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Mini-Review

To invade, or not to invade – that is the question for brain-to-computer interfacing

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ABSTRACT

To not invade the brain by using external devices to provide brain-to-computer interfacing is obviously desirable. But will it be efficacious? Invasive techniques provide higher resolution and hence provide more precise control, but non-invasive devices that utilize machine learning may provide control that approaches the resolution and precision of invasive devices. The answer at this point in time appears to be that, for smooth movement and conversational speech, invasive devices are needed. For all other needs, non-invasive techniques should suffice.

KEYWORDS: brain, computer, P300, infrared, eye gaze, SSVEP, EEG, ECOG, single unit recording.

1. Introduction

The problem of deciding which brain to computer interface (BCI) technique should be developed is vexing. Certainly, it would be preferable not to invade the brain with electrocorticography (ECoG), or intracortical electrodes (ICE) because of the inherent risk. However, low-resolution devices will not provide smooth movement, for example, though they can provide some movement. The dividing line between invasive and non-invasive techniques indicates that more and more efficacy is obtained by non-invasive devices despite their lower resolution. This is likely because of better signal decoding by using machine learning.

The modalities are listed across Table 1.

2. Modalities for communication

2.1. Residual digit movements

Residual digit movements are obviously achievable for paraplegics, but high quadriplegics and locked-in amyotrophic lateral sclerosis (ALS) subjects might be able to tap on a switch or keyboard to produce letters or activate icons that call for help, turn lights and music on or off, and so on.

2.2. EMG signals

Electromyography (EMG) signals may also be obtainable from quadriplegics and locked-in subjects, from the neck or face. EMG signals can trigger a switch that produces letters or activates icons on a computer. In combination with additional software such as E Z Keys+ [1] rapid rates of spelling and hence artificial speech in locked-in subjects is possible. However, the speech is slow and nowhere near conversational rate. Alternatively, the EMG signal can be used to control a cursor and hence the user can access the Internet.

2.3. Eye gaze devices

Eye gaze devices from LC Technologies Inc. [2] or Tobii Inc. [3] track the subject’s eye gaze and thus can control the computer, providing communication and Internet access.

2.4. Near-infrared light

Near-infrared light (fNIRS) can traverse the skull and penetrate about 1 cm into the cortex. It can detect changes in blood flow and hence differentiate between active and non-active brain areas. Previously it was considered slow but useful [4]. A more

Table 1. List of non-invasive and invasive modalities used for BCI.

	Non-invasive								**Invasive**	
Modalities	Digit movements	EMG	Eye gaze	Infra-red	Slow waves	P300	SSVEP	EEG	ECoG	Intra cortical electrodes

recent advance involves the use of ultrasound imaging to detect anatomic and functional activity of the brain using a small hand-held wand. This system has been shown to detect changes in the brain that indicate intention to move and thus can be used as a communication device [5]. Also see 'Hybrid BCI' section below which describes the combination of IR light with EEG.

2.5. Slow waves

Slow waves are detectable from the frontal cortex and can be controlled by the subject. Again, they are useful but as the name implies, slow [6].

2.6. P300 wave

The surprise potential. It is recorded from the vertex and occurs when the subject views a letter he needs as part of a word he wants to spell. As the name implies, it occurs 300 ms from the onset of the event. In that way, the subject can spell words and produce speech at a non-conversational rate. The P300 occurs upon the subject's reaction to the stimulus, not the stimulus itself [7]. It has also been used as a lie detector to provide legal evidence. Originally it was slow. Now it has been combined with a variety of stimuli [8] or a more rapid presentation of the stimuli [9] so that the Information transfer rate (ITR) was 5.04 bits per minute (bpm) in the latter study. The complexities of these variations are very well reviewed here [10].

2.7. Motor imagery

Motor imagery (MI) can also provide communication [11, 12]. Even movement can be controlled using motor imagery [13]. The subject imagines moving the right or left hand, for example, and the decoded EEG activity can accurately indicate which hand they intended to move and hence make a binary choice or move in a direction.

