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Towards Low-Power Embedded ECoG Decoding

Joe Saad*, Adrian Evans*, Ivan Miro-Panades*, Tetiana Aksenova†, Lorena Anghel‡

*Univ. Grenoble Alpes, CEA, LIST, Grenoble, France

†Univ. Grenoble Alpes, CEA, LETI, Clinatec, Grenoble, France

‡Univ. Grenoble Alpes, CEA, CNRS, Grenoble INP, IRIG-Spintec, Grenoble, France

Email: joe.saad@cea.fr

Abstract—The ability to read intents from the brain is no longer science fiction. This requires acquiring and decoding the brain signals to make them usable in different applications. The signal processing requires high computational capacities and consequently high energy consumption. This paper introduces the flows for brain signal decoding and focuses on electrocorticography (ECoG) approaches for motor imagery. SoA ECoG decoding algorithms require significant computing power creating a need for specialized low-power circuits for embedded use.

Index Terms—brain-computer interface (BCI), system-on-chip (SoC), decoder, ECoG

I. INTRODUCTION

The development of BCIs has been following the progress of machine learning (ML) algorithms as well as technological advances in electronics. The current trend aims for fully implantable devices with embedded computing for more use cases. Fig. 1 shows some BCI applications.

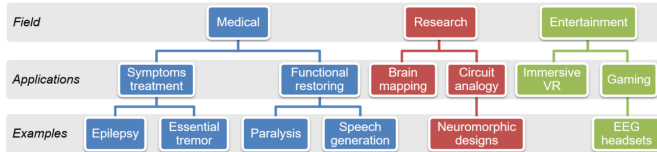


Fig. 1. Examples of BCI Applications.

Techniques for acquiring brain electrical signals can range from electroencephalography (EEG), non-invasive but limited in spatial resolution, to the implantation of microelectrode arrays (MEAs) in the brain for a better resolution but at the cost of a high risk of physiological complications. ECoG, being less invasive than MEAs and closer to the brain than EEG, makes a compromise between spatial resolution and low risk of infection. Decoding brain signals refers to the extraction of information that could be turned into a relevant action such as speech or motion. This work focuses on motor imagery approaches i.e. decoding mental intentions of motion such as regaining motor control for patients with paralysis.

II. BCI ALGORITHMS

ECoG-based approaches can extract information either directly from the signal such as the deep learning (DL) method used in [1] to detect finger binding with a discrete classifier, or indirectly by first computing intermediate variables called features. The latter method follows the pipeline shown in

Fig. 2 where the extracted features are fed into a decoder that outputs signals to control an effector (exoskeleton, screen, speech generator, spinal cord stimulator...).

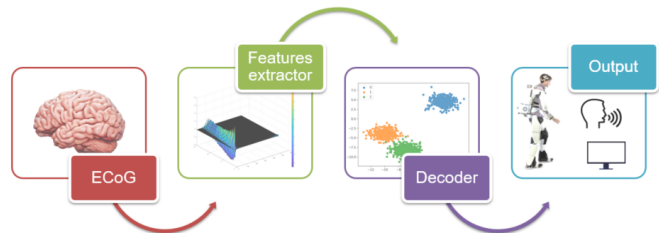


Fig. 2. Indirect ECoG Decoding Flow.

A. Features computing

Feature computing extracts information (e.g. time-frequency domain) that serves as an input to a decoder model. Wavelet transforms (WTs) are frequently used as it has been shown [2] that the original signal can be reconstructed from the wavelet coefficients. The WT, described in (1), relies on a convolution between the ECoG signal and a wavelet function that can be scaled and translated to extract similarities for different frequencies and times.

$$F(\tau, s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} f(t) \psi^* \left(\frac{t-\tau}{s} \right) dt \quad (1)$$

Where ψ , s and τ are the mother wavelet, frequency and time scaling factors, respectively. Features can be computed by decimating the wavelet coefficients $F(\tau, s)$. Different algorithmic implementations with complexity exist for WTs e.g. discrete wavelet transform (DWT) [3] and fast continuous wavelet transform (fCWT) [4]. DWT is a WT variant based on a power-of-two discretization of the s and τ parameters in (1) resulting in a $O(N)$ instead of a $O(N^2)$ complexity for direct convolution. fCWT uses a fast Fourier transform (FFT) to simplify the convolution into a multiplication in the frequency domain. The product is then expressed in the time domain using an inverse FFT with a $O(N \log(N))$ complexity.

