

# **Single-trial analysis of EEG for Enabling Cognitive User Interfaces**

Adam Gerson<sup>1</sup>, Lucas Parra<sup>2</sup> and Paul Sajda<sup>1</sup>

<sup>1</sup>Department of Biomedical Engineering

Columbia University

New York, NY 10027

<sup>2</sup>New York Center for Biomedical Engineering

City College of New York

New York, NY 10031

adg71@columbia.edu, parra@ccny.cuny.edu, ps629@columbia.edu

## **1. Introduction**

Establishment of robust direct brain-machine communication channels has enhanced function and performance of both impaired and normal nervous systems. The creation of direct links between brain and machine has been most strongly motivated by the need to provide a mode of communication for those silenced by conditions such as amyotrophic lateral sclerosis. Such brain-computer interfaces (BCI) [1] translate cortical activity involved with motor planning and motor response to select letters and words on a computer display or control robotic prosthesis. Perhaps the most striking results have been demonstrated through invasive systems based on multiunit microelectrode implants. Microelectrode arrays implanted in motor cortex have en-

abled monkeys to reach and grasp in three dimensions using a robotic arm and gripper without using their hands [2]. In fact, invasive systems have already allowed humans with ALS or high level spinal injury to communicate [3].

Invasive brain machine interfaces need not be limited to monitoring cortical activity. Representing an astonishing paradigm shift, neuroscientists in Brooklyn have assumed the role of animal trainer, wirelessly guiding rats using cortical microstimulation [4]. Rats were implanted with microelectrodes in left and right somatosensory (barrel) cortex and medial forebrain bundle (MFB). Rats following navigational cues provided by stimulating somatosensory cortex were subsequently rewarded through stimulation of MFB. Both navigational and reward stimuli are controlled by the rat trainers, however one can envisage a system in which motor cortex is monitored so reward centers are automatically stimulated if navigational cues are correctly executed. Direct micro-stimulation of cortical reward centers to improve motivation and task performance immediately raises ethical concerns. A more acceptable solution perhaps rests in developing a system that delivers reward through traditional sensory systems while monitoring reward centers to determine a set of optimal sensory stimuli that maximize reward impact. The advertising industry would certainly benefit from such a system. Clinically motivated cortical stimulation systems have successfully treated those suffering with Parkinson's [5] and Epilepsy [6] by stimulating the subthalamic nucleus and vagus nerve respectively. Cochlear implants have restored hearing by stimulating the auditory nerve [7] and visual cortical implants promise to restore vision [8].

Invasive brain machine interfaces are clearly well motivated, improving quality of life by restoring communication, motor control, hearing and possibly vision to a sizable segment of the population. Brain machine communication channels also enable cognitive user interfaces (CUI) designed to enhance healthy nervous system function, augmenting user performance during cognitively demanding tasks by boosting information processing capacity and reducing stress-induced deficiencies of executive control functions<sup>1</sup>. Widespread adoption of invasive cognitive interfaces is highly unlikely; as such, any cognitive user interface (CUI) must rely

---

<sup>1</sup>Visit DARPA's vision for Cognitive User Interfaces: <http://www.darpa.mil/ipto/programs/augcog/>

on non-invasive neuroimaging modalities. Functional magnetic resonance imaging has revolutionized neuroscience by delineating the anatomical origin of scores of cognitive processes. While fMRI studies are critical to the design of any CUI, the size, cost, and more importantly temporal resolution of scanners prohibits their use in any practical application. Millisecond temporal resolution and low-cost make electroencephalography (EEG) the most viable modality for cognitive interface design.

Robust classification algorithms are critical in order to realize practical benefits of EEG. Sensitivity to environmental noise is of obvious concern, however recent advances in sensor technology<sup>2</sup> suggest classifier development should focus on identifying neural sources. Traditionally, electrophysiological research relies on averaging across hundreds of stimulus or response locked trials to uncover the dynamics of neural activity from EEG. The underlying assumption has been that by averaging across trials, the contribution of background EEG activity is minimized relative to neural activity correlated with a stimulus. Such event related potential (ERP) analysis, however, masks variability between trials that may be of critical importance when striving to understand underlying cortical interactions. For example, one study describes an alpha phase distribution across trials that comprise averaged visual stimulus-evoked event related potentials [9]. The authors of this study suggest that visual stimuli in fact reset the phase of dynamic neural activity resulting in variability of alpha phase across stimulus locked trials. Any practical EEG based interface must account for inter-trial variability.

Immediate applications for cognitive user interfaces can be derived by teasing apart processing stages between sensory stimuli and motor response as outlined in Figure 1. Contemporary models indicate that sensory information is decomposed into discrete fundamental features that are subsequently integrated under constraints imposed by adjacent features and higher order areas associated with memory and reward. The process of sensorimotor integration is still subject to debate; however one hypothesis proposes that perceptual evidence accumulates lending weight to competing neuronal populations poised to execute motor plans for distinct postures. Motor responses are subsequently monitored and the outcome influences reward

---

<sup>2</sup>For example, non-contact bioelectrodes: [http://www.darpa.mil/dso/thrust/biosci/meta\\_eng/quasar.html](http://www.darpa.mil/dso/thrust/biosci/meta_eng/quasar.html)

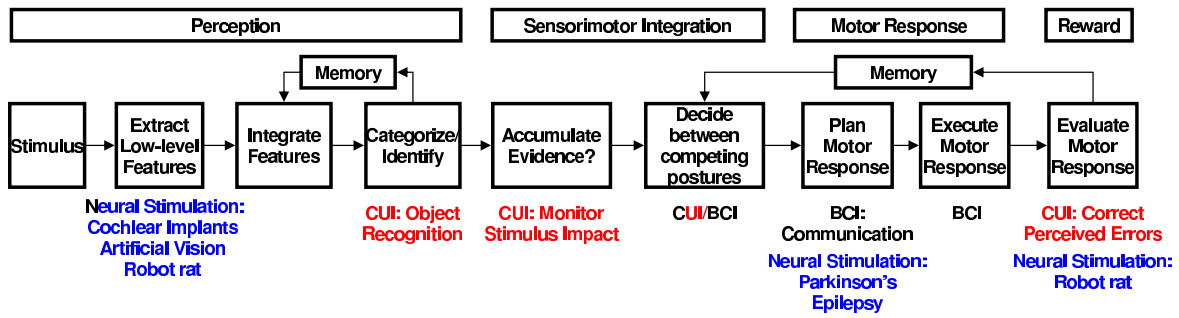


Figure 1: Stimulus response processing stages for cognitive user interface design

centers which feedback to influence subsequent decisions. Monitoring neural populations associated with perception, sensorimotor integration, and reward immediately suggests cognitive user interfaces for high-throughput object recognition and error correction. After reviewing linear classification methods, we present two examples of cognitive user interfaces designed expressly to augment cognition by enhancing throughput during an object recognition task and correcting response errors during stressful motor intensive tasks.

