G. Curio, and K. R. Müller. 2004. The Berlin Brain-Computer Interface for rapid response. *Biomedizinische Technik* 49(1):61–62.

Krauledat, M., G. Dornhege, B. Blankertz, and K. R. Müller. 2005. Robustifying EEG data analysis by removing outliers. *Chaos and Complexity* 2(2).

Krausz, G., R. Scherer, G. Korisek, and G. Pfurtscheller. 2003. Critical decision-speed and information transfer in the "Graz Brain-Computer Interface". *Applied Psychophysiology and Biofeedback* 28(3):233–240.

Krepki, R., G. Curio, B. Blankertz, and K. R. Müller. To appear. Berlin Brain-Computer Interface—the HCI communication channel for discovery. *International Journal of Human-Computer Studies*.

Krepki, Roman. 2004. Brain-Computer Interfaces: Design and implementation of an online BCI system of the control in gaming applications and virtual limbs. PhD thesis, Technische Universität Berlin, Fakultät IV—Elektrotechnik und Informatik.

Kronegg, J. and T. Pun. 2005. Measuring the performance of brain-computer interfaces using the information transfer rate. Brain-Computer Interface Technology: Third International Meeting, June 14–19, 2005, Rensselaerville, New York.

Kronegg, J., S. Voloshynovskiy, and T. Pun. 2005. Analysis of bit-rate definitions for brain-computer interfaces. In *Proceedings International Conference on Human-Computer Interaction (HCI'05)*, Las Vegas.

Krusienski, D. J., E. W. Sellers, T. M. Vaughan, D. J. McFarland, and J. R. Wolpaw. 2005. P300 speller matrix classification via stepwise linear discriminant analysis. Poster presented at the Brain-Computer Interface Technology Third International Meeting, Rensselaerville, New York.

Kübler, A. 2000. Brain-computer communication—development of a brain-computer interface for locked-in patients on the basis of the psychophysiological self-regulation training of slow cortical potentials (SCP). Tübingen: Schwäbische Verlagsgesellschaft.

Kübler, A., S. Häcker, E. M. Braun, M. Hautzinger, and T. Meyer. In preparation. Individually defined quality of life, depression, and variation of positive reinforcement in patients with ALS.

Kübler, A., B. Kotchoubey, T. Hinterberger, N. Ghanayim, J. Perelmouter, M. Schauer, C. Fritsch, E. Taub, and N. Birbaumer. 1999. The Thought Translation Device: a neurophysiological approach to communication in total motor paralysis. *Experimental Brain Research* 124(2):223–232.

Kübler, A., B. Kotchoubey, J. Kaiser, J. R. Wolpaw, and N. Birbaumer. 2001a. Brain-computer communication: unlocking the locked in. *Psychological Bulletin* 127(3):358–375.

Kübler, A., B. Kotchoubey, H. P. Salzmann, N. Ghanayim, J. Perelmouter, V. Homberg, and N. Birbaumer. 1998. Self-regulation of slow cortical potentials in completely paralyzed human patients. *Neuroscience Letters* 252(3):171–174.

Kübler, A. and N. Neumann. 2005. Brain-computer interfaces - the key for the conscious brain locked into a paralysed body. *Progress in Brain Research* 150:513–525.

Kübler, A., N. Neumann, J. Kaiser, B. Kotchoubey, T. Hinterberger, and N. P. Birbaumer. 2001b. Brain-computer communication: self-regulation of slow cortical potentials for verbal communication. *Archives of Physical Medicine and Rehabilitation* 82(11):1533–1539.

Kübler, A., N. Neumann, B. Wilhelm, T. Hinterberger, and N. Birbaumer. 2004. Predictability of brain-computer communication. *International Journal of Psychophysiology* 18:121–129.

Kübler, A., F. Nijboer, J. Mellinger, T. M. Vaughan, H. Pawelzik, G. Schalk, D. J. McFarland, N. Birbaumer, and J. R. Wolpaw. 2005a. Patients with ALS can use sensorimotor rhythms to operate a brain computer interface. *Neurology* 64(10):1775–1777.

Kübler, A., C. Weber, and N. Birbaumer. 2006. Locked-in—freigegeben für den Tod. wenn nur Denken und Fühlen bleiben—Neuroethik des Eingeschlossenseins. *Zeitschrift für Medizinische Ethik* 52:57–70.

Kübler, A., S. Winter, and N. Birbaumer. 2003. The Thought Translation Device: Slow cortical potential biofeedback for verbal communication in paralysed patients. In *Biofeedback - A Practitioner's Guide*, edited by M. S. Schwartz and F. Andrasik. New York: Guilford Press, 3rd edition.

Kübler, A., S. Winter, A. Ludolph, M. Hautzinger, and N. Birbaumer. 2005b. Severity of depressive symptoms and quality of life in patients with amyotrophic lateral sclerosis. *Neurorehabilitation and Neural Repair* 19(3):182–193.

Kumar, N. and A. G. Andreou. 1998. Heteroscedastic discriminant analysis and reduced rank HMMs for improved speech recognition. *Speech Communication* 26(4):283–297.

Lachaux, J. P., E. Rodriguez, J. Martinerie, and F. J. Varela. 1999. Measuring phase synchrony in brain signals. *Human Brain Mapping* 8(4):194–208.

Lahrmann, H., C. Neuper, G. R. Müller, R. Scherer, and G. Pfurtscheller. 2005. Usefulness of an EEG-based brain-computer interface to establish communication in ALS. *Journal of the Neurological Sciences* 238(1):485.

Lakerfeld, J., B. Kotchoubey, and A. Kübler. Submitted. Cognitive function in late stage ALS patients. *Journal of the Neurological Sciences*.

Lal, T., M. Schröder, J. Hill, H. Preissl, T. Hinterberger, J. Mellinger, M. Bogdan, W. Rosenstiel, T. Hofmann, N. Birbaumer, and B. Schölkopf. 2005a. A brain computer interface with online feedback based on magnetoencephalography. In *Proceedings of the 22nd International Conference on Machine Learning*: 465–472.

Lal, T. N. 2005. Machine learning methods for brain-computer interfaces. MPI Series in Biological Cybernetics, Bd. 12. Berlin: Logos Verlag.

Lal, T. N., O. Chapelle, J. Weston, and A. Elisseeff. in press. Embedded methods. In *Feature extraction, foundations and applications*, edited by I. Guyon, S. Gunn, M. Nikravesh, and L. Zadeh. Springer.

Lal, T. N., T. Hinterberger, G. Widman, M. Schröder, N. J. Hill, W. Rosenstiel, C. E. Elger, B. Schölkopf, and N. Birbaumer. 2005b. Methods towards invasive human brain computer interfaces. In *Advances in Neural Information Processing Systems (NIPS 04)*, edited by Lawrence K. Saul, Yair Weiss, and Léon Bottou, vol. 17. Cambridge, Mass.: The MIT Press.

Lal, T. N., M. Schröder, T. Hinterberger, J. Weston, M. Bogdan, N. Birbaumer, and B. Schölkopf. 2004. Support vector channel selection in BCI. *IEEE Transactions on Biomedical Engineering* 51(6):1003–1010.

Lalor, E. C., S. P. Kelly, C. Finucane, R. Burke, R. Smith, R. B. Reilly, and G. McDarby. 2005. Steady-state VEP-based brain-computer interface control in an immersive 3D gaming environment. *EURASIP Journal on Applied Signal Processing* 19:3156–3164.

Lang, W., M. Lang, F. Uhl, Ch. Koska, A. Kornhuber, and L. Deecke. 1988. Negative cortical DC shifts preceding and accompanying simultaneous and sequential movements. *Experimental Brain Research* 71(3):579–587.

Laskov, P., C. Schäfer, I. Kotenko, and K.-R. Müller. 2004. Intrusion detection in unlabeled data with quarter-sphere support vector machines (extended version). *Praxis der Informationsverarbeitung und Kommunikation* 27:228–236.

Lauer, R. T., P. H. Peckham, K. L. Kilgore, and W. J. Heetderks. 2000. Applications of cortical signals to neuroprosthetic control: a critical review. *IEEE Transactions on Rehabilitation Engineering* 8(2):205–208.

Laureys, S., F. Pellas, P. Van Eeckhout, S. Ghorbel, C. Schnakers, F. Perrin, J. Berre, M. E. Faymonville, K. H. Pantke, F. Damas, M. Lamy, G. Moonen, and S. Goldman. 2005. The locked-in syndrome: what is it like to be conscious but paralyzed and voiceless? *Progress in Brain Research* 150:495–511.

Lebedev, M. A. and M. A. L. Nicolelis. 2006. Brain machine interfaces: Past, present and future. *Trends in Neurosciences* 29(9):536–546.

Lee, P. L., J. C. Hsieh, C. H. Wu, K. K. Shyu, S. S. Chen, T. C. Yeh, and Y. T. Wu. 2006. The brain computer interface using flash visual evoked potential and independent component analysis. *Annals of Biomedical Engineering* 34(10):1641–1654.

Lee, Y. J., O. L. Mangasarian, and W. H. Wolberg. 2000. Breast cancer survival and chemotherapy: A support vector machine analysis. *DIMACS Series in Discrete Mathematics and Theoretical Computer Science* 55:1–10.

Leeb, R., C. Keinrath, C. Guger, and G. Pfurtscheller. 2003. Combining brain-computer interface and virtual reality technologies. In *Proceedings Annual Conference of the German, Austrian and Swiss Association of Biomedical Engineering (BMT 2003), Biomed Tech (Berl)* vol. 48 (Suppl.Vol.1): 34–35.

Leeb, R. and G. Pfurtscheller. 2004. Walking through a virtual city by thought. In *Proceedings of the 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society - EMBC 2004* vol. 6: 4503–4506, San Francisco.

Leeb, R., R. Scherer, C. Keinrath, C. Guger, and G. Pfurtscheller. 2005. Exploring virtual environments with an EEG-based BCI through motor imagery. *Biomedizinische Technik.*

Biomedical engineering (Berl) 50(4):86–91.

Lemm, S., B. Blankertz, G. Curio, and K. R. Müller. 2005. Spatio-spectral filters for improved classification of single trial EEG. *IEEE Transactions on Biomedical Engineering* 52(9):1541–1548.

Leon-Carrion, J., P. van Eeckhout, M. del R. Dominguez-Morales, and F. J. Perez-Santamaria. 2002. The locked-in syndrome: a syndrome looking for a therapy. *Brain Injury* 16(7):571–582.

Leuthardt, E. C., K. J. Miller, G. Schalk, R. P. Rao, and J. G. Ojemann. 2006a. Electrocorticography-based brain computer interface–the Seattle experience. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):194–198.

Leuthardt, E. C., G. Schalk, D. Moran, and J. G. Ojemann. 2006b. The emerging world of motor neuroprosthetics: a neurosurgical perspective. *Neurosurgery* 59(1):1–14.

Leuthardt, E. C., G. Schalk, J. R. Wolpaw, J. G. Ojemann, and D. W. Moran. 2004. A brain-computer interface using electrocorticographic signals in humans. *Journal of Neural Engineering* 1(2):63–71.

Levine, S. P., J. E. Huggins, S. L. BeMent, R. K. Kushwaha, L. A. Schuh, E. A. Passaro, M. M. Rohde, and D. A. Ross. 1999. Identification of electrocorticogram patterns as the basis for a direct brain interface. *Journal of Clinical Neurophysiology* 16(5):439–447.