2.8. Steady state visual evoked potential

Steady state visual evoked potential (SSVEP) may be one of the fastest methods [14]. Essentially, the icons or letters are targets that flicker at specific rates so that they can be detected using electrodes over the occipital lobe. Flickering can reduce the subject's compliance, so Nakanishi *et al.* [14] developed a flicker-free system that not only obviated that problem but also provided a high ITR rate of 91.2 ± 27.6 bpm (bits per minute) averaged over 18 subjects. Accuracy was 94 ± 2.44%. This surpassed the mean ITR of 56.4 for all other BCI systems, whether internal or external systems, to date, according to Nakanishi [14]. However, this was not as high as the 267 achieved by Gao Rong as quoted in their paper (unreferenced). This latter level was achieved using a much more complex system, unlikely to be available to subjects.

2.9. Hybrid BCI

EEG has been combined with ECoG, fNIRS, MI and P300. Motor imagery has been combined with SSVEP. Despite all these combinations, the ITR does not come close to the ITR of the SSVEP [14, 15]. Combination of EEG with fNIRS achieved an ITR of 4.70 bits per minute (bpm) and high accuracy of 82% when compared to either EEG or fNIRs alone [16]. Using a short trial length however, produced an ITR of 10 bpm for some subjects, with an average of 6.88 bpm. Also described in Shin *et al.*, [16] is a hybrid EEG and fNIRS using motor imagery of both force and speed with higher accuracy (ITR is not given).

2.10. Neural net decoding

Neural net decoding combined with EEG, fNIR, and other modalities, may be the key to developing high-resolution signals from non-invasive techniques. Early studies show promise [17]. EEGNet, a software program, was used successfully to decode four techniques: P300 visual-evoked potentials, error-related negativity responses, movement-related cortical potentials, and sensory motor rhythms. Improved accuracy was obtained [18-20]. Using neural net decoding to decode yes/no in Hindi and

English for locked-in subjects using silent speech produced an accuracy of 85% for decision between yes and no, and 92% for language [21]. ITR was not given. Many other techniques have been described using neural net computation and the future is bright for further development and better results.

2.11. ECoG and intracortical recordings

ECoG and intracortical recordings have been used to communicate. Ramsey and coworkers [22] used ECoG to communicate and later to decode speech. Other workers began using intracortical recordings in 1998 to communicate with and control a computer [23]. When it was realized that external devices could be just as efficacious, those invasive studies were not continued since they would be unethical. Intracortical local field potentials could also be used to control a computer [24].

The above discussion on communication is summarized in Table 2.

2.12. Conclusion regarding communication

No one is ethically justified any longer to invade the brain for communication when it can be done adequately, safely and expeditiously with non-invasive external devices.

3. Modalities for control of movement

3.1. EMG

First let's divide movement into smooth movement or non-smooth, chunky movements. EMG can be used to provide movements in quadriplegics and in some almost locked-in ALS subjects. Residual EMG activity in quadriplegics can control an exoskeleton or functional electrical stimulation systems attached to the extremity [25]. Exoskeleton control by EMG and proprioceptive feedback provide improved control compared to EMG activity alone [25].

3.2. EEG

An exoskeleton was driven by EEG from the motor cortex ipsilateral to the driven arm. This study involved 10 subjects with no controls, and produced a 6.2 point increase in the Action Research Arm Test with baseline of 13.4 [26]. Whether or not this is better than the EMG control described above is unknown. Another study looked at the difference between BCI-controlled robot and robot alone and found no difference until week 12 when the study had to end [27]. An intriguing on-going therapy is to record EEG while the subject imagined using the paralyzed arm, and use the EEG, activated by imagination, to drive an external muscle stimulator that activated the paralyzed muscles. The control study was to use the muscle stimulation system without the EEG activated by imagination. More rapid recovery of the paralyzed limb was demonstrated [28].

A thorough review of this area concludes that non-invasive BCI assists in recovery from stroke [29].