## 2. Machine Learning: Linear Methods

The merits of linear and non-linear methods were the subject of a debate held during the Second International Meeting on BCIs [10]. This discussion reviewed important factors to consider when fitting a learning algorithm to the problem of classifying EEG such as the degree of prior information, nature of data distributions, amount of training data, and computational costs [11] for online real-time cognitive interfaces. At the present time we prefer linear methods for EEG classification since a principled approach defining the origin of nonlinearities in EEG has yet to be clearly defined. Compared with non-linear methods, linear methods are consistent with the linearity of volume conduction, are less likely to over-fit noise, and have a significantly lower computational cost.

Linear methods for analyzing multi-channel EEG can be categorized as supervised or unsupervised. Traditionally implemented as an unsupervised method, ICA [13] decomposes signals into several independent components with time series that are viewed and analyzed separately.

Unsupervised methods do not leverage truth labels associated with experimental events such as stimulus type. Supervised methods, on the other hand, exploit training labels given knowledge of the task and/or subject responses. CSP [14] is an example of supervised source recovery widely used in EEG. This method weights electrodes according to the power captured for two classes of data. It finds orientations in the sensor space in which the power is simultaneously maximized for one class and minimized for the other. An alternative to maximizing power is to maximize the discrimination between two classes. Parra et al. [24] proposed a linear discrimination method that spatially integrates sensor values in well-defined temporal windows to recover sources that maximally discriminate two classes given labeled EEG.

All three methods linearly transform the original signals as,  $\mathbf{Y} = \mathbf{W}\mathbf{X}$  where  $\mathbf{X}$  are the observations (the original EEG signal matrix),  $\mathbf{W}$  is the transform matrix (or vector) that is calculated using the different linear approaches, and  $\mathbf{Y}$  is the resulting source matrix (or vector) representing the recovered sources. Note the recovery of sources  $\mathbf{Y}$  given an underlying linear mixture of observations in  $\mathbf{X}$ .

## 2.1 Independent Component Analysis

Independent Component Analysis (ICA) is a method of finding a linear transformation of input vectors  $\mathbf{X}$  that maximizes the statistical independence of output source vectors  $\mathbf{Y}$  such that  $\mathbf{Y} = \mathbf{W}\mathbf{X}$ . Principal component analysis (PCA) finds a transformation that decorrelates input vectors by finding a linear transformation resulting in orthogonal output vectors such that the inner product of the vectors is zero. Traditionally, the PCA transformation matrix consists of the normalized eigenvectors of the input vectors' covariance matrix. In contrast, ICA finds a transformation such that the mutual information between output vectors tends to zero. ICA transformations account for higher order statistical properties of sources as opposed to PCA which is based on second order statistics.

EEG is well suited for ICA analysis [13]. The application of ICA to any problem requires compliance with several assumptions. Most importantly, the underlying sources responsible

for generating a set of observations must be statistically independent. Applying ICA to EEG generates a set of statistically independent hypothetical neural or artifactual sources from sensor observations. ICA places no restrictions on the spatial structure of such sources, which might be widely distributed or spatially isolated. For example a widely distributed source could correspond to 60 Hz environmental noise affecting all sensors, while an ideal isolated source might correspond to activity in the somatosensory homunculus associated with tactile stimulation of the right index finger. ICA will not, however, generate sources corresponding to different neural processes that share the same underlying statistics. This limitation can most likely be overcome only by incorporating prior information concerning the functional significance of neural anatomy.

It is assumed that all mixing is linear and instantaneous. While mixing is most likely not linear given the dynamics of electromagnetic field propagation in nervous tissue, cerebrospinal fluid, skull and scalp, this assumption is nevertheless more realistic than attempting to account for nonlinearities introduced by neural anatomy. A rather popular assumption is that volume conduction in brain tissue is instantaneous therefore we do not need to be concerned with the introduction of propagation delays.

The information maximization algorithm [12] commonly used to apply ICA to EEG imposes two additional assumptions, namely that the probability density distributions of sources closely resemble the gradient of a generalized logistic sigmoid and that the number of independent sources is equal to the number of sensors. In [12], the gradient of a generalized logistic regression function is shown to resemble the probability density function of a Gaussian with high kurtosis. The statistics of EEG, as is the case of most natural signals, do in fact resemble a highly kurtotic Gaussian distribution so this assumption is approximately satisfied. The dimension of neural sources is unknown and so one of the key challenges in ICA analysis of EEG lies in determination of the optimal number sensors and source channels.

## 2.2 Common Spatial Patterns

The common spatial patterns (CSP) approach [14] finds an optimal set of spatial filters that produce features ideal for binary classification. Essentially, optimal spatial filters are determined through joint diagonalization of two covariance matrices derived from each task related class. The normalized covariance matrix of each single trial  $N \times T$  matrix  $\mathbf{X}$ , where  $N$  is the number of channels and  $T$  is the number of samples, is determined as  $C = \mathbf{X}\mathbf{X}'/\text{trace}(\mathbf{X}\mathbf{X}')$ . The average of covariance matrices from class 1 ( $C_1$ ) and class 2 ( $C_2$ ) trials are then summed to produce a composite covariance matrix  $C_c = C_1 + C_2$ . The eigenvectors and eigenvalues of this spatial covariance matrix yield a whitening transformation  $\mathbf{P} = (\lambda_c)^{-1/2}\mathbf{U}'_c$  where  $C_c = \mathbf{U}_c\lambda_c\mathbf{U}'_c$ . Transforming the average covariance matrices corresponding to the 2 classes,  $\mathbf{S}_1 = \mathbf{P}C_1\mathbf{P}'$  and  $\mathbf{S}_2 = \mathbf{P}C_2\mathbf{P}'$ , assures that  $\mathbf{S}_1$  and  $\mathbf{S}_2$  share common eigenvectors such that  $\mathbf{S}_1 = \mathbf{B}\lambda_1\mathbf{B}'$  and  $\mathbf{S}_2 = \mathbf{B}\lambda_2\mathbf{B}'$  where  $\lambda_1 + \lambda_2 = \mathbf{I}$ . The first and last eigenvectors of  $\mathbf{B}$  then represent optimal projections associated with class 1 and class 2 respectively. In other words projecting whitened EEG data along the vectors defined by the first and last eigenvectors of  $\mathbf{B}$  will yield feature vectors ideal for discrimination between EEG data associated with the two classes. The projection matrix is then defined as  $\mathbf{W} = (\mathbf{B}'\mathbf{P})'$  and an EEG trial is transformed as  $\mathbf{Y} = \mathbf{W}\mathbf{X}$ . The columns of  $\mathbf{W}^{-1}$  are the common spatial patterns and can be interpreted as time-invariant EEG source distribution vectors.

## 2.3 Linear Discrimination

Linear discrimination is also a supervised method and can be used to compute the optimal spatial integration of a large array of sensors for discrimination between two classes [24]. As with ICA and CSP, linear discrimination finds a transformation  $\mathbf{Y} = \mathbf{W}\mathbf{X}$  where  $\mathbf{X}$  is a 2-D  $N \times (M \times t)$  matrix representing  $M$  trials ( $M = I + J$ ,  $I$  trials for class 1 and  $J$  trials for class 2) of EEG data at  $t$  time points and  $N$  recording electrodes.  $\mathbf{W}$ , determined with logistic regression, is a spatial weighting coefficient vector defining a hyperplane maximally separating two classes. Timing information is exploited by discriminating and averaging within a short time window

relative to a known external event such as stimulus presentation or motor response.

