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A Natural Basis for Efficient Brain-Actuated Control

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Abstract—The prospect of noninvasive brain-actuated control of
computerized screen displays or locomotive devices is of interest to many
and of crucial importance to a few 'locked-in' subjects who experience
near total motor paralysis while retaining sensory and mental faculties.
Currently several groups are attempting to achieve brain-actuated control
of screen displays using operant conditioning of particular features of
the spontaneous scalp electroencephalogram (EEG) including central
μ-rhythms (9–12 Hz). A new EEG decomposition technique, independent
component analysis (ICA), appears to be a foundation for new research in
the design of systems for detection and operant control of endogenous EEG
rhythms to achieve flexible EEG-based communication. ICA separates
multichannel EEG data into spatially static and temporally independent
components including separate components accounting for posterior
alpha rhythms and central μ activities. We demonstrate using data from
a visual selective attention task that ICA-derived μ-components can show
much stronger spectral reactivity to motor events than activity measures
for single scalp channels. ICA decompositions of spontaneous EEG would
thus appear to form a natural basis for operant conditioning to achieve
efficient and multidimensional brain-actuated control in motor-limited
and locked-in subjects.

I. INTRODUCTION

Recent work in several laboratories has demonstrated that noninva-
sively recorded electric brain activity can be used to voluntarily con-
trol switches and communication channels, allowing a few so-called
locked-in near-totally paralyzed subjects the ability to communicate,
however slowly, with their families and aides ([4]; [14]; [2]). Com-
munication rates achieved to date are in the range of several bits a
minute, far from rates that would allow locked-in persons access to
normal social interaction. This communication briefly describes a tech-
nique for blind decomposition of electroencephalogram (EEG) data
into temporally and often functionally independent components that
would appear to provide a natural basis for optimizing brain-actuated
control ([7]; [9]). An example is given of a decomposition of sponta-
neous EEG in one subject into four components accounting for spatially
distinguishable though widely overlapping posterior alpha and central
μ-rhythmic activities. Learned control of the amplitude of motor-re-
lated central μ-rhythms in the alpha frequency range (8–12 Hz) ([5]) is
being used for brain-actuated control by at least two groups ([13]; [15]).
We demonstrate that the motor-response related spectral perturbations
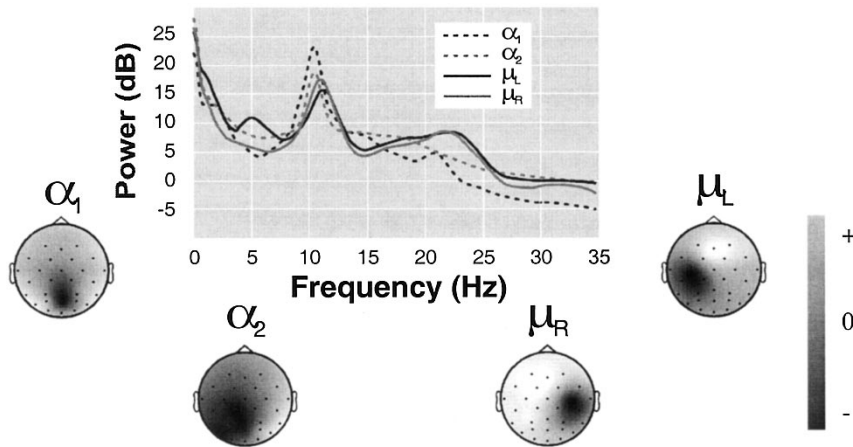demonstrated by the independent component analysis (ICA)-defined

Fig. 1. Scalp maps and mean power spectra of four independent components of the EEG of one subject in 554 3-s epochs beginning 1 s before target stimulus presentations. The ordinate gives root mean square power in all 31 scalp channels in relative log dB units. In the scalp maps, representing the projections to the scalp of the same four independent components, dark and light regions represent projections of opposite polarity.

μ-components may be 6 dB larger than at optimally placed single scalp channels. More generally, we suggest that ICA decomposition may form a natural basis for achieving efficient EEG-based brain-actuated control in locked-in subjects as well as the much larger group of motorically limited subjects.