3.3. ECoG

ECoG has been used to move a prosthetic hand into the supine or prone position with an accuracy of 79% (50% chance level) with digit movement accuracy of 68% (33.3% chance level with 4th and 5th digits tied together) [30]. A similar study demonstrated accurate control of 92% (50% chance) for supine or prone positions, and digit classification accuracy of 76% (20% chance level) which is an improvement [31].

3.4. Intracortical recordings

Intracortical recordings (ICR) of single units using a 96 channel Blackrock array in 2 quadriplegic

Table 2. Summary of modalities used in communication.

	Non-invasive								**Invasive**	
Modalities	Digit movement	EMG	Eye gaze	Infra-red	Slow waves	P300	SSVEP	EEG	ECoG	Intra cortical electrodes
Communicate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Warranted?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No

subjects demonstrated reach and grasp; One subject was implanted 5 years earlier and had only 15% of units remaining but could slowly operate the robot arm to reach and grasp [32]. Another group [33] used two Blackrock arrays and had 91.6% accuracy in reaching (6.2% chance level) in less time (112 versus 148 seconds). A third group used a surface functional electrical stimulation (FES) system controlled by single units acquired from a Blackrock array that generated digit movements and 6 different wrist movements in a locked-in individual [34]. A fourth group used Blackrock arrays to control an implanted FES system to control reach and grasp; 36 implanted electrodes resulted in 80 to 100% point-to-point accuracy and allowed self-paced drinking and eating with the subject's own arm [35].

All these studies resulted in somewhat smooth movements compared to ECoG or other modalities but a direct comparison has not been possible. These intra cortical recording (ICR) results are intriguing indeed, but whether or not they will be surpassed by those of ECoG remains to be seen. One group of Blackrock Array users admits that the signals from the array are not stable [36] and this obviously limits their long-term use. Sensory return (including proprioception) to the brain is another obvious essential requisite for the production of smooth movements and this is being addressed [37]. The overall conclusion at this stage of development is that ICR is likely the optimal modality for smooth movement. It is possible that ECoG may, along with neural net decoding, exceed the capabilities of ICR. But that remains to be proven.

The above discussion on movement is summarized in Table 3.

4. Control of speech

The aim of a speech prosthesis is to provide speech at a near conversational rate that includes at least 100 and expectantly several 100 words. Use of non-invasive modalities cannot in theory produce anything close to natural speech because their outputs are generally a click thus producing a single word either by spelling it out or by icon. Thus, natural, near conversational speech falls into the realm of invasive technologies.

4.1. ECoG

There is an excellent review as to the possibilities of using ECoG for speech [38]. Specific studies are not so optimistic. For example, using timing of neural signal modulation did not produce a clear result [39]. Another example: Neural decoding of single vowels during silent speech in a locked-in subject produced a low accuracy of <50% [40]. The results also showed that high gamma was not useful but beta was the most useful frequency. Another study [41] decoded spectro-temporal features of audible speech producing a rank of .91 (baseline 0.5, max rank = 1) but silent speech produced a lower rank of 0.55. A study using only a two-syllable choice task achieved 98% accuracy using support vector machine decoding [42]. Decoding of single words resulted in an average accuracy of 36% and for single phonemes an accuracy of 63% and the ITR was 33.6 words per minute [43]. A review discusses how to improve the electrode and the decoding process [44]. One study demonstrated that by recording single-unit activity from ICR simultaneously with local field potentials (LFPs) and ECoG using only a 7 x 13 mm electrode, from ventral speech cortex the accuracy was 59% [45]. This result was better than that obtained using one

Table 3. Summary of modalities used in movement control.

	Non-invasive								**Invasive**	
Modalities	Digit movement	EMG	Eye gaze	Infra-red	Slow waves	P300	SSVEP	EEG	ECoG	ICR (Intra cortical recording)
Some movement	n/a	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes
Smooth movement	n/a	No	No	No	No	No	No	No	Possible	Possible

Table 4. Summary of modalities used in speech.

