for the correct direction in which to zoom in. DASHER leverages this high-bandwidth *inward* communication channel to the user in order to improve the efficiency of the low-bandwidth *outward* channel. Whether these visual tasks will impede functioning of a BCI system remains to be discovered. This problem would be largely avoided in the discrete control case outlined above. In discrete mode, the DASHER interface moves only during brief zooming events. The system could alternate between periods in which the user studies DASHER in order to decide which section of the screen to zoom in on, and periods during which the BCI signal is measured in order to determine which target the user has chosen.

In contrast, a BCI user is less likely to become frustrated or inattentive when using DASHER than when using more repetitive paradigms such as the standard P300 speller. Trials with gazetrackers indicate that DASHER is considerably more fun, and less stressful, than on-screen keyboards.

IV. CONCLUSION

We wish to make the best possible use of the bits of information content that can be generated by severely disabled people. DASHER offers a paradigm for efficiently converting these bits to communication symbols. DASHER has proved its effectiveness for people able to use a gazetracker or make other motor actions. We believe that DASHER will be equally useful to users who retain functioning vision but are limited to communication through a BCI.

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ECoG Factors Underlying Multimodal Control of a Brain–Computer Interface

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***Abstract*—Most current brain–computer interface (BCI) systems for humans use electroencephalographic activity recorded from the scalp, and may be limited in many ways. Electrocorticography (ECoG) is believed to be a minimally-invasive alternative to electroencephalogram (EEG) for BCI systems, yielding superior signal characteristics that could allow rapid user training and faster communication rates. In addition, our preliminary results suggest that brain regions other than the sensorimotor cortex, such as auditory cortex, may be trained to control a BCI system using similar methods as those used to train motor regions of the brain. This could prove to be vital for users who have neurological disease, head trauma, or other conditions precluding the use of sensorimotor cortex for BCI control.**

***Index Terms*—Brain–computer interface (BCI), electrocorticography (ECoG), sensorimotor cortex.**

I. INTRODUCTION

Brain signals recorded from the electrocorticogram (ECoG) have many potential advantages for use with brain–computer interface (BCI) systems when compared to electroencephalogram (EEG). Our research is exploring the use of ECoG recorded from motor and nonmotor cortex to control a BCI. This paper presents preliminary evidence in support of this technique and describes further studies of ECoG-based BCI systems.

The potential advantages of using ECoG for BCI control are: 1) increased spatial resolution; 2) increased signal bandwidth; and 3) larger signal amplitude. Therefore, it may be possible to differentiate independent signals over a wide range of frequencies, on neighboring electrodes, using multiple strategies incorporating both motor and sensory imagery.

The control methodology used is based on the ability of subjects to voluntarily modulate one or more brain rhythms using imagery. Traditionally, motor imagery has been used because it was presumed to be the most accessible and reliable EEG signal. However, we propose that the advantages of ECoG will enable subjects to learn to use multiple modalities, including motor and sensory imagery, to control a BCI application. This would enable individuals with damage to the motor cortex due to stroke or other neurological disease to benefit from BCI systems.

We have the opportunity to evaluate this hypothesis because many of our subjects have electrodes placed over multiple nonmotor areas. Therefore, we are investigating the possibility of using non-motor imagery, focusing on auditory illusion combined with the more typical motor imagery task, while studying and utilizing unique ECoG principles.

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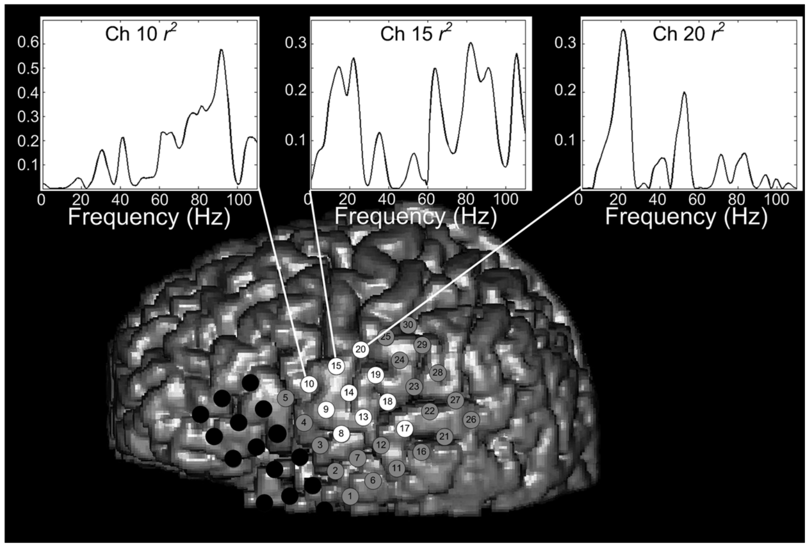