Levine, S. P., J. E. Huggins, S. L. BeMent, R. K. Kushwaha, L. A. Schuh, M. M. Rohde, E. A. Passaro, D. A. Ross, K. V. Elsievich, and B. J. Smith. 2000. A direct brain interface based on event-related potentials. *IEEE Transactions on Rehabilitation Engineering* 8 (2):180–185.

Linde, Y., A. Buzo, and R. M. Gray. 1980. An algorithm for vector quantizer design. *IEEE Transactions on Communications* COM-28(1):84–95.

Liu, A. K., J. W. Belliveau, and A. M. Dale. 1998. Spatiotemporal imaging of human brain activity using functional MRI constrained magnetoencephalography data: Monte Carlo simulations. *Proceedings of the National Academy of Sciences of the United States of America* 95(15):8945–8950.

Liu, J., A. Harris, and N. Kanwisher. 2002. Stages of processing in face perception: an MEG study. *Nature Neuroscience* 5(9):910–916.

Liu, J., M. Higuchi, A. Marantz, and N. Kanwisher. 2000. The selectivity of the occipitotemporal M170 for faces. *Neuroreport* 11(2):337–341.

Liu, X., D. B. McCreery, R. R. Carter, L. A. Bullara, T. G. Yuen, and W. F. Agnew. 1999. Stability of the interface between neural tissue and chronically implanted intracortical microelectrodes. *IEEE Transactions on Rehabilitation Engineering* 7(3):315–326.

Llinas, R., U. Ribary, D. Jeanmonod, E. Kronberg, and P. P. Mitra. 1999. Thalamocortical dysrhythmia: A neurological and neuropsychiatric syndrome characterized by magnetoencephalography. *Proceedings of the National Academy of Sciences of the United States of America* 96(26):15222–15227.

Loog, M. and R.P.W. Duin. 2004. Linear dimensionality reduction via a heteroscedastic extension of LDA: the Chernoff criterion. *IEEE Transactions on Pattern Analysis and*

Machine Intelligence 26(6):732–739.

Lotze, M., C. Braun, N. Birbaumer, S. Anders, and L. G. Cohen. 2003. Motor learning elicited by voluntary drive. *Brain* 126(4):866–872.

Lotze, M., H. Flor, W. Grodd, W. Larbig, and N. Birbaumer. 2001. Phantom movements and pain. An fMRI study in upper limb amputees. *Brain* 124(11):2268–2277.

Lotze, M., W. Grodd, N. Birbaumer, M. Erb, E. Huse, and H. Flor. 1999a. Does use of a myoelectric prosthesis prevent cortical reorganization and phantom limb pain? *Nature Neuroscience* 2(6):501–502.

Lotze, M., P. Montoya, M. Erb, E. Hülsmann, H. Flor, U. Klose, N. Birbaumer, and W. Grodd. 1999b. Activation of cortical and cerebellar motor areas during executed and imagined hand movements: an fMRI study. *Journal of Cognitive Neuroscience* 11 (5):491–501.

Low, A., B. Rockstroh, R. Cohen, O. Hauk, P. Berg, and W. Maier. 1999. Determining working memory from ERP topography. *Brain Topography* 12(1):39–47.

Lulé, D., V. Diekmann, J. Kassubek, A. Kurt, N. Birbaumer, A. C. Ludolph, and E. Kraft. In press. Cortical reorganization in amyotrophic lateral sclerosis: motor imagery and motor function. *Annals of Neurology*.

Lulé, D., A. Kurt, R. Jurgens, J. Kassubek, V. Diekmann, E. Kraft, N. Neumann, A. C. Ludolph, N. Birbaumer, and S. Anders. 2005. Emotional responding in amyotrophic lateral sclerosis. *Journal of Neurology* 252(12):1517–1524.

Lundqvist, C., A. Siosteen, C. Blomstrand, B. Lind, and M. Sullivan. 1991. Spinal cord injuries. clinical, functional, and emotional status. *Spine* 16(1):78–83.

Luo, A. and P. Sajda. 2006. Learning discrimination trajectories in EEG sensor space: application to inferring task difficulty. *Journal of Neural Engineering* 3(1):L1–6.

Lutzenberger, W., N. Birbaumer, T. Elbert, B. Rockstroh, W. Bippus, and R. Breidt. 1980. Self-regulation of slow cortical potentials in normal subjects and patients with frontal lobe lesions. *Progress in Brain Research* 54:427–430.

Lutzenberger, W., T. Elbert, B. Rockstroh, and N. Birbaumer. 1979. The effects of self-regulation of slow cortical potentials on performance in a signal detection task. *The International Journal of Neuroscience* 9(3):175–183.

Lutzenberger, W., T. Elbert, B. Rockstroh, and N. Birbaumer. 1982. Biofeedback produced slow brain potentials and task performance. *Biological Psychology* 14(1–2):99–111.

Makeig, S., A. Delorme, M. Westerfield, T. P. Jung, J. Townsend, E. Courchense, and T. J. Sejnowski. 2004. Electroencephalographic brain dynamics following manually responded visual targets. *PLoS Biology* 2(6):e176.

Makeig, S. and A. Delourme. EEGLAB. Available at http://sccn.ucsd.edu/eeglab/.

Makeig, S., M. Westerfield, T.-P. Jung, J. Covington, J. Townsend, T. Sejnowski, and E. Courchesne. 1999. Functionally independent components of the late positive event-related potential during visual spatial attention. *Journal of Neuroscience* 19(7):2665–2680.

Mantegazza et al, P. 2000. RTAI – real-time linux application interface for Linux. Available at http://www.rtai.org/.

Margalit, E., J. D. Weiland, R. E. Clatterbuck, G. Y. Fujii, M. Maia, M. Tameesh, G. Torres, S. A. D'Anna, D. V. Piyathaisere S. Desai, A. Olivi, E. Jr. de Juan, and M. S. Humayun. 2003. Visual and electrical evoked response recorded from subdural electrodes implanted above the visual cortex in normal dogs under two methods of anesthesia. *Journal of Neuroscience Methods* 123(2):129–137.

Mason, S. G., A. Bashashati, M. Fatourechi, K. F. Navarro, and G. E. Birch. Submitted. A comprehensive survey of brain interface technology designs. *Annals of Biomedical Engineering*.

Mason, S. G. and G. E. Birch. 2000. A brain-controlled switch for asynchronous control applications. *IEEE Transactions on Biomedical Engineering* 47(10):1297–1307.

Mason, S. G. and G. E. Birch. 2003. A general framework for brain-computer interface design. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(1): 70–85.

Mason, S. G. and G. E. Birch. 2005. Temporal control paradigms for direct brain interfaces—rethinking the definition of asynchronous and synchronous. In *Proceedings of HCI International*, Las Vegas.

Mason, S. G., R. Bohringer, J. F. Borisoff, and G. E. Birch. 2004. Real-time control of a video game with a direct brain-computer interface. *Journal of Clinical Neurophysiology* 21(6):404–408.

Mason, S. G., M. M. Jackson, and G. E. Birch. 2005a. A general framework for characterizing studies of brain interface technology. *Annals of Biomedical Engineering* 33(11):1653–1670.

Mason, S. G., J. Kronegg, J. E. Huggins, A. Schlögl, M. Fatourechi, R. Kaidar, R. Scherer, and A. Buttfield. 2005b. Asynchronous BCI performance evaluation. BCIinfo.org research papers. Available at http://bciinfo.org/Research_Info/documents/articles/AsynchBCIDiscussionSummaryBCI2005.pdf.

Maynard, E., C. Nordhausen, and R. Normann. 1997. The Utah intracortical electrode array: A recording structure for potential brain-computer interfaces. *Electroencephalography and Clinical Neurophysiology* 102(3):228–239.

Mazurek, M. E., J. D. Roitman, J. Ditterich, and M. N. Shadlen. 2003. A role for neural integrators in perceptual decision making. *Cerebral Cortex* 13(11):1257–1269.

Mazzone, P., A. Lozano, P. Stanzione, S. Galati, E. Scarnati, A. Peppe, and A. Stefani. 2005. Implantation of human pedunculopontine nucleus: a safe and clinically relevant target in Parkinson's disease. *Neuroreport* 16(17):1877–1881.

McFarland, D. J., C. W. Anderson, K. R. Müller, A. Schlögl, and D. J. Krusienski. 2006. BCI Meeting 2005—workshop on BCI signal processing: feature extraction and translation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14 (2):135–138.

McFarland, D. J., T. Lefkowicz, and J. R. Wolpaw. 1997a. Design and operation of an EEG-based brain-computer interface (BCI) with digital signal processing technology. *Behavioral Research Methods Instruments and Computers* 29(3):337–345.

McFarland, D. J., L. M. McCane, S. V. David, and J. R. Wolpaw. 1997b. Spatial filter selection for EEG-based communication. *Electroencephalography and Clinical Neurophysiology* 103(3):386–394.

McFarland, D. J., L. M. McCane, and J. R. Wolpaw. 1998. EEG-based communication and control: short-term role of feedback. *IEEE Transactions on Rehabilitation Engineering* 6(1):7–11.

McFarland, D. J., G. W. Neat, R. F. Read, and J. R. Wolpaw. 1993. An EEG-based method for graded cursor control. *Psychobiology* 21:77–81.

McFarland, D. J., W. A. Sarnacki, T. M. Vaughan, and J. R. Wolpaw. 2005. Brain-computer interface (BCI) operation: signal and noise during early training sessions. *Clinical Neurophysiology* 116(1):56–62.

McFarland, D. J., W. A. Sarnacki, and J. R. Wolpaw. 2003. Brain-computer interface (BCI) operation: optimizing information transfer rates. *Biological Psychology* 63(3):237–251.

McFarland, D. J. and J. R. Wolpaw. 2005. Sensorimotor rhythm-based brain-computer interface (BCI): Feature selection by regression improves performance. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 13(3):372–379.

Mehring, C., J. Rickert, E. Vaadia, S. Cardoso de Oliveira, A. Aertsen, and S. Rotter. 2003. Inference of hand movements from local field potentials in monkey motor cortex. *Nature Neuroscience* 6(12):1253–1254.

Meinicke, P., M. Kaper, F. Hoppe, M. Huemann, and H. Ritter. 2002. Improving transfer rates in brain computer interface: A case study. In *Advances in Neural Information Processing Systems (NIPS 01)*: 1107–1114, Cambridge, Mass. The MIT Press.

Meir, R. and G. Rätsch. 2003. An introduction to boosting and leveraging. In *Advanced Lectures on Machine Learning*, edited by S. Mendelson and A. Smola, LNAI. Springer.

Mellinger, J., T. Hinterberger, M. Bensch, M. Schröder, and N. Birbaumer. 2003. Surfing the web with electrical brain signals: the brain web surfer (BWS) for the completely paralysed. In *Proceedings of the 2nd World Congress of the International Society of Physical and Rehabilitation Medicine - ISPRM*, edited by Nachum Ring, Haim; Soroker: 731–738, Bologna (Monduzzi).

Mellinger, J., G. Schalk, C. Braun, H. Preissl, N. Birbaumer, and A. Kübler. 2005. A brain-computer interface (BCI) based on magnetoenecephalography (MEG). *Psychophysiology* 42(1):88.