### **3. Cognitive user interface for error correction**

Error related negativity (ERN) in EEG has been linked to perceived response errors and conflicts in decision-making. Single-trial detection of the ERN has been proposed as a means of correcting communication errors in a BCI system [23]. We have developed single-trial ERN detection to predict task-related errors. The system can be used as an automated real-time decision checker for time-sensitive control tasks. This open-loop error correction paradigm represents the first application of real-time cognitive event detection and demonstrates the utility of real-time EEG brain monitoring.

There has been a recent spike in studies of cortical regions associated with conflict monitoring during motor response. Functional MRI and EEG studies of interference tasks report significant increases in anterior cingulate cortex (ACC) activity preceding [15] and following [16] response selection that is believed to be associated with conflict monitoring [17] and emotional evaluation of errors [18]. Referred to as error related negativity (ERN) or medial frontal negativity (MFN) in EEG studies, such electrical activity is observed during flanker [17], Stroop [19], rapid serial visual presentation (RSVP) [20, 15], and gambling [18] tasks. During an Eriksen flanker task [21] subjects are instructed to indicate by button-press the class of a central character flanked by distractor characters (e.g. “< < < < <” or “< < > < <”). Errors in motor response are readily generated during this task, and are accompanied by ERN [22] associated with ACC.

Using a simple linear classifier, we have reported up to 79% correct detection of the ERN within 100 ms of the erroneous response [24]. More interestingly, we have described a set of adaptive, linear algorithms for artifact removal and ERN detection optimized for high-throughput real-time single-trial correction of human errors during an Eriksen flanker task [25]. The results obtained for a typical subject with 90% correct detection are shown in Figure 2. The previously described fronto-central error related negativity is observed within 100ms fol-



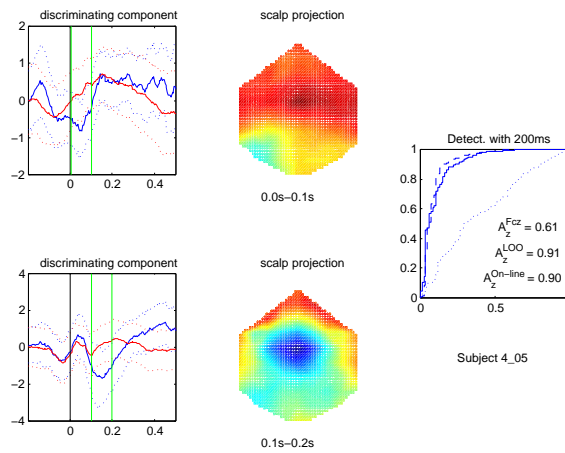


Figure 2: ERN detection using linear discrimination combining the time intervals 0-100ms and 100-200ms after response. (left) Discriminating component and (center) scalp projection graphs results were obtained with off-line linear classification. Similar results are obtained with on-line adaptation.(right) Single-trial ROC results compare  $A_z$  for off-line (LOO), on-line and using only  $F_{cz}$  electrode. Note that on-line and off-line are comparable.

lowing the response. In addition, a more prolonged bilateral posterior positivity is observed for correct trials, which further improves discrimination. This system is capable of significant improvement in human-machine performance as summarized in Table 1.

## 4. Cognitive user interface for image search

The appearance of a target image during a rapid serial visual presentation (RSVP) task elicits an EEG response associated with target recognition. We have demonstrated that the detection of these EEG signals on a single trial basis can be used to replace the slow manual response of a human operator, thereby significantly increasing the throughput of image search tasks. This paradigm has the potential to improve the performance of Image Analysts and radiologists who need to routinely survey large volumes of aerial imagery or medical images (e.g. mammograms) within short periods of time. In addition, the approach looks to measure the “bottleneck” between constant delay perceptual processing and more variable delay cognitive processing. Thus the detected signatures can be used to “gauge” if cognitive systems are capa-

Table 1: Summary of on-line error correction for each of 7 subjects

Subject	original error	% error
ID	rate in %	reduction <sup>a</sup>
1	6	23
2	10	-6
3	15	-1
4	15	49
5	13	27
6	14	47
7	18	12

<sup>a</sup>Negative values indicate degradation in performance.

ble/incapable of assimilating perceptual input for fast decision making.

#### 4.1 Rapid object recognition

Current models of visual object recognition propose information flows through a series of feed-forward processing stages in which low level features are extracted from a visual scene, then integrated under constraints imposed by adjacent and top-down connections [26]. The true nature of cortical circuits responsible for perception and recognition remains a mystery. In fact there is much debate as to whether recognition relies on information flow through cortico-cortical feedback loops or rather one feed-forward sweep through the visual system [27].

While direct functional imaging of cortical circuits is not yet feasible, indirect evidence from single unit recordings, event related potential and psychophysical studies describe macroscopic cortical regions comprising the visual system in terms of both anatomical spatial constraints and functional temporal constraints. The challenge in any such study is designing experiments that tease apart cortical processing stages involved with object recognition and delineate the spatial extent and temporal order, latency, duration, and influence of each stage in response to specific classes [28] of visual stimuli.

One experimental task that simulates natural saccadic scene acquisition is Rapid Serial Visual Presentation (RSVP) [29]. During an RSVP task a continuous sequence of images is presented in a static location. Electrophysiological studies of macaque monkey cortical cell response to RSVP stimuli indicate processing required for object recognition is completed within 150 milliseconds of stimulus onset [29]. Face selective neurons in superior temporal sulcus (STSa) were monitored while an image sequence of 7 differently oriented faces was presented (14-222 ms/image). Neurons consistently responded selectively to target face images of a specific orientation approximately 108 ms following target onset, regardless of presentation rate. Response duration was proportional to stimulus duration.

This study does not necessarily reflect visual processing time required for all classes of natural images. Face selective neuronal activity reflects responses of highly specialized cortical pathways that may not participate in processing particular subsets of natural scenes. Neuronal response times may also be related to early stages of the visual processing pathway dedicated to low-level feature extraction. In addition, since cortical response latencies are shorter in macaque than humans [30], these findings do not directly translate to visual object recognition processing time of humans. A seminal EEG-based RSVP study [31] established a significant difference between trial averaged frontal electrode event related potentials (ERPs) approximately 150 ms following presentation of target vs. distractor images. Lateral motor response related activity was observed approximately 375 ms after stimulus onset. Target images contained an animal in a random location within a natural scene while distractor images were natural scenes. More recently, a similar experiment reported EEG activity correlated with image categorization begins within 80 ms of image presentation [32]. These results demonstrate that EEG signatures of rapid object recognition/categorization can be seen, with a very short latency following stimulus presentation, by averaging across multiple trials.