Fig. 1. MRI showing electrode grid location and electrode numbers. Electrodes 8, 9, 10, 13, and 17 showed responses for auditory screening, and electrodes 14, 15, 18, 19, and 20 showed responses for facial and tongue motor imagery screening. Gray electrodes were recorded from, but showed no response, and black electrodes were not recorded from. Note that the electrode spacing for this grid is 1 cm center-to-center. Selected r^2 calculations are shown for channels 10, 15, and 20.

II. Methods

A. Subject Pool and Electrode Placement

The current subjects consisted of patients with either intractable epilepsy or chronic pain in which an electrode grid was implanted subdurally for monitoring and localization purposes. The implanted electrodes were most commonly an 8 × 8 grid, with a 2.3-mm contact diameter and a 5-mm center-to-center distance, or a series of 4 × 1 strips of electrodes with a 4-mm-diameter and 1-cm center-to-center distance.

Most epilepsy patients are monitored for approximately one week, while chronic pain patients have electrodes implanted for two weeks during which time cortical areas are stimulated to test for pain inhibition. Fig. 1 shows a brain magnetic resonance imaging (MRI) with an electrode grid superimposed at the location approximated from a post-operative computerized tomography (CT) image.

B. ECoG-Based BCI Control

The methodology for ECoG-based BCI control is based on the utilization of sensorimotor rhythms. The primary sensorimotor rhythms present are the μ (8–12 Hz), β (18–26 Hz), γ (35–45 Hz), and high-γ (80–100+ Hz) frequency bands. The power in the frequency bands is known to change magnitude in correlation with real or imagined movements [1]–[4]. A screening task is used to identify electrodes which show signal amplitude changes in response to changes in behavior. Specifically, subjects are shown visual cues on the monitor that prompts the subject to imagine a movement or sound.

The cue is presented for 2 s and interstimulus interval of 2 s. Using the general-purpose system BCI2000 [5], 2–3 min of data are acquired for each imagined movement or sound, and an r^2 analysis is performed by comparing the power content of the signals during the task versus a rest condition. The r^2 calculation gives the proportion of signal variance that can be accounted for by the task. Typical r^2 calculations yield results in the 0.2–0.3 range for BCI screening tasks. See Schalk *et al.* for typical results and a detailed description of the r^2 calculation [6]. One or more channels with high r^2 values in several frequency bands are chosen as control signals in an online BCI cursor control task. A high r^2 value indicates that there is a measurable difference in signal amplitude between conditions.

TABLE I
Selected Multimodal Imagery Screening and Control r^2 Results

Ch	μ range *screen*	μ range *control*	β range *screen*	β range *control*	High-γ *screen*	High-γ *control*
8	0.33	0.20	0.21	0.32	0.16	0.10
10	0.05	0.02	0.09	0.04	0.13	0.53
14	0.04	0.44	0.03	0.34	0.24	0.72
15	0.03	0.23	0.06	0.22	0.02	0.20
17	0.00	0.12	0.03	0.02	0.47	0.10
18	0.08	0.08	0.03	0.05	0.59	0.01
19	0.05	0.18	0.19	0.17	0.21	0.06
20	0.13	0.16	0.10	0.32	0.05	0.03

Example results from multimodal screening and cursor-control in one subject. For the screen task, the subject was presented with two visual cues which appeared at either the top or bottom of the screen. For the top cue, the instructions were to employ auditory imagery. For the bottom target, the instructions were to relax. For control tasks, tongue imagery was used to move the cursor up, and rest was used to move the cursor down. Data from nine cursor-control runs is included; a hit-rate of 75% or greater was achieved for six of these runs, and all runs had a hit-rate better than chance (50%). Refer to Fig. 1 for electrode channel locations.

C. Principles of Multimodal BCI Control

Methods of eliciting the auditory illusion response involved imagining one of several types of sounds for a period of time while a visual cue is present. Common instructions include imagining hearing a voice, a favorite song, or an environmental sound (e.g., a cell phone). The response during this period is compared to a rest period of the same duration, during which the subject is instructed to do nothing. The data is then analyzed using the r^2 analysis, which provides insight into which electrodes can be voluntarily modulated via auditory imagery.