Mellinger, J., G. Schalk, C. Braun, H. Preissl, W. Rosenstiel, N. Birbaumer, and A. Kübler. Under revision. An MEG-based brain-computer interface. *Neuroimage*.

Merzenich, M. M., D. N. Schindler, and M. W. White. 1974. Feasibility of multichannel scala tympani stimulation. *Laryngoscope* 84(11):1887–1893.

Miall, R. C., N. Jenkinson, and K. Kulkarni. 2004. Adaptation to rotated visual feedback: a re-examination of motor interference. *Experimental Brain Research* 154(2):201–210.

Middendorf, M., G. McMillan, G. Calhoun, and K. S. Jones. 2000. Brain-computer interfaces based on the steady-state visual-evoked response. *IEEE Transactions on Rehabilitation Engineering* 8(2):211–214.

Mika, S. 2002. Kernel fisher discriminants. PhD thesis, University of Technology, Berlin.

Mika, S., G. Rätsch, and K.-R. Müller. 2001. A mathematical programming approach to the Kernel Fisher algorithm. In *Advances in Neural Information Processing Systems (NIPS 00)*, edited by T. K. Leen, T. G. Dietterich, and V. Tresp vol. 13: 591–597, Cambridge, Mass. The MIT Press.

Mika, S., G. Rätsch, J Weston, B. Schölkopf, A. Smola, and K.-R. Müller. 2003. Constructing descriptive and discriminative non-linear features: Rayleigh coefficients in kernel feature spaces. *IEEE Transaction on Pattern Analysis and Machine Intelligence* 25(5): 623–628.

Mika, S., B. Schölkopf, A.J. Smola, K.-R. Müller, M. Scholz, and G. Rätsch. 1999. Kernel PCA and de–noising in feature spaces. In *Advances in Neural Information Processing Systems (NIPS 98)*, edited by M.S. Kearns, S.A. Solla, and D.A. Cohn: 536–542, Cambridge, Mass. MIT Press.

Millán, J. d. R., M. Franzé, J. Mouriño, F. Cincotti, and F. Babiloni. 2002a. Relevant EEG features for the classification of spontaneous motor-related tasks. *Biological Cybernetics* 86(2):89–95.

Millán, J. d. R. 2002. Brain-computer interfaces. In *Handbook of Brain Theory and Neural Networks*, edited by Michael A. Arbib. Cambridge, Mass.: The MIT Press, 2nd ed.

Millán, J. d. R. 2003. Adaptive brain interfaces. *Communications of the ACM* 46:74–80.

Millán, J. d. R. 2004. On the need for on-line learning in brain-computer interfaces. In *Proceedings of the International Joint Conference on Neural Networks*, Budapest, Hungary.

Millán, J. d. R., M. Franzé, J. Mouriño, F. Cincotti, and F. Babiloni. 2002b. Relevant EEG features for the classification of spontaneous motor-related tasks. *Biological Cybernetics* 86(2):89–95.

Millán, J. d. R. and J. Mouriño. 2003. Asynchronous BCI and local neural classifiers: an overview of the Adaptive Brain Interface project. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):159–161.

Millán, J. d. R., J. Mouriño, M. Franzé, F. Cincotti, M. Varsta, J. Heikkonen J, and F. Babiloni. 2002c. A local neural classifier for the recognition of EEG patterns associated to mental tasks. *IEEE Transactions on Neural Networks* 13(3):678–686.

Millán, J. d. R., F. Renkens, J. Mouriño, and W. Gerstner. 2004a. Noninvasive brain-actuated control of a mobile robot by human EEG. *IEEE Transactions on Biomedical Engineering* 51(6):1026–1033.

Millán, J. d. R., F. Renkens, J. Mouriño, and W. Gerstner. 2004b. Brain-actuated interaction. *Artificial Intelligence* 159(1–2):241–259.

Miller, N. E. 1969. Learning of visceral and glandular responses. *Science* 163(866): 434–445.

Miner, L. A., D. J. McFarland, and J. R. Wolpaw. 1998. Answering questions with an electroencephalogram-based brain-computer interface. *Archives of Physical Medicine and Rehabilitation* 79(9):1029–1033.

Moran, D. W. and A. B. Schwartz. 1999. Motor cortical representation of speed and direction during reaching. *Journal of Neurophysiology* 82(5):2676–2692.

Morrow, M. M. and L. E. Miller. 2003. Prediction of muscle activity by populations of sequentially recorded primary motor cortex neurons. *Journal of Neurophysiology* 89(4): 2279–2288.

Mosher, J. C., S. Baillet, and R. M. Leahy. 1999. EEG source localization and imaging using multiple signal classification approaches. *Journal of Clinical Neurophysiology* 16 (3):225–238.

Mouriño, J. 2003. EEG-based analysis for the design of adaptive brain interfaces. PhD thesis, Centre de Recerca en Enginyeria Biomdica, Universitat Politcnica de Catalunya, Barcelona, Spain.

Mouriño, J., J. d. R. Millán, F. Cincotti, S. Chiappa, R. Jané, and F. Babiloni. 2001. Spatial filtering in the training process of a brain computer interface. In *Proceedings 23rd Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society*.

Müller, G. R., C. Neuper, and G. Pfurtscheller. 2001. “Resonance-like” frequencies of sensorimotor areas evoked by repetitive tactile stimulation. *Biomedizinische Technik* 46 (7–8):186–190.

Müller, G. R., C. Neuper, and G. Pfurtscheller. 2003a. Implementation of a telemonitoring system for the control of an EEG-based brain-computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(1):54–59.

Müller, G. R., R. Scherer, C. Neuper, H. Lahrmann, P. Staiger-Sälzer, and G. Pfurtscheller. 2004a. EEG-basierende Kommunikation: Erfahrungen mit einem Telemonitoringsystem zum Patiententraining. In *Proceedings of 38th Ann. Conv. of the German Society for Medical and Biological Engineering in VDE* vol. 49: 230–231. Suppl. vol. Biomed Techn (Berl.).

Müller, K.-R., C. W. Anderson, and G. E. Birch. 2003b. Linear and nonlinear methods for brain-computer interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):165–169.

Müller, K.-R. and B. Blankertz. 2006. Toward non-invasive brain-computer interfaces. *IEEE Signal Processing Magazine*.

Müller, K.-R., M. Krauledat, G. Dornhege, G. Curio, and B. Blankertz. 2004b. Machine learning techniques for brain-computer interfaces. *Biomedizinische Technik* 49(1):11–22.

Müller, K.-R., S. Mika, G. Rätsch, K. Tsuda, and B. Schölkopf. 2001. An introduction to kernel-based learning algorithms. *IEEE Transactions on Neural Networks* 12(2):181–201.

Müller-Gerking, J., G. Pfurtscheller, and H. Flyvbjerg. 1999. Designing optimal spatial filters for single-trial EEG classification in a movement task. *Clinical Neurophysiology*

110(5):787–798.

Müller-Putz, G. R., R. Scherer, C. Brauneis, and G. Pfurtscheller. 2005a. Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components. *Journal of neural engineering* 2(4):123–130.

Müller-Putz, G. R., R. Scherer, C. Neuper, and G. Pfurtscheller. 2006. Steady-state somatosensory evoked potentials: suitable brain signals for brain-computer interfaces? *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(1):30–37.

Müller-Putz, G. R., R. Scherer, G. Pfurtscheller, and R. Rupp. 2005b. EEG-based neuroprosthesis control: a step towards clinical practice. *Neuroscience Letters* 382(1–2): 169–174.

Murase, N., J. Duque, R. Mazzocchio, and L. G. Cohen. 2004. Influence of interhemispheric interactions on motor function in chronic stroke. *Annals of Neurology* 55(3): 400–409.

Musallam, S., B. D. Corneil, B. Greger, H. Scherberger, and R. A. Andersen. 2004. Cognitive control signals for neural prosthetics. *Science* 305(5681):258–262.

Mussa-Ivaldi, F. A. and L. E. Miller. 2003. Brain-machine interfaces: computational demands and clinical needs meet basic neuroscience. *Trends in Neurosciences* 26(6): 329–334.

Nagai, Y., H. D. Crittchley, E. Feathersone, P. B. Fenwick, M. R. Trimble, and R. J. Dolan. 2004. Brain activity relating to the contingent negative variation: an fMRI investigation. modulation by volitional control of peripheral autonomic arousal. *NeuroImage* 21(4): 1232–1241.

National Instruments. Available atr http://www.ni.com/.

Nelson, W. T., L. J. Hettinger, J. A. Cunningham, M. M. Roe, M. W. Haas, and L. B. Dennis. 1997. Navigating through virtual flight environments using brain-body-actuated control. In *Proceedings Virtual Reality Annual International Symposium*: 30–37.

Nenadic, Z. 2006. Information discriminant analysis: Feature extraction with an information-theoretic objective. Technical report, Department of Biomedical Engineering, University of California, Irvine. Available at http://cbmspc.eng.uci.edu/PUBLICATIONS/tr:06a.pdf.

Nenadic, Z. and J. W. Burdick. 2005. Spike detection using the continuous wavelet transform. *IEEE Transactions on Biomedical Engineering* 52(1):74–87.

Nenadic, Z. and J. W. Burdick. 2006. A control algorithm for autonomous optimization of extracellular recordings. *IEEE Transactions on Biomedical Engineering* 53(5):941–955.

Neumann, N., A. Kübler, J. Kaiser, T. Hinterberger, and N. Birbaumer. 2003. Conscious perception of brain states: mental strategies for brain-computer communication. *Neuropsychologia* 41(8):1026–1036.

Neuper, C., G. R. Müller, A. Kübler, N. Birbaumer, and G. Pfurtscheller. 2003. Clinical application of an EEG-based brain-computer interface: a case study in a patient with severe motor impairment. *Clinical Neurophysiology* 114(3):399–409.

Neuper, C. and G. Pfurtscheller. 2001. Event-related dynamics of cortical rhythms: frequency-specific features and functional correlates. *International Journal of Psychophysiology* 43(1):41–58.

Neuper, C. and G. Pfurtscheller. 1999. Motor imagery and ERD. In *Event-Related Desynchronization. Handbook of Electroencephalography and Clinical Neurophysiology*, edited by G. Pfurtscheller and F. H. Lopes da Silva. Amsterdam: Elsevier.

Neuper, C., R. Scherer, M. Reiner, and G. Pfurtscheller. 2005. Imagery of motor actions: differential effect of kinesthetic and visual-motor mode of imagery in single-trial EEG. *Brain Research. Cognitive Brain Research* 25(3):668–677.

Neuper, C., A. Schlögl, and G. Pfurtscheller. 1999. Enhancement of left-right sensorimotor EEG differences during feedback-regulated motor imagery. *Journal of Clinical Neurophysiology* 16(4):373–382.

Newsome, W. T., K. H. Britten, and J. A. Movshon. 1989. Neuronal correlates of a perceptual decision. *Nature* 341(6237):52–54.

Nicolelis, M. A. 2003. Brain-machine interfaces to restore motor function and probe neural circuits. *Nature Reviews Neuroscience* 4(5):417–422.

Nicolelis, M. A., D. Dimitrov, J. M. Carmena, R. Crist, G. Lehew, J. D. Kralik, and S. P. Wise. 2003. Chronic, multisite, multielectrode recordings in macaque monkeys. *Proceedings of the National Academy of Sciences of the United States of America* 100 (19):11041–11046.