While the early onset of differential ERP activity noted in these studies suggests recognition is achieved following a single feed-forward sweep through the visual system [33], another study reports this activity is due to low-level feature recognition rather than object categorization [27]. A cued-target paradigm was designed to test for differences in ERPs resulting from

target and non-target visual stimuli with contextual rather than featural differences. Target categories (e.g. animal, furniture, dog) were presented about half a second before each image. Target and non-target image sets were identical ensuring no differences in low-level features. Event related potentials for the cued-target task are markedly different than the original single-category go/no-go task. A presentation locked ERP difference similar to that previously reported is only present when there are low-level featural differences between targets and non-targets. There is a later differential component about 150-300 ms following image presentation arising from contextual differences, the latency of which is correlated with reaction time. If this component is in fact associated with object recognition, its latency does permit inclusion, albeit brief, flow of information through cortico-cortical feedback loops. Of course this task requires interaction between visual stimulus response and verbal memory, which may add an additional processing stage. One hypothesis of interest is that the variable latency results from integration of ambiguous signals to reach a decision in posterior parietal cortex [34].

We have recently reported single-trial detection of spatial signatures in EEG related to visual target recognition within 200 milliseconds of image onset during an RSVP task [35]. This RSVP task differed from Thorpe's original experiment in that subjects were asked to detect target images within sequences (barrages) of 100 images [36] that had a 50% chance of containing a single target image. Target images consisted of a person/people comprising no more than 25% of a natural scene while distractor images were natural scenes. Subjects were instructed to press a button at the beginning of a sequence and release it if a target appeared. EEG from target and distractor trials was compared on a single-trial basis using linear discriminant analysis [24, 37] and a forward linear model was used to determine sensor projections of the discriminating source activity [24]. As shown in figure 3, this forward model indicated that discriminating activity began approximately 200 ms following image presentation moving anteriorly over sensory motor areas 300-400 ms following image presentation. Since these signatures are learned/detected single-trial, it is possible to analyze variability between trials as well as determine classification performance on new trials.

This experiment required that subjects make a motor response immediately after detecting

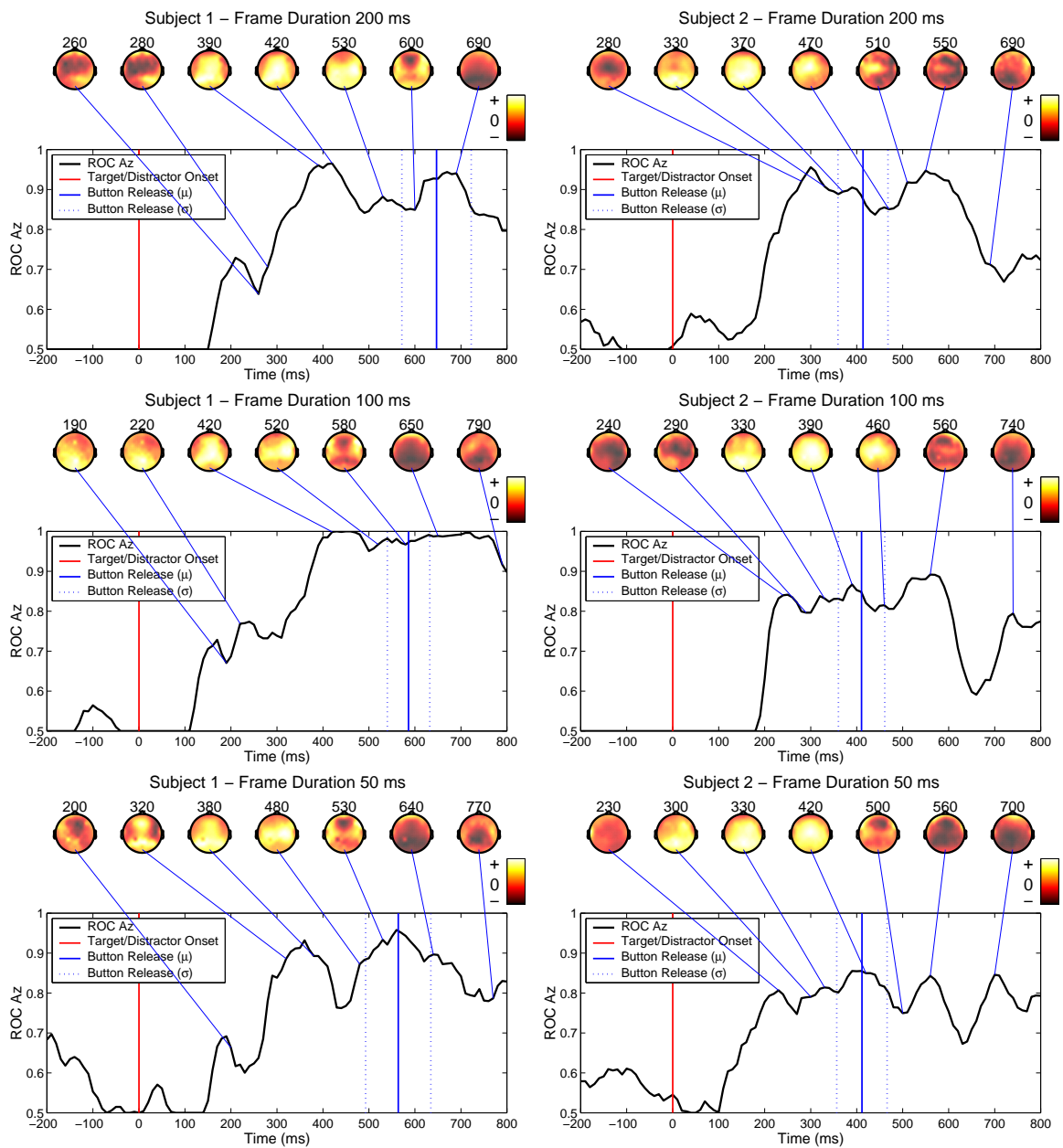


Figure 3: Area under ROC curve ( $A_z$ ) for leave-one-out test of optimal linear discriminating source as a function of the center of a 100 ms discrimination window, together with scalp plots showing sensor projections of discriminating sources, for both subjects at each image presentation rate. By sliding the window used to train a linear discriminator, we are able to study the temporal sequence of neuronal responses evoked by visual stimuli. Due to the high temporal resolution afforded by EEG this method provides an intuitive description of communication between visual and sensorimotor cortex. Results show multiple loci for discriminating activity (e.g. motor and visual). (left) subject 1 for images presented at 200, 100 and 50 ms per image. (right) subject 2.

the target. In order to decouple motor response from EEG activity related to target recognition, we revised our experimental protocol and instructed subjects to indicate target appearance by pressing a button after all images in the sequence were presented. Using the same linear discrimination method and forward model, optimal linear spatial EEG signatures were computed at multiple time windows of 50 ms duration reflecting cortical activity related to target recognition in the absence of motor activity. Figure 4 shows an example of applying optimal spatial linear discriminators learned at the peaks of a temporal classification performance curve. In Figure 4b we see the result of applying a discriminator learned at a 190ms time window to all 60 EEG channels 1 second before and after the stimulus presentation. As would be expected we see a peak in the trial averaged value near 190ms, indicating the detection of the target. In addition we see a strong negative peak near 330ms. A strong negative peak represents high negative correlation between the discriminator and sensors and indicates identical spatial activity, but opposite sign. Since the mean value for distractor trials is approximately zero, a high negative correlation would correspond to a peak on the plots of Figure 4a i.e. the fluctuation periods we see in Figures 4b-d should be roughly twice that seen in Figure 4a. Figure 4d shows the results when using a discriminator learned at 490ms. As expected a positive peak occurs near 490ms and, in addition, a small negative peak is present near 330ms. However there is no positive peak at 190ms, which might be expected if the signature were simple fluctuations of the same spatially localized areas. Likewise there is no strong positive peak in Figure 4b at 490ms. Thus these signatures appear to be significantly different, though they share some negative correlation with the activity near 330ms. Figure 4c is a discriminator learned at 330ms. It has a small negative peak at 220ms, though no significant peak at 490ms. Figure 4 also shows the scalp projections of the learned signatures. Here we see a sign reversal between the signatures at 190 and 330ms.