II. METHODS

1) Task: Event-related brain potentials (ERP's) were recorded from subjects who attended to randomized sequences of filled round disks appearing briefly inside one of five horizontally-arrayed outlined squares that were constantly displayed above a central fixation cross. During each 76-s block of trials, one of the five squares was colored green, marking the location to be covertly attended during the block. Filled white circles were displayed for 117 ms within one of the five squares in a pseudo-random sequence at interstimulus intervals (ISI's) of 250 to 1000 ms. Right-handed volunteer subjects were instructed to maintain fixation on the central cross while responding as soon as possible to stimuli presented in the attended square via a right-hand thumb button. For further details, see papers by [10], [11].

2) Data Collection: EEG data were collected from 29 scalp electrodes and from two periocular electrodes placed below the right eye and at the left outer canthus. All channels were referenced to the right mastoid with input impedance less than 5 kΩ. Data were sampled at 512 Hz within an analog pass band of 0.01–50 Hz. To further minimize line noise artifacts, EEG data were digitally low pass filtered below 40 Hz prior to analysis. Three-second intervals surrounding stimulus presentations were extracted from the data for this analysis.

3) Analysis: Infomax ICA [1] exploits temporal independence of source signal waveforms to perform blind separation, by finding a square "unmixing" matrix by gradient ascent that maximizes the joint entropy of a nonlinearly transformed ensemble of zero-mean input vectors (see [10]). The algorithm can be used on data from 100 or more channels. At the end of training, multiplying the input data matrix by the "unmixing" matrix gives a new matrix whose rows, called the *component activations*, are the time courses of relative strengths or activity levels of the respective independent components across conditions. The columns of the *inverse* of the unmixing matrix give the relative projection strengths of the respective components onto each of the scalp sensors. These may be interpolated to show the *scalp map* associated with each component. ICA scalp maps are similar to spatial PCA eigenvectors or *factor loadings*. Unlike components produced by PCA, however, component scalp maps found by ICA

are not constrained to be orthogonal and thus are free to accurately reflect the actual projections of functionally separate sources, if they are successfully separated. (More information and a collection of MATLAB and C-language routines for performing and visualizing the analysis are available at *www.cnl.salk.edu/~scott/ica.html*). For each subject, three-second EEG epochs (from 1000 ms before to 2000 ms after each stimulus presentation, $N = 2877$) were concatenated and submitted to infomax ICA analysis using MATLAB routines. Training time on a modern workstation was approximately four hours using the MATLAB (or 30 min using the C-language code). Scalp maps and power spectra for each of the resulting 31 components were plotted. Target-locked activations ($N = 554$) of selected components were submitted to wide band event-related spectral perturbation (ERSP) analysis ([8]) to determine their mean spectral reactivities to stimulus and motor response events. ERSP's were constructed by transforming overlapping 500-ms subepochs of the 3-s target response epochs to spectral power by Hanning-windowed FFT's, then summing log spectra for each subepoch sequentially. Finally, the mean log power spectrum in the prestimulus period was subtracted from the log spectrum for each subepoch.

III. RESULTS

Nearly all the larger independent EEG components could be segregated into components accounting for early or late activity in the averaged target event-related potential (ERP), components accounting for eye movements or muscle activities or components accounting for particular features of the ongoing EEG, including oscillatory activity ([3]). Decompositions from most subjects included components with a spectral peak in the alpha range. Further details will be reported elsewhere.

Fig. 1 shows scalp maps and mean power spectra of four independent components of the EEG from one subject. Two of the components (α_1 and α_2) had occipital maxima and two more (μ_L and μ_R) bipolar scalp distributions with polarity reversals over left and right central cortex respectively. The peak oscillatory frequency of the μ components was about 0.5 Hz higher than that of the α components. The μ component also contained broader peaks near 22–23 Hz.