Nicolelis, M. A. L. 2001. Actions from thoughts. *Nature* 409(6818):403–407.

Niedermeyer, E. 2005a. Maturation of the EEG: Development of waking and sleep patterns. In *Electroencephalography—Basic Principles, Clinical Applications, and Related Fields*, edited by E. Niedermeyer and F. H. Lopes da Silva. Philadelphia: Lippincott Williams & Wilkins, 5th edition.

Niedermeyer, E. 2005b. The normal EEG of the waking adult. In *Electroencephalography—Basic Principles, Clinical Applications, and Related Fields*, edited by E. Niedermeyer and F. H. Lopes da Silva. Philadelphia: Lippincott Williams & Wilkins, 5th edition.

Nielsen, K. D., A. F. Cabrera, and O. F. do Nascimento. 2006. EEG based BCI-towards a better control. Brain-computer interface research at Aalborg University. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):202–204.

Nijboer, F., I. Gunst, A. Furdea, S. von Hartlieb, D. McFarland, N. Birbaumer, and A. Kübler. In preparationa. A comparison between brain-computer interface performance based on auditory and visual feedback in healthy participants. *Journal of Neuroscience Methods*.

Nijboer, F., M. Jordan, T. Matuz, J. Mellinger, U. Mochty, B. Wilhelm, N. Birbaumer, and A. Kübler. In press. Brain computer interface research in Tübingen: toward a better understanding of how to control a BCI by patients with severe neurological diseases. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*.

Nijboer, F., U. Mochty, J. Mellinger, T. Matuz, M. Jordan, E. Sellers, T. M. Vaughan, D. J. McFarland, G. Schalk, J. R. Wolpaw, N. Birbaumer, and A. Kübler. 2005. Comparing sensorimotor rhythms, slow cortical potentials, and P300 for brain-computer interface (BCI) use by ALS patients—a within subjects design. Poster presented at Brain-Computer Interface Technology: Third International Meeting, Rensselaerville, New York, June 14-19.

Nijboer, F., E. Sellers, J. Mellinger an T. Matuz, U. Mochty, M. Jordan, D. Krusienski, J. R. Wolpaw, N. Birbaumer, and A. Kübler. In preparationb. P300-based brain-computer interface (BCI) performance in people with ALS.

Nunez, P. L., R. Srinivasan, A. F. Westdorp, R. S. Wijesinghe, D. M. Tucker, R. B. Silberstein, and P. J. Cadusch. 1997. EEG coherency I: statistics, reference electrode, volume conduction, Laplacians, cortical imaging, and interpretation at multiple scales. *Electroencephalography and Clinical Neurophysiology* 103(5):499–515.

Nykopp, T. 2001. Statistical modelling issues for the adaptive brain interface. Master's thesis, Helsinki University of Technology, Department of Electrical and Communications Engineering.

Obermaier, B., G. Müller, and G. Pfurtscheller. 2001. 'Virtual keyboard' controlled by spontaneous EEG activity. In *Artificial-Neural-Networks-ICANN-2001*, edited by G. Dorffner, H. Bischof, and K. Hornik: 636–641, Berlin. Springer. LNCS 2130.

Obermaier, B., G. R. Müller, and G. Pfurtscheller. 2003. "Virtual keyboard" controlled by spontaneous EEG activity. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(4):422–426.

OctaveForge. The GNU Octave Repository. Available at http://octave.sourceforge.net/.

OpenEEG. ModEEG – Open Source EEG amplifier. Available at http://openeeg.sourceforge.net/doc/modeeg/modeeg.html.

Oppenheim, A. V. and R. W. Schafer. 1989. Discrete-time signal processing. Prentice Hall Signal Processing Series. Prentice Hall.

Orr, G. B. and K.-R. Müller, editors. 1998. Neural networks: tricks of the trade, vol. LNCS 1524. Heidelberg: Springer.

Owen, A. M., M. R. Coleman, M. Boly, M. H. Davis, S. Laureys, and J. D. Pickard. 2006. Detecting awareness in the vegetative state. *Science* 313(5792):1402.

Pal. 2002. Computing discriminability and bias with the R software. Available from http://www.pallier.org/ressources/aprime/aprime.pdf.

Pang, C., J. G. Cham, Z. Nenadic, S. Musallam, Y. C. Tai, J. W. Burdick, and R. A. Andersen. 2005a. A new multi-site probe array with monolithically integrated parylene flexible cable for neural prostheses. In *Proceedings of the 27th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* vol. 2: 5352 – 5355 Vol. 7. IEEE.

Pang, C., J. G. Cham, Z. Nenadic, Y. C. Tai, J. W. Burdick, and R. A. Andersen. 2005b. A new neural recording electrode array with parylene insulating layer. In *Proceedings of the 9th International Conference on Miniaturized Systems for Chemistry and Life*

Sciences (μTAS) vol. 2: 675–677. IEEE.

Paninski, L., M. R. Fellows, N. G. Hatsopoulos, and J. P. Donoghue. 2004. Spatiotemporal tuning of motor cortical neurons for hand position and velocity. *Journal of Neurophysiology* 91(1):515–532.

Parra, L., C. Alvino, A. Tang, B. Pearlmutter, N. Yeung, A. Osman, and P. Sajda. 2002. Linear spatial integration for single-trial detection in encephalography. *Neuroimage* 17 (1):223–230.

Parra, L. C., C. D. Spence, A. D. Gerson, and P. Sajda. 2003. Response error correction—a demonstration of improved human-machine performance using real-time EEG monitoring. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2): 173–177.

Parra, L. C., C. D. Spence, A. D. Gerson, and P. Sajda. 2005. Recipes for the linear analysis of EEG. *Neuroimage* 28(2):326–341.

Pascual-Marqui, R. D. LORETA – low resolution brain electromagnetic tomography. Available at http://www.unizh.ch/keyinst/NewLORETA/LORETA01.htm.

Patterson, J. R. and M. Grabois. 1986. Locked-in syndrome: a review of 139 cases. *Stroke* 17(4):758–764.

Paz, R., T. Boraud, C. Natan, H. Bergman, and E. Vaadia. 2003. Preparatory activity in motor cortex reflects learning of local visuomotor skills. *Nature Neuroscience* 6(8): 882–890.

Peckham, P. H., M. W. Keith, K. L. Kilgore, J. H. Grill, K. S. Wuolle, G. B. Thrope, P. Gorman, J. Hobby, M. J. Mulcahey, S. Carroll, V. R. Hentz, and A. Wiegner. 2001. Efficacy of an implanted neuroprosthesis for restoring hand grasp in tetraplegia: a multicenter study. *archphysmed* 82(10):1380–1388.

Perelmouter, J. and N. Birbaumer. 2000. A binary spelling interface with random errors. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 8(2):227–232.

Perelmouter, J., B. Kotchoubey, A. Kübler, E. Taub, and N. Birbaumer. 1999. Language support program for thought-translation devices. *Automedica* 18:67–84.

Perrin, F., J. Pernier, O. Bertrand, and J. Echallier. 1989. Spherical splines for potential and current density mapping. *Electroencephalography and Clinical Neurophysiology* 72 (2):184–187.

Perrin, F., J. Pernier, O. Bertrand, and J. Echallier. 1990. Corrigendum eeg 02274. *Electroencephalography and Clinical Neurophysiology* 76:565.

Pesaran, B., J. S. Pezaris, M. Sahani, P. P. Mitra, and R. A. Andersen. 2002. Temporal structure in neuronal activity during working memory in macaque parietal cortex. *Nature Neuroscience* 5(8):805–811.

Pfingst, B. E. 2000. Auditory prostheses. In *Neural Prostheses for Restoration of Sensory and Motor Function*, edited by J. K. Chapin and K. A. Moxon. Boca Raton, Florida: CRC Press, Inc.

Pfurtscheller, G. 2005. EEG event-related desynchronization (ERD) and event related synchronization (ERS). In *Electroencephalography—Basic Principles, Clinical Applications, and Related Fields*, edited by E. Niedermeyer and F. H. Lopes da Silva. Philadelphia: Lippincott Williams & Wilkins, 4th edition.

Pfurtscheller, G. 1989. Functional topography during sensorimotor activation studied with event-related desynchronization mapping. *Journal of Clinical Neurophysiology* 6(1): 75–84.

Pfurtscheller, G. and A. Aranibar. 1977. Event-related cortical desynchronization detected by power measurements of scalp EEG. *Electroencephalography and Clinical Neurophysiology* 42(6):817–826.

Pfurtscheller, G. and A. Aranibar. 1979. Evaluation of event-related desynchronization (ERD) preceding and following self-paced movements. *Electroencephalography and Clinical Neurophysiology* 46(2):138–146.

Pfurtscheller, G., C. Brunner, A. Schlögl, and F. H. Lopes da Silva. 2006a. Mu-rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. *Neuroimage* 31(1):153–159.

Pfurtscheller, G. and F. H. Lopes da Silva. 1999. Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clinical Neurophysiology* 110(11):1842–1857.

Pfurtscheller, G., D. Flotzinger, and J. Kalcher. 1993. Brain-computer interface—a new communication device for handicapped persons. *Journal of Microcomputer Applications* 16(3):293–299.

Pfurtscheller, G., D. Flotzinger, M. Pregenzer, J. R. Wolpaw, and D. J. McFarland. 1995–1996. EEG-based brain computer interface (BCI). Search for optimal electrode positions and frequency components. *Medical Progress through Technology* 21(3):111–121.

Pfurtscheller, G., B. Graimann, J. E. Huggins, S. P. Levine, and L. A. Schuh. 2003a. Spatiotemporal patterns of beta desynchronization and gamma synchronization in corticographic data during self-paced movement. *Clinical Neurophysiology* 114(7):1226–1236.

Pfurtscheller, G., C. Guger, G. Müller, G. Krausz, and C. Neuper. 2000a. Brain oscillations control hand orthosis in a tetraplegic. *Neuroscience Letters* 292(3):211–214.

Pfurtscheller, G., J. Kalcher, C. Neuper, D. Flotzinger, and M. Pregenzer. 1996. On-line EEG classification during externally-paced hand movements using a neural network-based classifier. *Electroencephalography and Clinical Neurophysiology* 99(5):416–425.

Pfurtscheller, G., R. Leeb, C. Keinrath, D. Friedman, C. Neuper, C. Guger, and M. Slater. 2006b. Walking from thought. *Brain Research* 1071(1):145–152.

Pfurtscheller, G., G. R. Müller, J. Pfurtscheller, H. J. Gerner, and R. Rupp. 2003b. "Thought"—control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia. *Neuroscience Letters* 351(1):33–36.

Pfurtscheller, G., G. R. Müller-Putz, A. Schlögl, B. Graimann, R. Scherer, R. Leeb, C. Brunner, C. Keinrath, F. Lee, G. Townsend, C. Vidaurre, and C. Neuper. 2006c. 15 years of BCI research at Graz University of technology: current projects. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):205–210.

Pfurtscheller, G. and C. Neuper. 1997. Motor imagery activates primary sensorimotor area in humans. *Neuroscience Letters* 239(2–3):65–68.

Pfurtscheller, G. and C. Neuper. 2001. Motor imagery and direct brain-computer communication. *Proceedings of the IEEE* 89(7):1123–1134.