III. Results

A. Multimodal Control

Results from several subjects have shown that motor and auditory imagery can be modulated during a BCI task (Fig. 1), such as a one-dimensional cursor control task, in which changes in power in selected frequency bands are translated into the movement of a cursor towards

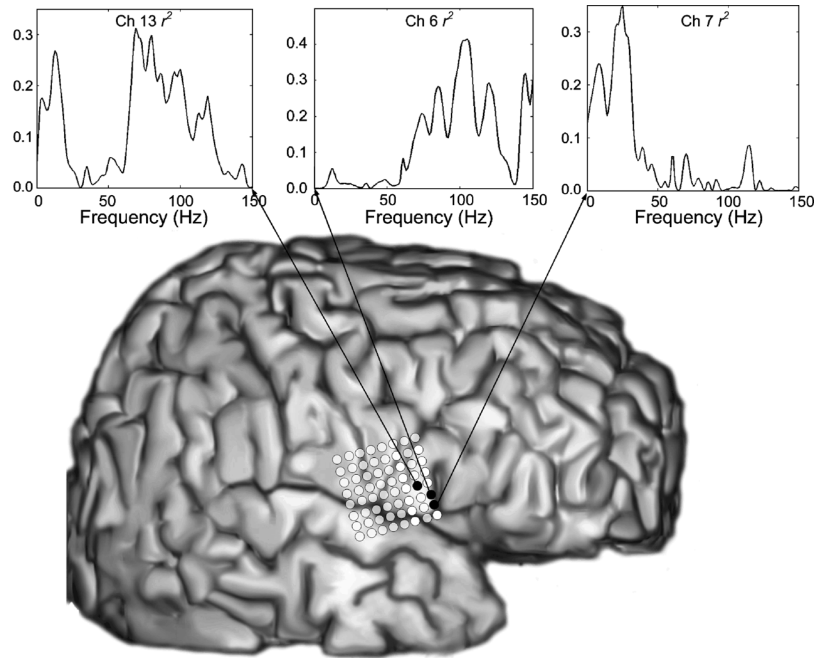

Fig. 2. MRI of a chronic pain patient with grid placement over sensorimotor cortex. Differing responses are seen on neighboring electrodes in multiple frequency bands during a cursor control task. The r^2 measures differences in power content between moving the cursor to a top target versus a bottom target. Facial and tongue motor imagery were used to direct the cursor up.

one of several targets [7]. Recent studies have shown that responses to auditory stimuli have similar characteristics with motor rhythms, in that there is a suppression of the μ and β rhythms, and an increase in γ and high-γ oscillations [8], similar to the response seen for real and imagined motor tasks. In addition, several studies have been done in which brain activity during auditory illusions is recorded via functional imaging techniques, and show that there can be a strong response in areas near the Sylvian fissure and parietal-temporal boundary [9]–[11]. Therefore, we trained subjects to use auditory imagery to elicit responses in multiple frequency bands to drive a BCI cursor task.

Detailed results for multiple subjects, including performance measures such as hit-rate are, are presented in a related study [12]. Data from nine cursor-control runs is included from one subject in Table I; a hit-rate of 75% or greater was achieved for six of these runs, and all runs had a hit-rate better than chance (50%). Table I shows screening and cursor-control results from a subject who used a combination of auditory and motor imagery to perform a BCI task. Changes in frequency content correlated with different target locations during both screening and control were seen in several electrodes spanning motor cortex and Sylvian fissure, for both auditory and motor imagery modalities.

B. ECoG Considerations

Fig. 2 illustrates several of the key advantages of ECoG for BCI. Most importantly, independent signals are recorded with a 5-mm electrode spacing, as shown on channels 6, 7, and 13 in Fig. 2. In addition, all of these electrodes are located over the same sulcus, precluding anatomical separation to account for signal variability. This increased spatial resolution permits the isolation of multiple BCI control modalities, such as facial motor imagery, arm motor imagery, and auditory imagery from neighboring electrodes. Furthermore, auditory attention studies using the same electrode size and spacing have shown that independent responses to auditory stimuli are produced on adjacent electrodes [13].

Independent spectral content up to 150 Hz and higher are shown on adjacent electrodes for both Figs. 1 and 2. Multiple responses from a single channel are also demonstrated, including activity in the low-frequency μ/β bands as in EEG, high-frequency γ bands unique to ECoG, and components of both low and high frequency bands occurring simultaneously.