Fig. 2 shows the mean target-related ERSP results for the four components. Activities of the central components were suppressed at three frequencies, near 11, 23, and 33 Hz following the motor response (median response time or RT, 346 ms). Inspection revealed that the onset of this suppression was reliably time locked to the moment of motor response in single trials, consistent with the well-known
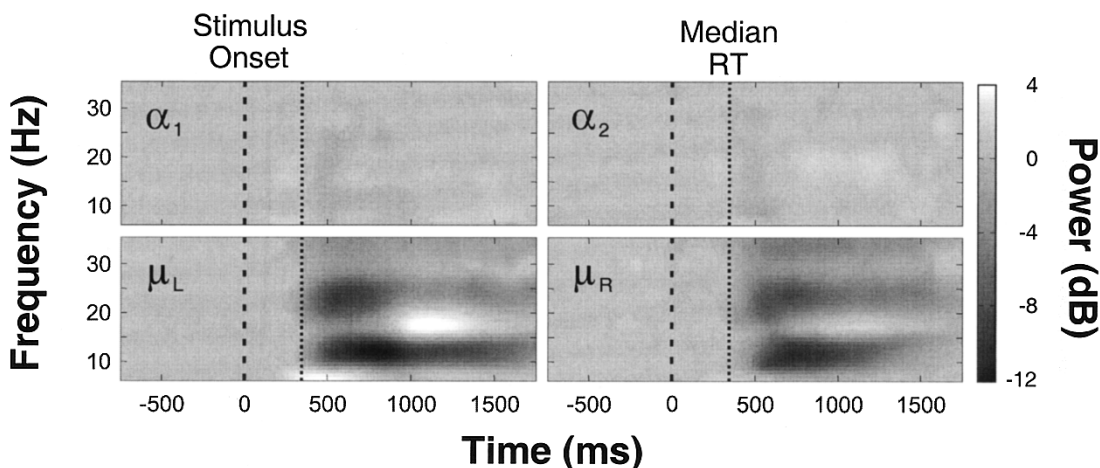
Fig. 2.   Mean target-related event-related spectral perturbation (ERSP) plots for the same four components. The abscissa shows time relative to target presentation; the ordinate, EEG frequency. Times of stimulus presentation and median reaction time (RT) are indicated with broken lines. The color scale shows increases and decreases in spectral power from the pre-stimulus baseline in dB units. The two components labeled μ (*lower panels*) showed marked and prolonged suppression at three frequencies (near 11 Hz, 23 Hz and 33 Hz) following median reaction time (RT), plus brief augmentations near 16 Hz near 1000 ms. By contrast, ERSP features for the posterior alpha components (*upper panels*) were much weaker and shorter-lasting.
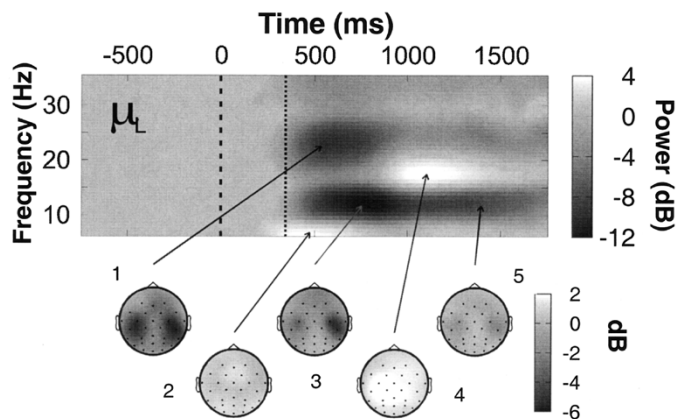

Fig. 3.   The ERSP of the left-hemisphere μ-component μ_{L} (Fig. 2, *lower left*) reproduced above five scalp maps showing the distribution of spectral suppression at five time/frequency extrema. Note the difference in size and scale between the larger ICA-component and smaller single-channel spectral deviations (e.g., minima of approximately -12 dB in the ICA components versus -6 dB in single channels).

μ-rhythm blocking following movements. By contrast, the posterior alpha component ERSP's (*upper panels*) contained much weaker and shorter lasting spectral changes.

In Fig. 3, the five scalp maps below the ERSP image for the μ_{L} component (Fig. 2, lower left) show the raw scalp distribution of spectral suppression or enhancement at the five indicated peak time/frequency points. Note that the maximum suppression achieved in the component ERSP (near 12 Hz and 700 ms, *upper scale*) was near -12 dB, whereas the maximum suppression at single scalp channels (*lower scale*) was less than -6 dB. (In a later analysis of 14 subjects to be reported more fully elsewhere, the suppression advantage using ICA averaged about 5 dB). The scalp distribution of μ-rhythm suppression (*head* 2) peaked just posterior to the scalp region overlying the left and right central sulci, whereas the scalp projection of the μ_{L} component itself (cf., Fig. 1) contained two projection areas anterior and posterior to the left central sulcal region. The bilateral μ-rhythm suppression (Fig. 3, *heads* 1–3) is fairly well explained by the parallel suppression of mu-fre-

quency activity in both the left μ_{L} and right central μ_{R} components (cf., Fig. 1).