Pfurtscheller, G., C. Neuper, and N. Birbaumer. 2005a. Human brain-computer interface. In *Motor Cortex in Voluntary Movements: a distributed system for distributed functions. Series: Methods and New Frontiers in Neuroscience*, edited by A. Riehle and E. Vaadia. New York: CRC Press.

Pfurtscheller, G., C. Neuper, C. Brunner, and F. Lopes da Silva. 2005b. Beta rebound after different types of motor imagery in man. *Neuroscience Letters* 378(3):156–159.

Pfurtscheller, G., C. Neuper, D. Flotzinger, and M. Pregenzer. 1997. EEG-based discrimination between imagination of right and left hand movement. *Electroencephalography and Clinical Neurophysiology* 103(6):642–651.

Pfurtscheller, G., C. Neuper, C. Guger, W. Harkam, H. Ramoser, A. Schlögl, B. Obermaier, and M. Pregenzer. 2000b. Current trends in Graz brain-computer interface (BCI) research. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 8(2): 216–219.

Pfurtscheller, G., C. Neuper, G. R. Müller, B. Obermaier, G. Krausz, A. Schlögl, R. Scherer, B. Graimann, C. Keinrath, D. Skliris, M. Wörtz, G. Supp, and C. Schrank. 2003c. Graz-BCI: State of the art and clinical applications. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):177–180.

Pfurtscheller, G., C. Neuper, H. Ramoser, and J. Müller-Gerking. 1999. Visually guided motor imagery activates sensorimotor areas in humans. *Neuroscience Letters* 269(3): 153–156.

Pfurtscheller, G., C. Neuper, A. Schlögl, and K. Lugger. 1998. Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters. *IEEE Transactions on Rehabilitation Engineering* 6(3):316–325.

Pfurtscheller, G., R. Scherer, R. Leeb, C. Keinrath, C. Neuper, F. Lee, B. Graimann, A. Schlögl, and H. Bischof. In press. Viewing moving objects in virtual reality can change the dynamics of sensorimotor EEG rhythms. *Presence-Teleoperators and Virtual Environments*.

Pham, D.-T. 1996. Blind separation of instantaneous mixture of sources via the Gaussian mutual information criterion. *IEEE Transactions on Signal Processing* 44(11):2668–2779.

Pham, M., T. Hinterberger, N. Neumann, A. Kübler, N. Hofmayer, A. Grether, B. Wilhelm, J. J. Vatine, and N. Birbaumer. 2005. An auditory brain-computer interface based on the self-regulation of slow cortical potentials. *Journal for Neurorehabilitation and Neural Repair* 19(3):206–218.

Philiastides, M. G. and P. Sajda. 2006. Temporal characterization of the neural correlates of perceptual decision making in the human brain. *Cerebral Cortex* 16(4):509–518.

Piccione, F., F. Giorgi, P. Tonin, K. Priftis, S. Giove, S. Silvoni, G. Palmas, and F. Beverina. 2006. P300-based brain computer interface: Reliability and performance in healthy and paralysed participants. *Clinical Neurophysiology* 117(3):531–537.

Pierce, J. R. 1980. An introduction to information theory: symbols, signals and noise. New York: Dover Publications, 2nd edition.

Pineda, J. A., D. S. Silverman, A. Vankov, and J. Hestenes. 2003. Learning to control brain rhythms: making a brain-computer interface possible. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):181–184.

Platt, M. L. and P. W. Glimcher. 1999. Neural correlates of decision variables in parietal cortex. *Nature* 400(6741):233–238.

Poggio, T. and F. Girosi. 1990. Networks for approximation and learning. *Proceedings of the IEEE* 78(9):1481–1497.

Polich, J., editor. 2003. Detection of change: Event-related potential and fMRI findings. Boston: Kluwer Academic Publishers.

Polich, J. 1989. Habituation of P300 from auditory stimuli. *Psychobiology* 17:19–28.

Pope, A. T., E. H. Bogart, and D. S. Bartolome. 1995. Biocybernetic system evaluates indices of operator engagement on automated task. *Biological Psychology* 40(1–2): 187–195.

Posner, M. I. 1980. Orienting of attention. *Quarterly Journal of Experimental Psychology* 32(1):3–25.

Pregenzer, M. and G. Pfurtscheller. 1999. Frequency component selection of an EEG-based brain to computer interface. *IEEE Transactions on Rehabilitation Engineering* 7 (4):413–419.

Pregenzer, M., G. Pfurtscheller, and D. Flotzinger. 1994. Selection of electrode positions for an EEG-based brain computer interface (BCI). *Biomedizinische Technik* 39(10): 164–169.

Pregenzer, M., G. Pfurtscheller, and D. Flotzinger. 1996. Automated feature selection with a distinction sensitive learning vector quantizer. *Neurocomputing* 11(1):19–29.

Principe, J. C., J. W. Fisher III, and D. Xu. 2000. Information theoretic learning. In *Unsupervised Adaptive Filtering*, edited by Simon Haykin. New York: Wiley.

Prinzel, L. J., F. G. Freeman, M. W. Scerbo, P. J. Mikulka, and A. T. Pope. 2000. A closed-loop system for examining psychophysiological measures for adaptive task allocation. *International Journal of Aviation Psychology* 10(4):393–410.

Puce, A., T. Allison, M. Asgari, J. C. Gore, and G. McCarthy. 1996. Differential sensitivity of human visual cortex to faces, letterstrings, and textures: A functional magnetic resonance imaging study. *Journal of Neuroscience* 16(16):5205–5215.

Pudil, P., J. Novovicová, and J. Kittler. 1994. Floating search methods in feature selection. *Pattern Recognition Letters* 15(11):1119–1125.

Pulvermuller, F., B. Mohr, H. Schleichert, and R. Veit. 2000. Operant conditioning of left-hemispheric slow cortical potentials and its effect on word processing. *Biological*

Psychology 53(2–3):177–125.

QT4. QT library version 4. Available at http://www.trolltech.com/.

Quick, R. F. 1974. A vector magnitude model of contrast detection. *Kybernetik* 16(2): 65–67.

Ramoser, H., J. Müller-Gerking, and G. Pfurtscheller. 2000. Optimal spatial filtering of single trial EEG during imagined hand movement. *IEEE Transactions on Rehabilitation Engineering* 8(4):441–446.

Raymond, J., I. Sajid, L. A. Parkinson, and J. H. Gruzelier. 2005. Biofeedback and dance performance: a preliminary investigation. *Applied Psychophysiology and Biofeedback* 30(1):64–73.

Renyi, A. 1961. On measures of entropy and information. In *Proceedings of the Fourth Berkeley Symposium Mathematical Statistics and Probability*: 547–561, Berkeley Calif. University of California Press.

Rieke, F., D. Warland, R. de Ruyter van Steveninck, and W. Bialek. 1999. Spikes—exploring the neural code. Cambridge Mass: The MIT Press.

Rijsbergen, C. J. 1979. Information retrieval. Available at http://www.dcs.gla.ac.uk/˜iain/keith/.

Ringholz, G. M., S. H. Appel, M. Bradshaw, N. A. Cooke, D. M. Mosnik, and P. E. Schulz. 2005. Prevalence and patterns of cognitive impairment in sporadic ALS. *Neurology* 65 (4):586–590.

Rizzolatti, G., L. Fogassi, and V. Gallese. 2001. Neurophysiological mechanisms underlying the understanding and imitation of action. *Nature reviews. Neuroscience* 2(9): 661–670.

Rizzuto, D. S., A. N. Mamelak, W. W. Sutherling, I. Fineman, and R. A. Andersen. 2005. Spatial selectivity in human ventrolateral prefrontal cortex. *Nature Neuroscience* 8(4): 415–417.

Roberts, S. J. and W. D. Penny. 2000. Real-time brain-computer interfacing: a preliminary study using Bayesian learning. *Medical & Biological Engineering & Computing* 38(1): 56–61.

Rockstroh, B., N. Birbaumer, T. Elbert, and W. Lutzenberger. 1984. Operant control of EEG and event-related and slow brain potentials. *Biofeedback and Self-Regulation* 9(2): 139–160.

Rockstroh, B., T. Elbert, W. Lutzenberger, and N. Birbaumer. 1982. The effects of slow cortical potentials on response speed. *Psychophysiology* 19(2):211–217.

Rohde, M. M., S. L. BeMent, J. E. Huggins, S. P. Levine, R. K. Kushwaha, and L. A. Schuh. 2002. Quality estimation of subdurally recorded, event-related potentials based on signal-to-noise ratio. *IEEE Transactions on Biomedical Engineering* 49(1):31–40.

Romo, R., A. Hernandez, A. Zainos, C. Brody, and E. Salinas. 2002. Exploring the cortical evidence of a sensory-discrimination process. *Philosophical Transactions of the Royal Society of London. Series B, Biological sciences* 357(1424):1039–1051.

Ron Angevin, R., A. Reyes-Lecuona, and A. Diaz-Estrella. 2004. The use of virtual reality to improve BCI training techniques. In *Proceedings of the 2nd International Brain-Computer Interface Workshop and Training Course* vol. 49 (Suppl.Vol.1): 79–80, Graz, Austria. Biomed Tech (Berl).

Rose, F. D., B. M. Brooks, and A. A. Rizzo. 2005. Virtual reality in brain damage rehabilitation: review. *Cyberpsychology & Behavior: the Impact of the Internet, Multimedia and Virtual Reality on Behavior and Society* 8(3):241–262. discussion 263–71.

Rossion, B., C. A. Joyce, G. W. Cottrell, and M. J. Tarr. 2003. Early laterization and orientation tuning for face, word, object processing in the visual cortex. *NeuroImage* 20 (3):1609–1624.

Rottig, D., B. Leplow, K. Eger, A. C. Ludolph, M. Graf, and S. Zierz. 2006. Only subtle cognitive deficits in non-bulbar amyotrophic lateral sclerosis patients. *Journal of Neurology* 253(3):333–339.

Roweis, S. T. and L. K. Saul. 2000. Nonlinear dimensionality reduction by locally linear embedding. *Science* 290(5500):2323–2326.

rtsBCI. Graz brain-computer interface real-time open source package. Available at http://sourceforge.net/projects/biosig/.

Rydesäter, P. TCP/UDP/IP toolbox. Available at http://www.mathworks.com/matlabcentral/fileexchange.

Saad, D., editor. 1998. On-line learning in neural networks. Cambridge University Press.

Sajda, P., A. Gerson, K. R. Müller, B. Blankertz, and L. Parra. 2003. A data analysis competition to evaluate machine learning algorithms for use in brain-computer interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):184–185.

Salanova, V., H. H. Morris, P. C. Van Ness, H. Luders, D. Dinner, and E. Wyllie. 1993. Comparison of scalp electroencephalogram with subdural electrocorticogram recordings and functional mapping in frontal lobe epilepsy. *Archives of Neurology* 50(3):294–299.

Sammon, Jr., J. W. 1969. A nonlinear mapping for data structure analysis. *IEEE Transactions on Computers* C-18(5):401–409.

Sanchez-Vives, M. V. and M. Slater. 2005. From presence to consciousness through virtual reality. *Nature reviews. Neuroscience* 6(4):332–339.

Santhanam, G., S. I. Ryu, B. M. Yu, A. Afshar, and K. V. Shenoy. 2006. A high-performance brain-computer interface. *Nature* 442(7099):195–198.