IV. Discussion

Our focus is determining the concepts of nonmotor combined with motor control of a BCI system. In doing so, we have found that most concepts of ECoG-based BCI are applicable to both multiple control modalities, including motor and auditory based systems. The remainder of this paper discusses the implications and remaining questions concerning multimodal control, and also the characteristics of ECoG which are common to multiple imagery types and cortical areas. Finally, we discuss future directions for ECoG systems.

A. Implications of Multimodal Control

There are several parameters that need to be studied to find optimal conditions for a sensory imagery task, such as the length of the cue presentation for imagined activity, the number of trials needed to obtain an acceptable signal-to-noise ratio (SNR), and most importantly, ascertaining exactly what the subject is imagining during a trial. There are potentially several different ways to interpret the instruction "imagine hearing a word;" the subject may imagine hearing someone else say the word, imagine hearing himself saying it, or imagine the motor activity in the mouth and tongue that would allow him to produce the word. Conversely, a prevailing theory in BCI research is that, with training, the subject will stop using imagery to elicit changes in brain states to drive the BCI, and will simply think about moving the cursor [14], [15]. If the ultimate goal is to train a user to control a BCI system, then the precise thought process used for control is not as important, and may ultimately be analogous to asking a person how they move an arm to reach for an object. However, if the goal is to understand brain function, then a more precise methodology is likely necessary to extract information from differing behavioral experiments, such as imagining hearing a word versus imagining producing that word.

B. ECoG Characteristics

ECoG signals are superior to EEG signals for BCI purposes in several respects. First, because the electrodes are closer to the signal source, the amplitude of the signal is in the 50–100 μV range, compared to the 5–10 μV range obtainable with scalp electrodes, resulting in a much higher SNR and better artifact rejection. Second, EEG bandwidth is limited to about 50 Hz by several tissue layers (the meninges, blood, bone, and skin) that the signal must travel through before reaching the scalp. ECoG is placed on the surface of the cortex, and can, therefore, record at a much higher bandwidth, and does not suffer spatial blurring. Leuthardt *et al.* have shown that there is significant information in the high gamma ($>$80 Hz) power bands strongly correlated with movement direction [2]. Third, the spatial resolution achievable with ECoG is in the millimeter range, compared to centimeter with EEG, allowing very accurate signal source localization. Last, ECoG does not suffer from EMG or EOG interference, because the electrodes are under the skull; however, the reference electrode may still record EMG activity if it is placed on the surface of the skull.

Figs. 1 and 2 and Table I illustrate the concepts central to ECoG-based BCI systems. Large r^2 values in high-γ frequency bands demonstrate that significant information is present in these bands of the ECoG signal during both screening tasks and BCI cursor control. Furthermore, these signal characteristics are present only on individual channels, even with an electrode spacing of 5 mm as in Fig. 2 (even within the same sulcus). Therefore, it should be possible to extract independent features from neighboring electrodes using imagery of multiple body parts with training. Most current ECoG studies have been done with grids with 1-cm spacing [2] (see Fig. 1 for an example), and it was unclear how fine a spatial resolution could be achieved without signal characteristics overlapping on neighboring channels. This study has shown that resolution on the mm scale is possible with ECoG.

Table I shows an increase in β and high-γ activity on several channels when the subject is provided with visual feedback of performance. Results from this and other ongoing studies suggest that providing real-time feedback performance is crucial for eliciting high-γ activity, which has been shown to be somatotopically specific for different body parts [4], and thus could provide fine discrimination of multiple motor and sensory imagery modalities for BCI control. This, coupled with the fact that the ECoG amplitude is intrinsically larger and yields a higher SNR, allows subjects to be trained to high levels of proficiency in a much shorter period of time when compared to EEG, often within the first session [2].

C. Future Directions

In addition to the characteristics described here, ECoG may also have other potential advantages for prosthetic applications. It has been proposed that ECoG electrodes are more robust to inflammatory responses and tissue encapsulation. Although this has not been explored in human patients, there are related bodies of work that suggest that implanted ECoG electrodes will be well tolerated and remain viable. In the case of chronic pain patients, after the initial testing phase (described in the methods), a subset of the ECoG grid, usually 4–8 electrodes, is implanted permanently over motor cortex. Chronic implantation and stimulation is generally well tolerated and has a low incidence of procedure related side effects [16]. We are performing ongoing experiments in both epilepsy and chronic pain ECoG patients to look at acute inflammatory responses and impedance spectroscopy to characterize changes in the electrode-tissue interface. There are several nonhuman primate studies that suggest that local field potentials (LFPs) may be more robust to long-term inflammatory tissue changes than single unit neural recordings. Anderson *et al.* have reported continuing to record LFPs after losing single unit recordings from chronically implanted microelectrodes [17]. Additionally, the LFPs were found to have directional specificity encoded in their signal patterns and were highly correlated to simultaneously-recorded single units. Additional, long term studies in nonhuman primates will be necessary to fully evaluate the long-term safety and efficacy of ECoG electrodes for prosthetic applications.