These studies indicate significant differential activity associated with object categorization arising as early as 190ms after image presentation within a barrage of images. Single-trial analysis of spatial activity in high density EEG leads to fluctuations in discriminating performance with a period that is independent of stimulus presentation rate. Further analysis decoupling

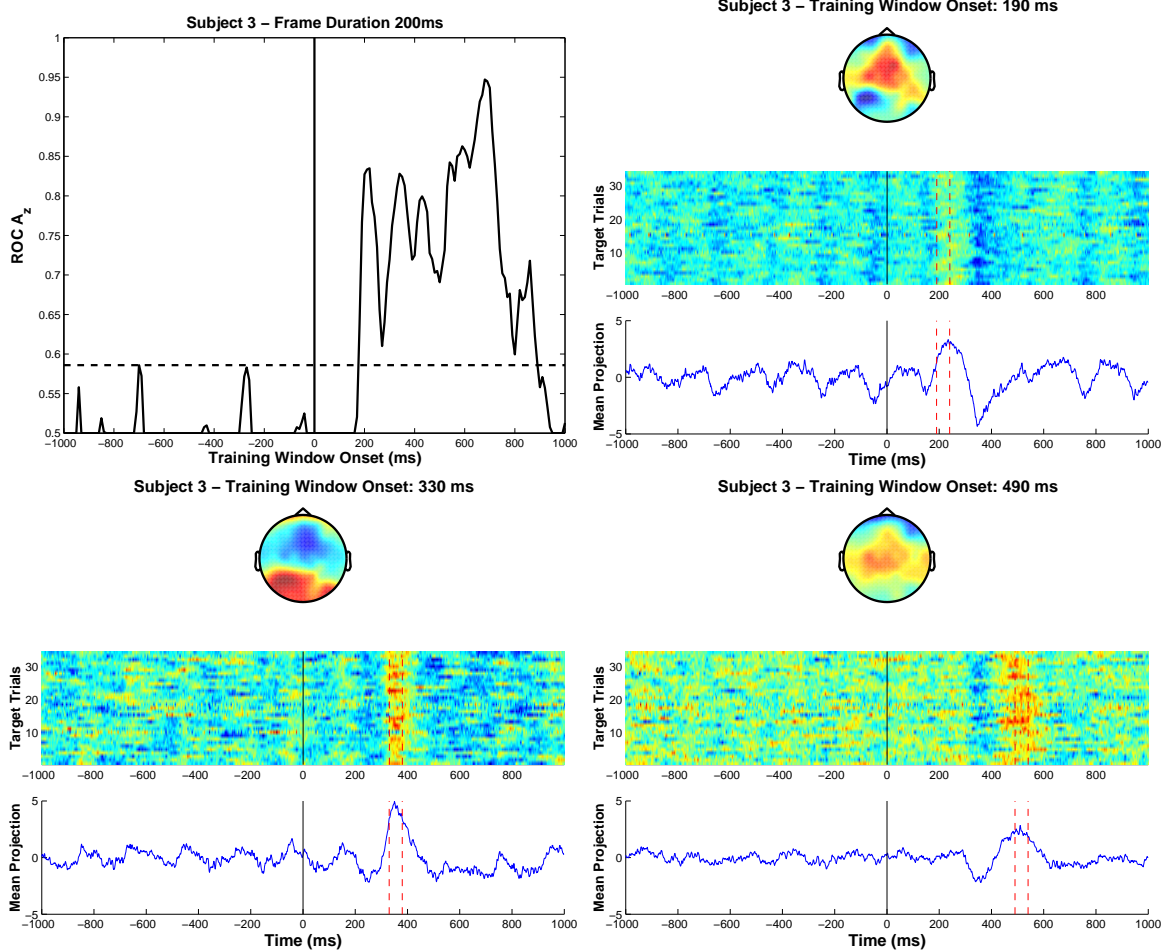


Figure 4: Optimal discriminating activity related to object recognition in the absence of motor activity (a) ROC performance results ( $A_z$ ). Shown are leave-one-out discrimination results for the optimal linear discriminator learned within a 50 ms window and applied within the same window. Results are computed 1 sec before and after stimulus locked presentation. Note that this RSVP tasks includes a barrage of images and therefore multiple images are presented during this 2 sec interval. The dashed horizontal line indicates maximum value before stimulus locked image presentation and therefore all values less then this value are considered noise. (b-d) Results of applying the optimal spatial linear discriminator learned at three different times (b) 190 ms, (c) 330 ms and (d) 490 ms, to the EEG data. Shown are scalp projections for the discriminator, single-trial results of applying the discriminator across the 2 sec interval and the trial averaged response of the discriminator. Vertical dotted lines indicate time interval in which each discriminator was trained. In the scalp plots, red indicates strong positive coupling to the sensors and blue strong negative coupling. In the single-trial plots, red indicates large positive values when the signals are projected onto the discriminator (i.e. high probability of target) and blue large negative values (i.e. low probability of target).

motor response seems to suggest that optimal discriminating components learned at different times are often negatively correlated with activity at other times, indicating a strong spatially overlapped fluctuation or oscillation of EEG activity, while other discriminating components have signatures with little correlation with such activity. This appears to indicate that different signatures are present at different times for discriminating target from distractor.

Such reports provide evidence that object recognition is achieved through a series of activations in distinct cortical regions and places temporal limits on processing time in the absence of motor response. As of yet studies do not indicate the degree of interaction between these processing stages, the spatial extent of each region, or the nature of the underlying cortical circuits. Our current exploration with simultaneous EEG/fMRI should provide additional clues, however it is clear that more sophisticated experimental designs and imaging modalities are necessary to clarify the nature of neural activity responsible for human object recognition.

## **4.2 Image Reprioritization Interface**

These findings effect the design of an interface to increase search speeds of image analysts. EEG signatures of object recognition detected via the linear discriminator can be used to reprioritize an image sequence, placing detected targets in the front of an image stack as shown in Figure 5. Image sequences are reordered based on single-trial classification of EEG. Images with classifier output exceeding a threshold are classified as targets and moved to the beginning of the sequence.