Saon, G. and M. Padmanabhan. 2000. Minimum Bayes error feature selection for continuous speech recognition. In *Advances in Neural Information Processing Systems (NIPS 99)*: 800–806, Cambridge, Mass. The MIT Press.

Scerbo, M. W., F. G. Freeman, and P. J. Mikulka. 2003. A brain-based system for adaptive automation. *Theoretical Issues in Ergonomics Science* 4(1–2):200–219.

Schack, B., N. Vath, H. Petsche, H. G. Geissler, and E. Moller. 2002. Phase-coupling of theta-gamma EEG rhythms during short-term memory processing. *International Journal of Psychophysiology* 44(2):143–163.

Schalk, G., D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw. 2004. BCI2000: a general-purpose brain-computer interface (BCI) system. *IEEE Transactions on Biomedical Engineering* 51(6):1034–1043.

Schalk, G., J. R. Wolpaw, D. J. McFarland, and G. Pfurtscheller. 2000. EEG-based communication: presence of an error potential. *Clinical Neurophysiology* 111(12):2138–2144.

Schalk et al, G. BCI2000 project. available at http://www.bciresearch.org/BCI2000/bci2000.html.

Scheffers, M. K., R. Johnson, and D. S. Ruchkin. 1991. P300 in patients with unilateral temporal lobectomies: the effects of reduced stimulus quality. *Psychophysiology* 28(3): 274–284.

Scherberger, H., M. R. Jarvis, and R. A. Andersen. 2005. Cortical local field potential encodes movement intentions in the posterior parietal cortex. *Neuron* 46(2):347–354.

Scherer, R., B. Graimann, J. E. Huggins, S. P. Levine, and G. Pfurtscheller. 2003. Frequency component selection for an ECoG-based brain-computer interface. *Biomedizinische Technik* 48(1–2):31–36.

Scherer, R., F. Lee, R. Leeb, A. Schlögl, H. Bischof, and G. Pfurtscheller. Submitted. Towards asynchronous (uncued) brain-computer communication: Navigation through virtual worlds. *IEEE Transactions on Biomedical Engineering*.

Scherer, R., G. R. Müller, C. Neuper, B. Graimann, and G. Pfurtscheller. 2004a. An asynchronously controlled EEG-based virtual keyboard: improvement of the spelling rate. *IEEE Transactions on Biomedical Engineering* 51(6):979–984.

Scherer, R., A. Schlögl, G. R. Müller-Putz, and G. Pfurtscheller. 2004b. Inside the Graz-BCI: rtsBCI. In *Biomedizinische Technik: Proceedings of the 2nd International Brain-Computer Interface Workshop and Training Course (Graz)*: 81–82. Boenick U and Bolz A (Berlin Schiele & Schön).

Scherg, M. 1992. Functional imaging and localization of electromagnetic brain activity. *Brain Topography* 5(2):103–111.

Scherg, M. 1994. From EEG source localization to source imaging. *Acta neurologica Scandinavica. Supplementum* 152:29–30.

Schlögl, A. 2000a. The electroencephalogram and the adaptive autoregressive model: theory and applications. Aachen, Germany: Shaker Verlag.

Schlögl, A. 2000b. The electroencephalogram and the adaptive autoregressive model: theory and applications. PhD thesis, Technical University Graz, Graz.

Schlögl, A. A general data format (GDF) for biomedical signals. Available at http://biosig.sourceforge.net/gdf/.

Schlögl, A. Missing values and NaN-toolbox for Matlab. Available at http://www.dpmi.tu-graz.ac.at/˜schloegl/matlab/NaN/.

Schlögl, A. Time series analysis toolbox for Matlab. Available at http://www.dpmi.tu-graz.ac.at/˜schloegl/matlab/tsa/.

Schlögl, A., P. Anderer, M. J. Barbanoj, G. Gruber G. Klösch, J. L. Lorenzo, O. Filz, M. Koivuluoma, I. Rezek, S. J. Roberts, A. Värri, P. Rappelsberger, G. Pfurtscheller, and G. Dorffner. 1999a. Artifact processing of the sleep EEG in the "SIESTA"-project. In *Proceedings EMBEC'99*: 1644–1645, Vienna, Austria.

Schlögl, A., P. Anderer, S. J. Roberts, M. Pregenzer, and G. Pfurtscheller. 1999b. Artefact detection in sleep EEG by the use of Kalman filtering. In *Proceedings EMBEC'99*: 1648–1649, Vienna, Austria.

Schlögl, A., D. Flotzinger, and G. Pfurtscheller. 1997a. Adaptive autoregressive modeling used for single-trial EEG classification. *Biomedizinische Technik* 42(6):162–167.

Schlögl, A., C. Keinrath, R. Scherer, and G. Pfurtscheller. 2003. Information transfer of an EEG-based brain-computer interface. In *Proceedings of the 1st International IEEE EMBS Conference on Neural Engineering*: 641–644.

Schlögl, A., B. Kemp, T. Penzel, D. Kunz, S.-L. Himanen, A. Värri, G. Dorffner, and G. Pfurtscheller. 1999c. Quality control of polysomnographic sleep data by histogram and entropy analysis. *Clinical Neurophysiology* 110(12):2165–2170.

Schlögl, A., F. Lee, H. Bischof, and G. Pfurtscheller. 2005. Characterization of four-class motor imagery EEG data for the BCI-competition 2005. *Journal of Neural Engineering* 2(4):L14–L22.

Schlögl, A., K. Lugger, and G. Pfurtscheller. 1997b. Using adaptive autoregressive parameters for a brain-computer-interface experiment. In *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* vol. 4: 1533–1535.

Schlögl, A., C. Neuper, and G. Pfurtscheller. 2002. Estimating the mutal information of an EEG-based Brain-Computer Interface. *Biomedizinische Technik* 47(1–2):3–8.

Schlögl, A. and G. Pfurtscheller. 1998. Considerations on adaptive autoregressive modelling in EEG analysis. In *Proc. of 1st Int. Symposium on Communication Systems and Digital Signal Processing CSDSP'98*, edited by Z. Ghassemlooy and M. R. Saatchi vol. 1: 367–370.

Schlögl et al., A. BIOSIG—an open source software package for biomedical signal processing. Available at http://biosig.sourceforge.net.

Schölkopf, B., J. C. Platt, J. Shawe-Taylor, A. J. Smola, and R. C. Williamson. 2001. Estimating the support of a high-dimensional distribution. *Neural Computation* 13(7): 1443–1471.

Schölkopf, B. and A. Smola. 2002. Learning with kernels. Cambridge, Mass.: The MIT Press.

Schölkopf, B., B. Smola, and K. R. Müller. 1998. Nonlinear component analysis as a kernel eigenvalue problem. *Neural Computation* 10(5):1299–1319.

Schraudolph, N. N. 1999. Local gain adaptation in stochastic gradient descent. In *ICANN99. Ninth International Conference on Artificial Neural Networks* vol. 2: 569–574.

Schröder, M., T. N. Lal, T. Hinterberger, M. Bogdan, N. J. Hill, N. Birbaumer, W. Rosenstiel, and B. Schölkopf. 2005. Robust EEG channel selection across subjects for brain computer interfaces. *EURASIP Journal on Applied Signal Processing, Special Issue: Trends in Brain Computer Interfaces* 19:3103–3112.

Schultz, W. 2004. Neural coding of basic reward terms of animal learning theory, game theory, microeconomics and behavioural ecology. *Current Opinion in Neurobiolology* 14(2):139–147.

Schwartz, A., D. M. Taylor, and S. I. Tillery. 2001. Extraction algorithms for cortical control of arm prosthetics. *Current Opinion in Neurobiology* 11(6):701–707.

Schwartz, A. B. 2004a. Direct cortical control of 3D neuroprosthetic devices. In *4th Forum of European Neuroscience*, Lisbon, Portugal.

Schwartz, A. B. 2004b. Cortical neural prosthetics. *Annual Review of Neuroscience* 27: 487–507.

Schwartz, A. B., R. E. Kettner, and A. P. Georgopoulos. 1988. Primate motor cortex and free arm movements to visual targets in three-dimensional space. I. Relations between single cell discharge and direction of movement. *Journal of Neuroscience* 8(8):2913–2927.

Sellers, E., G. Schalk, and E. Donchin. 2003. The P300 as a typing tool: tests of brain computer interface with an ALS patient. *Psychophysiology* 40:77.

Sellers, E. W. and E. Donchin. 2006. A P300-based brain-computer interface: initial tests by ALS patients. *Clinical Neurophysiology* 117(3):538–548.

Sellers, E. W., D. J. Krusienski, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw. In press. A P300 event-related potential brain-computer interface (BCI): The effects of matrix size and inter stimulus interval on performance. *Biological Psychology*.

Sellers, E. W., A. Kübler, and E. Donchin. 2006a. Brain computer interface research at the University of South Florida Cognitive Psychophysiology Laboratory: the P300 Speller. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):221–224.

Sellers, E. W., T. M. Vaughan, D. J. McFarland, D. J. Krusienski, S. A. Mackler, R. A. Cardillo, G. Schalk, S. A. Binder-Macleod, and J. R. Wolpaw. 2006b. Daily use of a brain-computer interface by a man with ALS. Poster presented at the Society for Neuroscience annual meeting, Atlanta, GA.

Serby, H., E. Yom-Tov, and G. F. Inbar. 2005. An improved p300-based brain-computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 13(1): 89–98.

Serruya, M. D., N. G. Hatsopoulos, L. Paninski, M. R. Fellows, and J. P. Donoghue. 2002. Instant neural control of a movement signal. *Nature* 416(6877):141–142.

Shadlen, M. N. and W. T. Newsome. 2001. Neural basis of perceptual decision making in the parietal cortex (area LIP) of the rhesus monkey. *Journal of Neurophysiology* 86(4): 1916–1936.

Shannon, C. E. and W. Weaver. 1949. The mathematical theory of communication. Urbana: University of Illinois Press.

Shenoy, K. V., D. Meeker, S. Cao, S. A. Kureshi, B. Pesaran, C. A. Buneo, A. P. Batista, P. P. Mitra, J. W. Burdick, and R. A. Andersen. 2003. Neural prosthetic control signals from plan activity. *Neuroreport* 14(4):591–596.

Shenoy, P., M. Krauledat, B. Blankertz, R. P. N. Rao, and K.-R. Müller. 2006. Towards adaptive classification for BCI. *Journal of Neural Engineering* 3(1):R13–R23.

Sheridan, T. B. 1992. Telerobotics, automation, and human supervisory control. Cambridge, Mass.: The MIT Press.

Shpigelman, L., Y. Singer, R. Paz, and E. Vaadia. 2003. Spikernels: Embedding spiking neurons in inner product spaces. In *Advances in Neural Information Processing Systems (NIPS 02)*, edited by S. Becker, S. Thrun, and K. Obermayer vol. 15, Cambridge, MA. The MIT Press.

Singh, K. and S. H. Scott. 2003. A motor learning strategy reflects neural circuitry for limb control. *Nature Neuroscience* 6(4):399–403.

Sitaram, R., A. Caria, R. Veit, K. Uludag, T. Gaber, A. Kübler, and N. Birbaumer. 2006. Functional magnetic resonance imaging based BCI for neurorehabilitation. Paper presented at the 3rd International Brain-Computer Interface Workshop and Training Course, Graz, Austria.

Sitaram, R., Y. Hoshi, and C. Guan, editors. 2005. Near infrared spectroscopy based brain-computer interfaces, vol. 5852. Bellingham, Wash.: Society of Photo-Optical Instrumentation Engineers.