IV. DISCUSSION

ICA separated temporally independent and spatially stable alpha and μ-rhythms from other neural and artifactual EEG sources. For the subject shown, ICA revealed at least four alpha- and beta-band components that could be measured separately by experimenters and might presumably be used as a basis for learned control. The components shown here were obtained reliably in decompositions of various data subsets. Although blocking of μ-rhythms associated with (noncued) voluntary or imagined movements is the basis for current brain-actuated control efforts ([14]), it appears reasonable to assume that the same μ-components identified here as blocking after stimulus-triggered motor responses might also be blocked before or during imagined thumb movements, and could possibly, therefore, be subject to direct voluntary control by the subject.

ICA increased the strength of motor-related signal changes in the μ-component shown in Fig. 3 by 6 dB over measures from single channels. Recent analysis of 14 subjects, to be reported fully elsewhere, has confirmed that ICA-filtered EEG signals show reliably stronger μ blocking than single-channel spectral measures. By contrast, single-channel measures, or measures combining heuristic combinations of channels such as Laplacian derivations ([12]), may not use all the response information contained in the component projections identified by ICA. Nor might they be expected to separate the activities of these components from artifactual and other neural EEG components as efficiently as ICA filtering. Thus ICA appears to provide a more natural and efficient basis for research in operant training of single or multiple endogenous features of EEG signals. For the relatively large number of relatively incapacitated subjects who retain some control of ocular and/or facial muscles, ICA might also be used to efficiently segregate, monitor and effect control using potentials associated with eye blinks and other muscle activity, as well as EEG features. ICA might then be used for efficient operant conditioning of EMG-plus-EEG-based communication by these subjects, as well as for precise monitoring of their extent motor abilities for clinical and rehabilitation planning purposes. However, the extent to which ICA-derived spatial filters may actually increase the reliability and speed of brain-computer interfaces remains to be determined.

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Brain–Computer Interfaces Based on the Steady-State Visual-Evoked Response

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Abstract—The Air Force Research Laboratory has implemented and evaluated two brain–computer interfaces (BCI's) that translate the steady-state visual evoked response into a control signal for operating a physical device or computer program. In one approach, operators self-regulate the brain response; the other approach uses multiple evoked responses.

Index Terms—Brain–computer interface (BCI), human–computer interface, neural self-regulation.

I. INTRODUCTION

The Alternative Control Technology (ACT) program of the Air Force Research Laboratory is engaged in the design and evaluation of a variety of hands-free controls. These include eye, head, speech, electromyographic and electroencephalographic (EEG) systems that allow communication with computers while the operators' hands remain engaged in other activities. For example, alternative controls may enable maintenance technicians to manually operate test equipment while accessing schematics on a head-mounted display.

In general, EEG-based control uses selected aspects of the brain's electrical activity. However, this definition does not dictate a specific control methodology. Interestingly, several different EEG-based control devices based on visual evoked responses have been developed in parallel at various research institutions. For example, Farwell and Donchin [1] developed a control based on the "P300," a brain response that varies as a function of stimulus probability and task relevance [1]. Careful design of the task format and procedures allowed these authors to use the natural variance of the P300 for task control. Sutter [2], [3] developed a control device based on the natural variation in cortical visual evoked potentials to determine the user's direction of gaze relative to a matrix of flickering stimuli [2], [3]. This system capitalizes on the cortical magnification that occurs when a flickering stimulus is visually fixated.

EEG-based research in the ACT program has harnessed the steady-state visual-evoked response (SSVER) as an effective communication medium for brain–computer interfaces (BCI's) [4]. Two methods of using the SSVER for control have been employed. In one, operators are trained to exert voluntary control over the strength of their SSVER. In the second, multiple SSVER's are used for control. The latter requires little or no training because the system capitalizes on the naturally occurring responses. The purpose of this paper is to describe these SSVER-based BCI's and to summarize research findings.

II. BCI BASED ON SELF-REGULATION OF THE SSVER

A. Communication Task

Communication between the operator and the computer is binary in the sense that only two control actions are possible. For example, a