	Non-invasive								**Invasive**	
Modalities	Digit movement	EMG	Eye gaze	Infra-red	Slow waves	P300	SSVEP	EEG	ECoG	ICR (Intra cortical recording)
Speech	n/a	No	No	No	No	No	No	No	Yes	Yes

modality. Another study using high-density ECoG electrodes demonstrated an improved accuracy of 75% by limiting the word choice to only four words [46].

A different approach was taken by Chang and his group [47]. Instead of searching for word, phoneme or phrase representations over the cortex using ECoG, they focused on placing high-density ECoG electrodes over the ventral motor articulatory cortex with the aim of mapping the representation of the articulators, namely the tongue, lips, jaw and larynx. Using this technique combined with a tracking system it was possible to directly measure the vocal tract and relate its movements to cortical activity [48]. Furthermore, recordings in the superior temporal gyrus demonstrated a posterior area that identifies speech onset and an anterior area that identifies sustained speech responses [49]. These results suggest a method of identifying parsing of speech.

4.2. ICR

Recording single-unit activity in the auditory cortex while listening to speech allowed identification of the speech [50]. In a separate study, recording from speech motor cortex in a locked-in subject provided decoding of 23 of 39 English phonemes [51]. In addition, linear discriminant analysis decoding was used to drive the computer cursor over a formant frequency plane from one phoneme to another over seconds. This technique was too slow to be useful in restoring near conversational speech. However, phoneme sounds were classified from the single-unit results [52]. In another study, involving ICR in an intact human, short phrases were decoded offline using an artificial neural net for both audible and silent speech with correlation values between 0.9 and 0.8 [53].

The results with ECoG are very encouraging as are those with ICR of single units. More studies are needed in both areas to decide the optimal modality.

The above discussion on speech is summarized in Table 4.

4.3. Other issues that impact the choice

Longevity of recordings

Non-invasive modalities are preferred if efficacy is adequate. Clearly in the case of restoring speech, for example, they are not adequate. Invasive ECoG recordings have been tested over months but not years, so longevity cannot be assessed. ICR electrodes are notorious for not enduring beyond a few years with the Blackrock array; specifically 85% loss of single units occurs over three years [36]. However, the neurotrophic electrode has survived over a decade in a locked-in subject who died while the electrode was still active. Conditioning studies were performed at year nine, indicating that single unit recordings were functional and not arbitrary waveshapes [54].

Risk

With non-invasive studies, there is essentially no risk. The risk with any invasive technique is high especially if there is any electrode lead or a pedestal that exits the scalp. This occurs with ECoG implants and the Blackrock array. Risk is lowered with the neurotrophic electrode and its implanted electronics where no wire exits through the scalp. Unfortunately, the number of channels is no more than 3, severely limiting its capabilities.

5. Conclusion

Non-invasive devices are preferred if efficacy can be obtained as is possible with communication. Combining non-invasive systems with neural net decoding is already advancing their capabilities. Combining neural net decoding with ECoG or with ICR has already been shown to improve decoding. Despite the risks of invasive recordings, ECoG and ICR may be essential for smooth movement control and conversational speech only when combined with neural net decoding.

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CONFLICT OF INTEREST STATEMENT

The author has no conflict of interest associated with this review.

GLOSSARY

'Digit movement' refers to any residual digit movement that the subject can use.

'EMG': Electromyography.

'Eye gaze technology' is exemplified by devices that detect eye gaze position and translate that into commands.

'Near infra-red therapy' refers to the use of near infra-red light that traverses the skull and activates the brain underneath.

'Slow waves' refer to the detection of 1-3 Hz EEG activity that can be controlled by the subject to provide a communication pathway.

'P300' refers to a technique of detecting a surprise potential when the subject views a letter of interest even for a few milliseconds.

'SSVEP' refers to steady state visual evoked potentials that can be controlled by the subject either by looking at the flickering areas or gazing off the flickering area (target or movement is detected due to the changes in the pattern of EEG recording over the occipital lobe).

'EEG': Electroencephalographic recording from the scalp.

'ECoG': Electrocorticographic recording from the brain surface.

'ICR': Intracortical recording from electrodes placed within the cortex.

'BPM' : bits per minute

'ITR' : information transfer rate

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