Sitaram, R., H. Zhang, C. Guan, M. Thulasidas, Y. Hoshi, A. Ishikawa, K. Shimizu, and N. Birbaumer. Submitted. Temporal classification of multi-channel near infrared spectroscopy signals of motor imagery for developing a brain-computer interface.

Skrandies, W. 2005. Brain mapping of visual evoked activity—topographical and functional components. *Acta Neurologica Taiwanica* 14(4):164–178.

Slater, M., A. Steed, and Y. Chrysanthou. 2002. Computer graphics and virtual environments: from realism to real-time. Harlow, UK: Addison-Wesley.

Slater, M. and M. Usoh. 1993. Presence in immersive virtual environments. In *Proceedings IEEE Virtual Reality Annual International Symposium*: 90–96, Seattle, Wash.

Smith, E. and M. Delargy. 2005. Locked-in syndrome. *BMJ* 330(7488):406–409.

Smith, M. E., A. Gevins, H. Brown, A. Karnik, and R. Du. 2001. Monitoring task loading with multivariate EEG measures during complex forms of human-computer interaction. *Human Factors* 43(3):366–380.

Smola, A. J. and B. Schölkopf. 1998. A tutorial on support vector regression. NeuroCOLT Technical Report NC-TR-98-030, Royal Holloway College, University of London, UK.

Snyder, L. H., A. P. Batista, and R. A. Andersen. 1997. Coding of intention in the posterior parietal cortex. *Nature* 386(6621):167–170.

Solodkin, A., P. Hlustik, E. E. Chen, and S. L. Small. 2004. Fine modulation in network activation during motor execution and motor imagery. *Cerebral Cortex* 14(11):1246–1255.

Sonnenburg, S., G. Rätsch, and B. Schölkopf. 2005. Large scale genomic sequence SVM classifiers. In *Proceedings of the International Conference on Machine Learning, ICML.*

Spalding, M. C., M. Velliste, B. Jarosiewicz, and A. B. Schwartz. 2005. 3-D cortical control of an anthropomorphic robotic arm for reaching and retrieving. Program No. 401.3. 2005 Abstract Viewer/Itinerary Planner. Washington, DC. Online. Society for Neuroscience.

Spataro, L., J. Dilgen, S. Retterer, A. J. Spence, M. Isaacson, J. N. Turner, and W. Shain. 2005. Dexamethasone treatment reduces astroglia responses to inserted neuroprosthetic devices in rat neocortex. *Experimental Neurology* 194(2):289–300.

Speckmann, E. J., H. Caspers, and C. W. Elger. 1984. Neuronal mechanisms underlying the generation of field potentials. Berlin: Springer.

Squires, K. C., E. Donchin, R. I. Herning, and G. McCarthy. 1977. On the influence of task relevance and stimulus probability on event-related-potential components. *Electroencephalography and Clinical Neurophysiology* 42(1):1–14.

Squires, K. C., C. Wickens, N. K. Squires, and E. Donchin. 1976. The effect of stimulus sequence on the waveform of the cortical event-related potential. *Science* 193(4258): 1142–1146.

Stanislaw, H. and N. Todorow. 1999. Calculation of signal detection measures. *Behaviour Research Methods, Instruments & Computers* 31(1):137–149.

Sterman, M. B. 1977. Sensorimotor EEG operant conditioning: experimental and clinical effects. *Pavlovian Journal of Biological Sciences* 12(2):63–92.

Sterman, M. B. and C. A. Mann. 1995. Concepts and applications of EEG analysis in aviation performance evaluation. *Biological Psychology* 40(1–2):115–130.

STIM. The society to increase mobility. Available at http://www.neurotechnetwork.org/home.html.

Stipacek, A., R. H. Grabner, C. Neuper, A. Fink, and A. C. Neubauer. 2003. Sensitivity of human EEG alpha band desynchronization to different working memory components and increasing levels of memory load. *Neuroscience Letters* 353(3):193–196.

Strehl, U., T. Trevorrow, R. Veit, T. Hinterberger, B. Kotchoubey, M. Erb, and N. Birbaumer. 2006. Deactivation of brain areas during self-regulation of slow cortical potentials in seizure patients. *Applied Psychophysiology and Biofeedback* 31(1):85–94.

Studierstube. Augmented reality project. Available at http://www.studierstube.org.

Sugiyama, S. and K.-R. Müller. 2005. Input-dependent estimation of generalization error under covariate shift. *Statistics and Decisions* 23(4):249–279.

Super, H., H. Spekreijse, and V. A. Lamme. 2001. Two distinct modes of sensory processing observed in monkey primary visual cortex. *Nature Neuroscience* 4(3):304–310.

Sutter, E. E. 1992. The brain response interface: communication through visually-induced electrical brain responses. *Journal of Microcomputer Applications* 15(1):31–45.

Sutton, R. S. 1992. Adapting bias by gradient descent: an incremental version of delta-bar-delta. In *AAAI 92. Proceedings Tenth National Conference on Artificial Intelligence*: 171–176.

Sutton, R. S. and A. G. Barto. 1998. Reinforcement learning: An introduction. Cambridge, Mass.: The MIT Press.

Sykacek, P., S. Roberts, M. Stokes, E. Curran, M. Gibbs, and L. Pickup. 2003. Probabilistic methods in BCI research. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):192–195.

Talwar, S. K., S. Xu, E. S. Hawley, S. A. Weiss, K. A. Moxon, and J. K. Chapin. 2002. Rat navigation guided by remote control. *Nature* 417(6884):37–38.

Tarr, M. J. and W. H. Warren. 2002. Virtual reality in behavioral neuroscience and beyond. *Nature Neuroscience* 5(Suppl):1089–1092.

Tax, D. M. J. and R. P. W. Duin. 2001. Uniform object generation for optimizing one-class classifiers. *Journal for Machine Learning Research* 155–173.

Taylor, D. M. and A. B. Schwartz. 2001. Using virtual reality to test the feasibility of controlling an upper limb fes system directly from multiunit activity in the motor cortex. In *Proceedings of the 6th Annual IFESS Conference*, Cleveland, Ohio.

Taylor, D. M., S. I. H. Tillery, and A. B. Schwartz. 2002. Direct cortical control of 3D neuroprosthetic devices. *Science* 296(5574):1829–1832.

Taylor, D. M., S. I. H. Tillery, and A. B. Schwartz. 2003. Information conveyed through brain-control: cursor versus robot. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):195–199.

Tenenbaum, J. B., V. de Silva, and J. C. Langford. 2000. A global geometric framework for nonlinear dimensionality reduction. *Science* 290(5500):2319–2323.

Tesche, C. D. and J. Karhu. 1997. Somatosensory evoked magnetic fields arising from sources in the human cerebellum. *Brain Research* 744(1):23–31.

Thomson, D. J. 1982. Spectrum estimation and harmonic analysis. *Proceedings of the IEEE* 70(9):1055–1096.

Thorpe, S., D. Fize, and C. Marlot. 1996. Speed of processing in the human visual system. *Nature* 381(6582):520–522.

Thulasidas, M., C. Guan, and J. Wu. 2006. Robust classification of eeg signal for brain-computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(1):24–29.

Tillery, S. H., D. Taylor, R. Isaacs, and A. Schwartz. 2000. Online control of a prosthetic arm from motor cortical signals. In *Society for Neuroscience Abstracts* vol. 26.

Tillery, S. I. and D. M. Taylor. 2004. Signal acquisition and analysis for cortical control of neuroprosthetics. *Current Opinion in Neurobiolology* 14(6):758–762.

Tillery, S. I. H., D. M. Taylor, and A. B. Schwartz. 2003. Training in cortical control of neuroprosthetic devices improves signal extraction from small neuronal ensembles. *Reviews in the Neurosciences* 14(1–2):107–119.

Titchener, E. L. 1897. An outline of psychology. Hampshire, England: Macmillan.

Todorov, E., R. Shadmehr, and E. Bizzi. 1997. Augmented feedback presented in a virtual environment accelerates learning of a difficult motor task. *Journal of motor behavior* 29 (2):147–158.

Tomioka, R., G. Dornhege, K. Aihara, and K. R. Müller. 2006. An iterative algorithm for spatio-temporal filter optimization. In *Proceedings of the 3rd International Brain-Computer Interface Workshop and Training Course 2006*: 22–23. Verlag der Technischen Universität Graz.

Torkkola, K. 2003. Feature extraction by non-paramatric mutual information maximization. *Journal of Machine Learning Research* 3(7–8):1415–1438.

Townsend, G., B. Graimann, and G. Pfurtscheller. 2004. Continuous EEG classification during motor imagery - simulation of an asynchronous BCI. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 12(2):258–265.

Townsend, G., B. Graimann, and G. Pfurtscheller. 2006. A comparison of common spatial patterns with complex band power features in a four-class BCI experiment. *IEEE Transactions on Biomedical Engineering* 53(4):642–651.

Trejo, L. J., R. Rosipal, and B. Matthews. 2006. Brain-computer interfaces for 1-D and 2-D cursor control: designs using volitional control of the EEG spectrum or steady-state visual evoked potentials. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):225–229.

Truccolo, W., U. T. Eden, M. R. Fellows, J. P. Donoghue, and E. N. Brown. 2005. A point process framework for relating neural spiking activity to spiking history, neural ensemble and extrinsic covariate effects. *Journal of Neurophysiology* 93(2):1074–1089.

Turk, M. and A. Pentland. 1991. Face recognition using eigenfaces. *Journal of Cognitive Neuroscience* 3(1):71–86.

Turner, J. N., W. Shain, D. H. Szarowski, M. Andersen, S. Martins, M. Isaacson, and H. Craighead. 1999. Cerebral astrocyte response to micromachined silicon implants. *Experimental Neurology* 156(1):33–49.

Oosterom, A.van. 1991. History and evolution of methods for solving the inverse problem. *Journal of Clinical Neurophysiology* 8(4):371–380.

van Schie, H. T., R. B. Mars, M. G. H. Coles, and H. Bekkering. 2004. Modulation of activity in medial frontal and motor cortices during error observation. *Nature Neuroscience* 7(5):549–554.

VanRullen, R. and S. J. Thorpe. 2001. The time course of visual processing: from early perception to decision-making. *Journal of Cognitive Neuroscience* 13(4):454–461.

Vapnik, V. N. 1995. The Nature of Statistical Learning Theory. New York: Springer Verlag.

Vapnik, V. N. 1998. Statistical learning theory. New York: Wiley.

Vaughan, T. M., W. J. Heetderks, L. J. Trejo, W. Z. Rymer, M. Weinrich, M. M. Moore, A. Kübler, B. H. Dobkin, N. Birbaumer, E. Donchin, E. W. Wolpaw, and J. R. Wolpaw.

2003a. Brain-computer interface technology: A review of the Second International Meeting. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2): 94–109.

Vaughan, T. M., D. J. McFarland, G. Schalk, W. A. Sarnacki, D. J. Krusienski, E. W. Sellers, and J. R. Wolpaw. 2006. The Wadsworth BCI research and development program: At home with BCI. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):229–233.

Vaughan, T. M., D. J. McFarland, G. Schalk, W. A. Sarnacki, L. Robinson, and J. R. Wolpaw. 2001. EEG-based brain-computer interface: development of a speller application. *Society for Neuroscience Abstracts* 26.