The onset of the temporal window selected to train the linear classifier has a significant impact on resequencing performance. Figure 6 shows reprioritization performance across 3 presentation rates resulting from 100 ms discrimination training windows centered 250 ms, 300 ms, and 400 ms following stimulus onset. For comparison, sequences were reordered according to button releases. For this case, target images were classified as targets if they preceded button releases by the mean latency between stimulus onset and button release. Mean button release latencies were determined across trials for each frame duration. Also plotted is



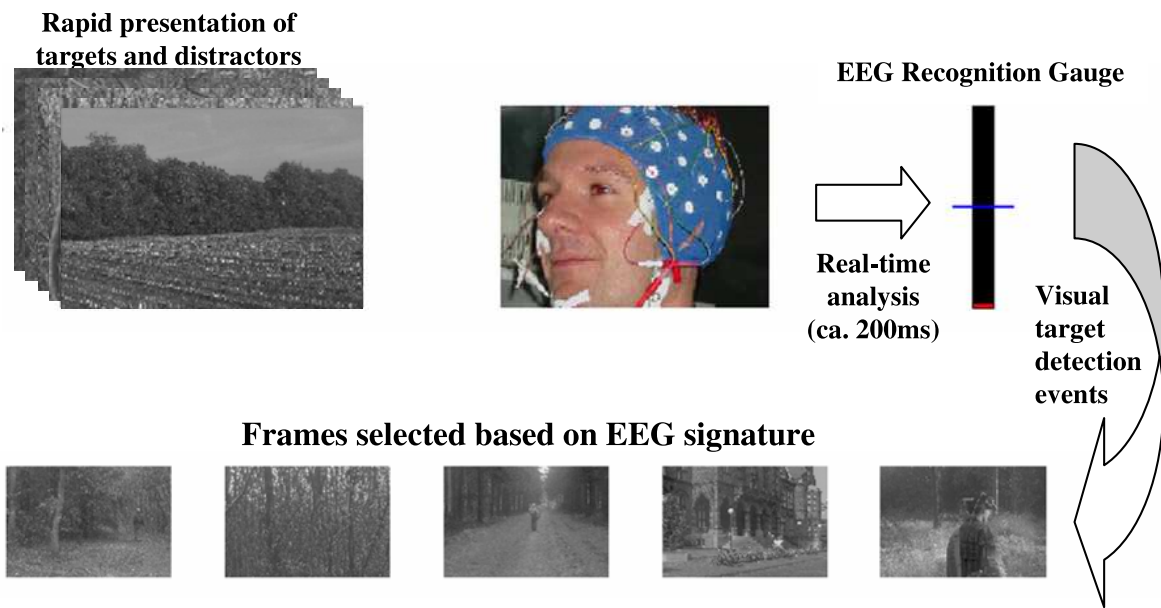


Figure 5: Image Reprioritization Interface - During sequence reprsioritization, images are moved to the beginning of the image deck if classifier output associated with a robust EEG signature is greater than an optimal threshold.

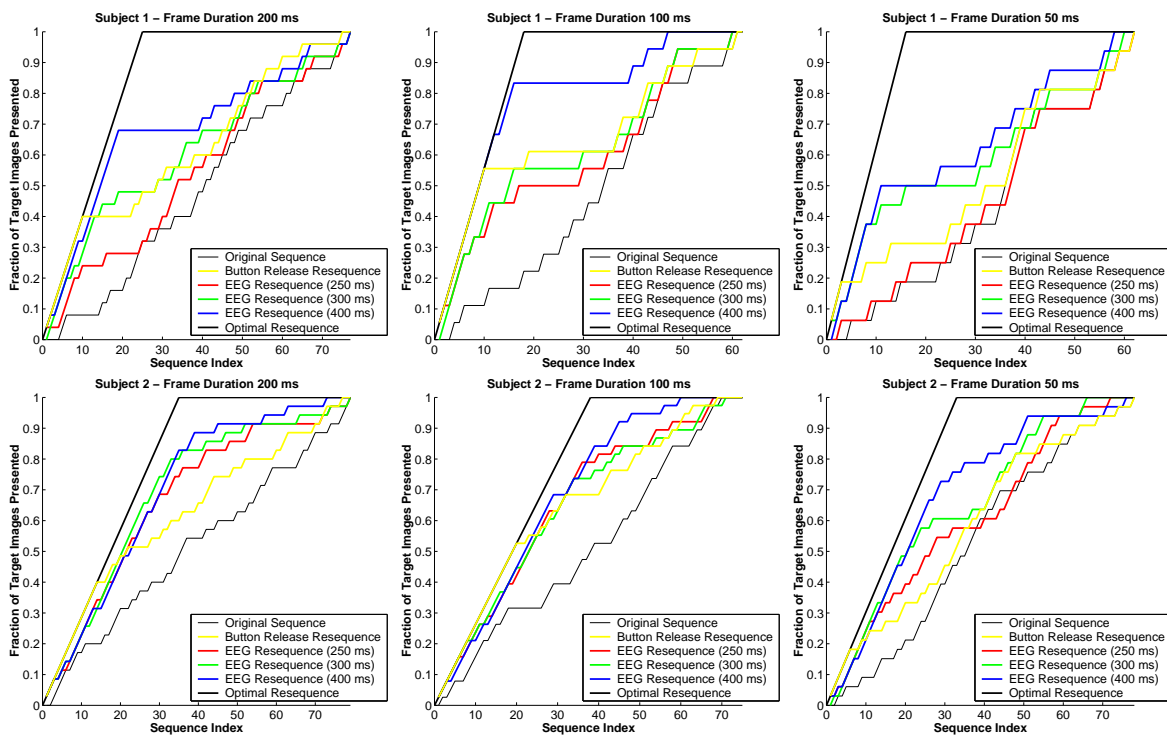


Figure 6: Resequencing performance (measured by the fraction of target images presented as a function of sequence index) using detected EEG signatures and button release. (top) subject 1 for images presented at 200, 100 and 50 msec per image. (bottom) subject 2.

the optimal resequencing, which would place all targets before distractors. For subject 1, the best performance was for using a discrimination window centered at 400 msec (200 msec before the mean button press). Windows at earlier times, for example at 250msec, were often worse than the button release results. The late response, together with the scalp plots of Figure 3, suggest the most robust signature for subject 1 to be generated via motor planning activity. Subject 2 results were more consistent across the three time windows, with efficient reprioritization for 250, 300 and 400 msec. Together with Figure 3, this suggests that both a visual and motor component provide robust signatures for detection of targets and reprioritization of the image sequence. In most cases, the detected EEG signatures result in a reprioritization for more efficient image search compared to the overt response.

## 5 Conclusion

Cognitive user interfaces are redefining the limits of human prowess by enriching perception, cognition, and action. From the perspective of neuroscience, inter-trial variability in EEG derived from CUI design may explain the source of psychophysical observations such as response time variability and provide clues describing interaction of processing stages between stimulus and motor response within the context of ongoing EEG activity. Understanding factors that contribute to differences between trials suggests robust classification schemes that enable development of a myriad of next generation interfaces.