Another potential benefit of ECoG over implantable microelectrodes is in the development of supporting hardware for a completely implantable system. There are a number of groups involved in developing wireless technology for recording multichannel single unit neuron data [18]. One of the major hurdles in these efforts is achieving the large bandwidth required for single unit recordings (25–50 kHz/channel). In contrast, the ECoG signal can be recorded at a much lower bandwidth (200 Hz/channel) which would greatly reduce the overall wireless transmission rate needed for a fully implantable device.

Finally, the millimeter-scale resolution possible with ECoG elucidates the need to study the effects of electrode size and spacing on the ability to record independent signals on each channel. Therefore, we are exploring the use of μ-ECoG (defined as ECoG electrodes having contacts and spacing on the scale of 100 s of micrometers) to study signal characteristics on increasingly smaller scales. μ-ECoG electrodes are formed using thin-film polymers, resulting in a thinner, more flexible device, and can include a fenestrated substrate that reduces the amount of material in the body, and allows fluid perfusion through the device.

V. Conclusion

The concept of using motor imagery recorded from EEG for BCI control is well established. However, motor areas constitute a relatively small percentage of the entire brain, and may be deficient or underdeveloped in those with neurological diseases, head trauma, or long-term paralysis. Therefore, it is important to study the possibility of using and training alternative brain areas to control a BCI application. Furthermore, minimally invasive recording techniques such as ECoG show much promise as a viable and improved alternative to EEG.

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An Enhanced Time-Frequency-Spatial Approach for Motor Imagery Classification

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***Abstract*—Human motor imagery (MI) tasks evoke electroencephalogram (EEG) signal changes. The features of these changes appear as subject-specific temporal traces of EEG rhythmic components at specific channels located over the scalp. Accurate classification of MI tasks based upon EEG may lead to a noninvasive brain–computer interface (BCI) to decode and convey intention of human subjects. We have previously proposed two novel methods on time-frequency feature extraction, expression and classification for high-density EEG recordings (Wang and He 2004; Wang, Deng, and He, 2004). In the present study, we refined the above time-frequency-spatial approach and applied it to a one-dimensional "cursor control" BCI experiment with online feedback. Through offline analysis of the collected data, we evaluated the capability of the present refined method in comparison with the original time-frequency-spatial methods. The enhanced performance in terms of classification accuracy was found for the proposed approach, with a mean accuracy rate of 91.1% for two subjects studied.**

***Index Terms*—Brain–computer interface (BCI), electroencephalography, motor imagery, time-frequency analysis, time-frequency-spatial analysis.**

I. Introduction

The ultimate goal of brain–computer interface (BCI) techniques is to provide those people with severe motor disabilities alternative means of communication and control [1], [2]. Typically, an electroencephalogram (EEG)-based BCI system extracts, from scalp-recorded EEG, features encoding human intention and conveys the resulting control signals to the external world [1]–[7]. One type of BCI is based upon detection and classification of the change of EEG rhythms during different motor imagery (MI) tasks, such as the imagination of left- and right-hand movements. The performance and reliability of such BCI applications rely heavily on the accuracy of classifying MI tasks, which in turn rests on extraction and representation of MI-related EEG features.

However, experimental investigations by means of different imaging modalities have revealed that MI may evoke neural activation extending multiple brain regions, including primary motor area, supplementary motor area, premotor area, and prefrontal area, etc. From the scalp EEG signals, it has also been found that imagination of movement leads to short-lasting and circumscribed attenuation (or accentuation) in mu (8–12 Hz) and beta (13–28 Hz) rhythmic activities, known as event-related desynchronization (or synchronization) (ERD/ERS) [4]. The precise timing and frequency of ERD/ERS also vary among subjects. All the above findings suggest the complexity of MI feature, since it spans all the time, frequency, and spatial domains. Simply expressing MI features in one (or two) domain(s) while disregarding the other(s) may result in lose of information that may contribute to more accurate MI classification.

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