Vaughan, T. M., D. J. McFarland, G. Schalk, E. Sellers, and J. R. Wolpaw. 2003b. Multichannel data from a brain-computer interface (BCI) speller using a P300 (i.e., oddball) protocol. *Society for Neuroscience Abstracts* 28.

Vaughan, T. M., L. A. Miner, D. J. McFarland, and J. R. Wolpaw. 1998. EEG-based communication: analysis of concurrent EMG activity. *Electroencephalography and Clinical Neurophysiology* 107(6):428–433.

Vaughan, T. M. and J. R. Wolpaw, editors. 2006. The third international meething on brain-computer interface technology: Making a difference, vol. 14.

Vaughan, T. M., J. R. Wolpaw, and E. Donchin. 1996. EEG-based communication: prospects and problems. *IEEE Transactions on Rehabilitation Engineering* 4(4):425–430.

Vaughan et al, G. V. GNU autoconf, automake and libtool. Available at http://sources.redhat.com/autobook/.

Vidaurre, C. 2006. On-line adaptive classification for brain-computer interfaces. PhD thesis, Dept. Ingeniería Eléctrica y Electrónica, Universidad Pública de Navarra.

Vidaurre, C., A. Schlögl, R. Cabeza, and G. Pfurtscheller. 2004a. About adaptive classifiers for brain computer interfaces. *Biomedizinische Technik* 49(1):85–86.

Vidaurre, C., A. Schlögl, R. Cabeza, and G. Pfurtscheller. 2004b. A fully on-line adaptive brain computer interface. *Biomedizinische Technik* 49(2):760–761.

Vidaurre, C., A. Schlögl, R. Cabeza, R. Scherer, and G. Pfurtscheller. 2005. Adaptive on-line classification for EEG-based brain computer interfaces with AAR parameters and band power estimates. *Biomedizinische Technik* 50(11):350–354.

Vidaurre, C., A. Schlögl, R. Cabeza, R. Scherer, and G. Pfurtscheller. 2006. A fully on-line adaptive BCI. *IEEE Transactions on Biomedical Engineering* 53(6):1214–1219.

VRjuggler. Open source virtual reality tool. Available at http://www.vrjuggler.org.

Wackermann, J. 1999. Towards a quantitative characterisation of functional states of the brain: from the non-linear methodology to the global linear description. *International Journal of Psychophysiology* 34(1):65–80.

Walter, W. G., R. Cooper, V. J. Aldridge, W. C. McCallum, and A. L. Winter. 1964. Contingent negative variation: An electric sign of sensorimotor association and expectancy in the human brain. *Nature* 25:380–384.

Wang, T., H. Deng, and B. He. 2004. Classifying EEG-based motor imagery tasks by means of time-frequency synthesized spatial patterns. *Clinical Neurophysiology* 115 (12):2744–2753.

Wang, Y., P. Berg, and M. Scherg. 1999. Common spatial subspace decomposition applied to analysis of brain responses under multiple task conditions: a simulation study. *Clinical Neurophysiology* 110(4):604–614.

Wang, Y., R. Wang, X. Gao, B. Hong, and S. Gao. 2006. A practical VEP-based brain-computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 14(2):234–239.

Weber et al, D. Bioelectromagnetism matlab toolbox. Available at http://eeg.sourceforge.net/.

Webster, J. S., P. T. McFarland, L. J. Rapport, B. Morrill, L. A. Roades, and P. S. Abadee. 2001. Computer-assisted training for improving wheelchair mobility in unilateral neglect patients. *Archives of Physical Medicine and Rehabilitation* 82(6):769–775.

Weiskopf, N., K. Mathiak, S. W. Bock, F. Scharnowski, R. Veit, W. Grodd, R. Goebel, and N. Birbaumer. 2004a. Principles of a brain-computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI). *IEEE Transactions on Biomedical Engineering* 51(6):966–970.

Weiskopf, N., F. Scharnowski, R. Veit, R. Goebel, N. Birbaumer, and K. Mathiak. 2004b. Self-regulation of local brain activity using real-time functional magnetic resonance imaging (fMRI). *Journal of Physiology, Paris* 98(4–6):357–373.

Weiskopf, N., R. Veit, M. Erb, K. Mathiak, W. Grodd, R. Goebel, and N. Birbaumer. 2003. Physiological self-regulation of regional brain activity using real-time functional magnetic resonance imaging (fMRI): methodology and exemplary data. *NeuroImage* 19 (3):577–586.

Welch, G. and G. Bishop. 2001. An introduction to the Kalman filter. Technical Report 95–041, University of North Carolina at Chapel Hill.

Welch, P. 1967. The use of fast fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. *IEEE Trans. Audio Electroacoustics* AU-15:70–73.

Wessberg, J., C. R. Stambaugh, J. D. Kralik, P. D. Beck, M. Laubach, J. K. Chapin, J. Kim, S. J. Biggs, M. A. Srinivasan, and M. A. Nicolelis. 2000. Real-time prediction of hand trajectory by ensembles of cortical neurons in primates. *Nature* 408(6810):361–365.

Wigmore, V., C. Tong, and J. R. Flanagan. 2002. Visuomotor rotations of varying size and direction compete for a single internal model in motor working memory. *Journal of experimental psychology. Human perception and performance* 28(2):447–457.

Wilhelm, B., M. Jordan, and N. Birbaumer. In press. Communication in locked-in syndrome effects of imagery on salivary pH. *Neurology*.

Wilson, J. A., E. A. Felton, P. C. Garell, G. Schalk, and J. C. Williams. 2006. ECoG factors underlying multimodal control of a brain-computer interface. *IEEE Transactions* *on Neural Systems and Rehabilitation Engineering* 14(2):246–250.

Wolpaw, J. R., N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan. 2000a. Brain-computer interface technology: a review of the first inernational meeting. *IEEE Transactions on Rehabilitation Engineering* 8(2):164–173.

Wolpaw, J. R., N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan. 2002. Brain-computer interfaces for communication and control. *Clinical Neurophysiology* 113(6):767–791.

Wolpaw, J. R., D. Flotzinger, G. Purtscheller, and D. J. McFarland. 1997. Timing of EEG-based cursor control. *Journal of Clinical Neurophysiology* 14(6):529–538.

Wolpaw, J. R. and D. J. McFarland. 2004. Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans. *Proceedings of the National Academy of Sciences of the United States of America* 101(51):17849–17854.

Wolpaw, J. R. and D. J. McFarland. 1994. Multichannel EEG-based brain-computer communication. *Electroencephalography and Clinical Neurophysiology* 90(6):444–449.

Wolpaw, J. R., D. J. McFarland, G. W. Neat, and C. A. Forneris. 1991. An EEG-based brain-computer interface for cursor control. *Electroencephalography and Clinical Neurophysiology* 78(3):252–259.

Wolpaw, J. R., D. J. McFarland, and T. M. Vaughan. 2000b. Brain-computer interface research at the Wadsworth Center. *IEEE Transactions on Rehabilitation Engineering* 8 (2):222–226.

Wolpaw, J. R., D. J. McFarland, T. M. Vaughan, and G. Schalk. 2003. The Wadsworth Center brain-computer interface (BCI) research and development program. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 11(2):204–207.

Wolpaw, J. R., H. Ramoser, D. J. McFarland, and G. Pfurtscheller. 1998. EEG-based communication: improved accuracy by response verification. *IEEE Transactions on Rehabilitation Engineering* 6(3):326–333.

Wood, F., M. J. Black, C. Vargas-Irwin, M. Fellows, and J. P. Donoghue. 2004. On the variability of manual spike sorting. *IEEE Transactions on Biomedical Engineering* 51 (6):912–918.

Wood, F., Prabhat, J. P. Donoghue, and M. J. Black. 2005. Inferring attentional state and kinematics from motor cortical firing rates. In *27th International Conference of the IEEE Engineering in Medicine and Biology Society*: 149–152.

Wood, F., S. Roth, and M. J. Black. 2006. Modeling neural population spiking activity with Gibbs distributions. In *Advances in Neural Information Processing Systems (NIPS 05)* vol. 17, Cambridge, MA. The MIT Press.

Wu, W., M. J. Black, M. J. D. Mumford, Y. Gao, E. Bienenstock, and J. P. Donoghue. 2004a. Modeling and decoding motor cortical activity using a switching Kalman filter. *IEEE Transactions on Biomedical Engineering* 51(6):933–942.

Wu, W., Y. Gao, E. Bienenstock, J. P. Donoghue, and M. J. Black. 2005. Bayesian population decoding of motor cortical activity using a Kalman filter. *Neural Computation* 18

(1):80–118.

Wu, W., A. Shaikhouni, J. P. Donoghue, and M. J. Black. 2004b. Closed-loop neural control of cursor motion using a Kalman filter. In *Conference Proceedings, 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*: 4126–4129.

Xu, N., X. Gao, B. Hong, X. Miao, S. Gao, and F. Yang. 2004. BCI Competition 2003–Data set IIb: enhancing P300 wave detection using ICA-based subspace projections for BCI applications. *IEEE Transactions on Biomedical Engineering* 51(6):1067–1072.

Yamato, M., A. Monden, K. Matsumoto, K. Inoue, and K. Torii. 2000. Quick button selection with eye gazing for general GUI environment. In *International Conference on Software: Theory and Practice (ICS2000).*

Yom-Tov, E. and G. F. Inbar. 2003. Detection of movement-related potentials from the electro-encephalogram for possible use in a brain-computer interface. *Medical & Biological Engineering & Computing* 41(1):85–93.

Yoo, S. S., T. Fairneny, N. K. Chen, S. E. Choo, L. P. Panych, H. Park, S. Y. Lee, and F. A. Jolesz. 2004. Brain-computer interface using fMRI: spatial navigation by thoughts. *Neuroreport* 15(10):1591–1595.

Zaveri, H. P., W. J. Williams, L. D. Iasemidis, and J. C. Sackellares. 1992. Time-frequency representation of electrocorticograms in temporal lobe epilepsy. *IEEE Transactions on Biomedical Engineering* 39(5):502–509.

Zenner, H. P., H. Leysieffer, M. Maassen, R. Lehner, T. Lenarz, J. Baumann, S. Keiner, P. K. Plinkert, and Jr. J. T. McElveen. 2000. Human studies of a piezoelectric transducer and a microphone for a totally implantable electronic hearing device. *The American Journal of Otology* 21(2):196–204.

Zhang, Z., Y. Wang, Y. Li, and X. Gao. 2004. BCI competition 2003—data set IV: An algorithm based on CSSD and FDA for classifying single-trial EEG. *IEEE Transactions on Biomedical Engineering* 51(6):1081–1086.

Ziehe, A. and K. R. Müller. 1998. TDSEP—an efficient algorithm for blind separation using time structure. In *Proceedings of the 8th International Conference on Artificial Neural Networks, ICANN'98*, edited by L. Niklasson, M. Bodén, and T. Ziemke, Perspectives in Neural Computing: 675–680, Berlin. Springer Verlag.

Zien, A., G. Rätsch, S. Mika, B. Schölkopf, T. Lengauer, and K.-R. Müller. 2000. Engineering support vector machine kernels that recognize translation initiation sites. *BioInformatics* 16(9):799–807.

Zrenner, E. 2002. Will retinal implants restore vision? *Science* 295(5557):1022–1025.