Immediate applications stem from our understanding of motor and visual systems. While suffering from low bit rate, brain computer interfaces for communication and control provide an outlet for those battling motor neuron diseases such as amyotrophic lateral sclerosis. In fact, communication interfaces based on attentional modulation of a well studied event related potential known as the P300 have demonstrated significant improvements in classification accuracy resulting in higher throughput<sup>3</sup>. [38, 39] Modulation of P300 latency and amplitude provides a means to assess perceptual load [40] and processing capacity for a subset of tasks [41]. ERN based interfaces designed for error correction may help prevent disasters during crisis situations that require quick decisions during motor intensive tasks in stressful environments such as military cockpits. The ability to monitor human object recognition leads to the development of interfaces designed to improve search speeds of imagery analysts, or assess the impact of visual stimuli [42]. In fact the timing of visual stimulus presentation with respect to the phase of ongoing alpha observed in EEG can alter perception and affect stimulus salience [43, 44, 45].

Realization of clinically motivated EEG based interfaces will very soon become accessible. EEG has proven effective in detection and characterization of neurological disorders such as epilepsy, schizophrenia [46], depression, Parkinsons and Alzheimers diseases [47]. Discovery

---

<sup>3</sup>For a description of the P300 speller visit:

[http://ida.firrst.fraunhofer.de/projects/bci/competition/albany\\_desc/albany\\_desc\\_ii.html](http://ida.firrst.fraunhofer.de/projects/bci/competition/albany_desc/albany_desc_ii.html)

of changes in EEG up to several hours prior to epileptic seizure onset [48] has motivated development of seizure prediction algorithms [49] that could permit the implementation of devices capable of preventing seizures from occurring [50]. Detection of motor planning in pre-motor cortex will permit development of thought enabled robotic prostheses and muscle stimulators for amputees or patients with spinal cord injury [51]. EEG indices of illusory tones perceived by patients suffering with tinnitus [52] have already resulted in novel treatments based on EEG triggered sound therapy<sup>4</sup>. The interfaces illustrated here only hint at those undreamed.

## Acknowledgments

This work was supported by the Defence Advanced Research Projects Agency (DARPA) under contract N00014-01-C-0482 and the DoD Multidisciplinary University Research Initiative (MURI) program administered by the Office of Naval Research under Grant N00014-01-1-0625.

## References

- [1] J.R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, and G. Schalk “Brain-computer interface technology: a review of the first international meeting,” *IEEE Transactions on Rehabilitation Engineering*, Vol. 8, pp. 164-173, June 2000.
- [2] J. M. Carmena, 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. L. Nicolelis, “Learning to control a brain-machine interface for reaching and grasping by primates,” *PLoS Biology*, Vol. 1, Issue 2, pp. 193-208, October 13, 2003.
- [3] P. R. Kennedy and B. King, Dynamic interplay of neural signals during the emergence of cursor related cortex in a human implanted with the neurotrophic electrode. In J. K. Chapin

---

<sup>4</sup>For a description of tinnitus sound therapy visit: <http://www.otosonics.com>

- and K. A. Moxon (eds.), *Neural Prostheses for Restoration of Sensory and Motor Function*. CRC Press, pp. 221-233, 2000.
- [4] S. K. Talwar, et. al., “Rat navigation guided by remote control,” *Nature*, Vol. 417, pp. 37-38, May 2, 2002.
- [5] P. Krack, A. Batir, N. Van Blercom, S. Chabardes, V. Fraix, C. Ardouin, A. Koudsie, P. D. Limousin, A. Benazzouz, J. F. LeBas, A.-L. Benabid, and P. Pollak, “Five-Year Follow-up of Bilateral Stimulation of the Subthalamic Nucleus in Advanced Parkinson’s Disease,” *N Engl J Med*, Vol. 349, pp. 1925-1934, Nov 13, 2003.
- [6] D. K. Nguyen and S. S. Spencer, “Recent advances in the treatment of epilepsy,” *Arch Neurol*, Vol. 60, No. 7, pp. 929-935, July 2003.
- [7] B. E. Pfungst, Auditory Prostheses. In J. K. Chapin and K. A. Moxon (eds.), *Neural Prostheses for Restoration of Sensory and Motor Function*, CRC Press, Inc., Boca Raton, Florida, pp. 3-43, 2000.
- [8] Normann, R.A., et al., R. A. Normann, E. M. Maynard, P. J. Rousche, D. J. Warren, “A neural interface for a cortical vision prosthesis.” *Vision Research*, Vol. 39, No. 15, pp. 2577-2587, 1999.
- [9] S. Makeig, M. Westerfield, T.-P. Jung, S. Enghoff, J. Townsend, E. Courchesne, and T. J. Sejnowski, “Dynamic Brain Sources of Visual Evoked Responses,” *Science*, Vol. 295, pp. 690-694, January 2002.
- [10] K.-R. Müller, C. W. Anderson, and G. E. Birch, “Linear and Nonlinear Methods for Brain-Computer Interfaces” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 11, No. 2, pp. 165-169, 2003.
- [11] T. Hastie, R. Tibshirani, J. Friedman, *The Elements of Statistical Learning; data mining, inference, and prediction*, Springer, New York, 2003.

- [12] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Computation*, Vol. 7, pp. 1129-1159, 1995.
- [13] S. Makeig, A. Bell, T. Jung, and T. Sejnowski, "Independent component analysis of electroencephalographic data," *Advances in Neural Information Processing Systems*, Vol. 8, pp. 145-151, 1996.
- [14] H. Ramoser, J. Mueller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans. Rehab. Engin.*, Vol. 8, No. 4, pp. 441-446, 2000.
- [15] S. Nieuwenhuis, N. Yeung, W. van den Wildenberg, and K. R. Ridderinkhof, "Electrophysiological correlates of anterior cingulate function in a go/no-go task: Effects of response conflict and trial type frequency," *Cognitive, Affective, & Behavioral Neuroscience*, Vol. 3, No. 1, pp. 17-26, 2003.
- [16] V. van Veen, J. D. Cohen, M. M. Botvinick, V. A. Stenger, and C. S. Carter, "Anterior Cingulate Cortex, Conflict Monitoring, and Levels of Processing," *NeuroImage*, Vol. 14, pp. 1302-1308, 2001.
- [17] M. Botvinick, L. E. Nystrom, K. Fissell, C. S. Carter, and J. D. Cohen, "Conflict monitoring versus selection-for-action in anterior cingulate cortex," *Nature*, Vol. 402, pp. 179-181, Nov. 11, 1999.
- [18] W. J. Gehring and A. R. Willoughby, "The Medial Frontal Cortex and the Rapid Processing of Monetary Gains and Losses," *Science*, Vol. 295, pp. 2279-2282, March 22, 2002.
- [19] W. J. Gehring and D. E. Fencsik, "Functions of the Medial Frontal Cortex in the Processing of Conflict and Errors," *Journal of Neuroscience*, Vol. 21, No. 23, pp. 9430-9437, Dec. 1, 2001.