B. Decoding models

As shown in Fig. 2, features need to be decoded into effector inputs. The decoder model can be linear or not depending on the used features and computation constraints.

The work of [3] presents a probabilistic neural network (PNN) decoder of relative wavelet energy features following a non-linear Bayesian classifier approach. The model was tested offline on 8 ECoG channel outputs to classify left small-finger and tongue movement. The tests have yielded a maximum accuracy of 91.8% in offline decoding and no tests have been reported on real-time applications.

In [1], a 83.3% accuracy on finger bending detection is reached using an online method with a direct decoder. The proof-of-concept is demonstrated on a robotic arm. No power consumption estimation was reported in the two studies to evaluate the solutions implantability. In addition to that, the two previous models are fixed after the training phase, meaning that any evolution in the ECoG signals due to brain plasticity can result in a lower accuracy.

Adaptive decoders present a promising alternative that could solve the fixed-model issue by modifying it to adapt with the brain plasticity. A proof-of-concept [5] has been demonstrated for a BCI that has enabled the control of an exoskeleton by tetraplegic patients when decoding brain signals corresponding to motor intentions. The model uses features computed with a complex continuous wavelet transform (CCWT) of the ECoG signals coming from 64 electrodes channels [6]. A hidden Markov model (HMM) controls the output probabilities of independent linear decoders to ensure a stable behavior. Even after 167 days of implantation, it yields an average accuracy of 92% for the gating output [5]. The implementation satisfies the real-time constraint. The computation is done on an external computer consuming tens of watts currently limiting its implantability.

III. BCI PLATFORMS

In parallel to the development of decoding algorithms, research is currently focused on embedded computing in BCI to achieve a fully implantable autonomous system capable of decoding brain signals.

The work in [7] presents a fully implantable 16-channel system that can detect early seizures from ECoG signals. The entire system consumes 230.4 μ W when all channels are used. The features extraction step is optimized on hardware (HW) to output 10 feature vectors per second (real-time for BCI applications). The RISC processor is however only tested with a K-nearest neighbor (KNN) algorithm applied to a specific application with no tests for motor imagery.

Another approach in [8] describes a distributed-chip platform using brain MEA. The chips can be used for seizure detection, spike sorting but also movement decoding. The designed SoC supports a FFT HW module for optimized feature extraction and a linear support vector machine (SVM) accelerator for decoding. The design satisfies the power consumption and time constraints for fully-implantable BCIs. The major drawback of this approach is its high invasiveness as measurements are collected with MEAs (96 per node) distributed across many brain regions.

The presented approaches are summarized in Tab. I and evaluated based on the type of brain signals, channels number,

power budget (PB) (less than 100 mW) and real-time compatibility (RT) (less than 100 ms decoding time) for implantable BCIs, adaptability potential and accuracy.

TABLE I
SUMMARY OF THE PRESENTED WORKS

Ref work	Characteristics						
	Signal	Channels	Method	PB	RT	Adaptive	Accuracy
[1]	ECoG	48/62/64	DL	-	yes	no	83.3%
[3]	ECoG	8	DWT + PNN	-	-	no	91.8% ^a
[5]	ECoG	64	fCWT + REW-MSLM ^b	no	yes	yes	92% ^c
[7]	ECoG	16	KNN	yes	yes	no	-
[8]	MEA	96 x N ^d	FFT + SVM	yes	yes	-	-

^aMaximum reached accuracy.

^bRecursive exponentially weighted Markov-switching multi-linear model.

^cAccuracy of the HMM gate prediction.

^dNumber of implanted nodes.

IV. CONCLUSION

The works presented in this study show a gap between the progress of adaptive algorithms for real-time online decoding and the existing implantable HW platforms. To address this bottleneck, a SoC capable of adaptive decoding is needed within a limited power consumption and time budget.

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