- [20] H. Bokura, S. Yamaguchi, and S. Kobayashi, "Electrophysiological correlates for response inhibition in a Go/NoGo task," *Clinical Neurophysiology*, Vol. 112, pp. 2224-2232, 2001.
- [21] B. A. Eriksen and C. W. Eriksen, "Effects of noisy letters upon the identification of a target letter in nonsearch task," *Percept. Psychophys.*, Vol. 16, pp. 143-149, 1974.
- [22] M. Falkenstein, J. Hoorman, S. Christ, and J. Hohnsbein, "ERP components on reaction errors and their functional significance: a tutorial," *Biological Psychology*, Vol. 52, pp. 87-107, 2000.
- [23] G. Schalk, J. Wolpaw, D. McFarland, and G. Pfurtscheller, "EEG-based communication: presence of an error potential," *Clinical Neurophysiology*, Vol. 111, pp. 2138-2144, 2000.
- [24] L. Parra, C. Alvino, A. Tang, B Pearlmutter, N. Yeung, A. Osman, and P. Sajda, "Linear Spatial Integration for Single Trial Detection in Encephelography," *NeuroImage*, Vol. 17, pp. 223-230, 2002.
- [25] L. Parra, C. Spence, A. Gerson and P. Sajda, "Response Error Correction - A Demonstration of Improved Human-Machine Performance Using Real-Time EEG Monitoring" *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 11, No. 2, pp. 173-177, 2003.
- [26] K. Baek and P. Sajda, "A probabilistic network model for integrating visual cues and inferring intermediate-level representations," In *Third International Workshop on Statistical and Computational Theories of Vision*, Nice, France, October, 2003.
- [27] J. Johnson and B. Olshausen, "Timecourse of neural signatures of object recognition," *Journal of Vision*, Vol. 3, pp. 499-512, 2003.
- [28] E. Rosch, C. B. Mervis, W. D. Gray, D. M. Johnson, and P. Boyes-Braem, "Basic objects in natural categories," *Cognitive Psychology*, Vol. 8, pp. 382-439, 1976.

- [29] C. Keysers, K.-K. Xiao, P. Fldik, and D. I. Perrett, "The speed of sight," *Journal of Cognitive Neuroscience*, Vol. 13, No. 1, pp. 90101, 2001.
- [30] J. Liu, A. Harris, and N. Kanwisher, "Stages of processing in face perception: an MEG study," *Nature Neuroscience*, Vol. 5, No. 9, pp. 910-916, Sep. 2002.
- [31] S. Thorpe, D. Fize, and C. Marlot, "Speed of processing in the human visual system," *Nature*, Vol. 381, No. 6582, pp. 520-522, June 6, 1996.
- [32] R. VanRullen and S. Thorpe, "The time course of visual processing: From early perception to decision-making," *Journal of Cognitive Neuroscience*, Vol. 13, No. 4, pp. 454461, 2001.
- [33] R. VanRullen and S. J. Thorpe, "Surfing a Spike wave down the ventral stream," *Vision Research*, Vol. 42, pp. 2593-2615, 2002.
- [34] J. I. Gold and M. N. Shadlen, "Banburismus and the brain: decoding the relationship between sensory stimuli, decisions, and reward," *Neuron*, Vol. 36, pp. 299-308, 2002.
- [35] P. Sajda, A. Gerson, and L. Parra, "High-throughput image search via single-trial event detection in a rapid serial visual presentation task," In *1st International IEEE EMBS Conference on Neural Engineering*, Capri, Italy, March 2003.
- [36] J. van Hateren and A. van der Schaaf, "Independent component filters of natural images compared with simple cells in primary visual cortex," *Proc.R.Soc.Lond. B*, Vol. 265, pp. 359366, 1998.
- [37] M. I. Jordan and R. A. Jacobs, "Hierarchical mixtures of experts and the EM algorithm," *Neural Computation*, Vol. 6, pp. 181214, 1994.
- [38] L. A. Farwell and E. Donchin, E., "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and Clinical Neurophysiology*, Vol. 70, No. 6, pp. 510-523, 1988.



- [39] E. Donchin, K. M. Spencer, and R. Wijensinghe, "The mental prosthesis: Assessing the speed of a P300-based brain-computer interface." *IEEE Trans. Rehab. Eng.*, Vol. 8, pp. 174-179, 2000.
- [40] J. B. Isreal, C. D. Wickens, G. L. Chesney, and E. Donchin, "The event-related brain potential as an index of display-monitoring workload," *Human Factors*, Vol. 22, No. 2, pp. 211-224, April 22, 1980.
- [41] A. Kok, "On the utility of P3 amplitude as a measure of processing capacity," *Psychophysiology*, Vol. 38, pp. 557-577, 2001.
- [42] M. Wells, "In Search of the Buy Button," *Forbes*, September 1, 2003.
- [43] R. VanRullen and C. Koch, "Is perception discrete or continuous?" *Trends in Cognitive Sciences*, Vol. 7, No. 5, pp. 207-213. 2003.
- [44] F. J. Varela, A. Toro, E. R. John, and E. L. Schwartz, "Perceptual framing and cortical alpha rhythm," *Neuropsychologia*, Vol. 19, No. 5, pp. 675-686, 1981.
- [45] M. Gho and F. J. Varela, "A quantitative assessment of the dependency of the visual temporal frame upon the cortical rhythm," *Journal of Physiology*, Vol. 83, No. 2, pp. 95-101, 1988.
- [46] J. M. Ford, "Schizophrenia: The broken P300 and beyond," *Psychophysiology*, Vol. 36, pp. 667-682, 1999.
- [47] S. Baillet, J. C. Mosher, R. M. Leahy, "Electromagnetic Brain Mapping," *IEEE Signal Processing Magazine*, pp. 14-30, November 2001.
- [48] B. Litt, R. Esteller, J. Echauz, M. DAlessandro, R. Shor, T. Henry, P. Pennell, C. Epstein, R. Bakay, M. Dichter, and Vachtsevanos, "Epileptic seizures may begin hours in advance of clinical onset: A report of five patients," *Neuron*, Vol. 30, pp. 51-64, 2001.

- [49] S. D. Cranstoun, H. C. Ombao, R. von Sachs, W. Guo, and B. Litt, "Time-Frequency Spectral Estimation of Multichannel EEG Using Auto-SLEX Method," *IEEE Transaction on Biomedical Engineering*, Vol. 49, No. 9, pp. 988-996, September 2002.
- [50] B. Litt, "Engineering Devices to Treat Epilepsy: A Clinical Perspective," *2001 Proceedings of the 23rd Annual EMBS International Conference*, October 25-28, Istanbul, Turkey, pp. 4124-4127, October 2001.
- [51] W. Craelius, "The Bionic Man: Restoring Mobility," *Science*, Vol. 295, pp. 1018-1021, February 2002.
- [52] A. Kadner, E. Viirre, D. C. Wester, S. F. Walsh, J. Hestenes, A. Vankov, and J. A. Pineda, "Lateral inhibition in the auditory cortex: an EEG index of tinnitus?" *Neuroreport*, Vol. 13, No. 4, pp. 443-446, March 25, 2002.