The Next-Generation Brain Machine Interface System For Neuroscience Research and Neuroprosthetics Development

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***Abstract*—Brain-machine interface (BMI) is one of the most important tools in the neuroscience research and neuroprosthetics development. The investigation and development of BMI have achieved significant progress in the past decade. However, several bottlenecks from the electrical engineering perspective still have to be overcome. The next generation BMI system would feature bi-directional neural interface with on-chip neural feature extraction and machine learning. Moreover, the high integration, compact packing and wireless operation would allow the experiments in freely behaving animals. This paper reviews the state-of-the-art designs, summarizes the key design requirements and challenges in a BMI system, and provides insights in both circuit and system level design.**

***Index Terms*—Brain machine interface (BMI), bi-directional neural interface, in-vivo experiment, system-on-chip (SoC)**

I. Introduction

A brain-machine interface (BMI) or brain-computer interface (BCI) is an artificial pathway between the brain and the external world [1, 2]. Since introduced by J. Vidal in 1973 [3], the research and development of BMI received growing attention from the scientific community as well as the public. The BMI has become one of the most important tools in neuroscience study and neuroprosthetics development. However, most research of BMI to date relies on experiments with tethered or sedated animals, using rack-mount equipment, which significantly restricts the experimental methods and paradigms. Moreover, most research has been focused on neural signal recording or decoding in an open-loop approach [1, 4]. Towards the development of the next generation BMI system, several bottlenecks have to be overcome. In this paper, the key design requirements are summarized, and the challenges and opportunities of BMI development are reviewed.

Fig. 1 shows the high-level block diagram of a typical brain-machine interface system. The system consists of neural recorders, neural stimulators, neural feature extraction units, a closed-loop controller, a wireless transceiver, and peripheral modules. The importance of integrating bidirectional neural interface and the support of on-chip closed-loop operation can be understood from several perspectives: i) the development of the neuroprosthetic device with sensory feedback, ii) the closed-loop treatment of neural disorders such as epilepsy, Parkinson diseases and depression, iii) restoring motor function by bridging lost biological connection, and iv) the study of neuroscience and neurology including both *in-vitro* and *in-vivo* studies [5].

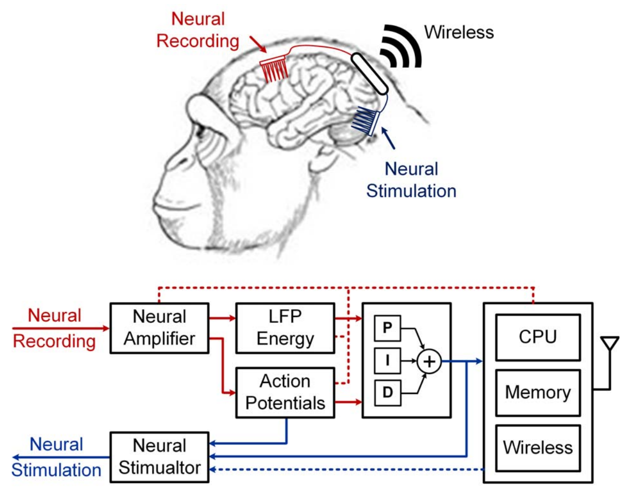

Fig. 1. The high-level block diagram of a typical brain machine interface system. The system consists of neural recorder, neural stimulator, neural feature extraction processor, closed-loop controller, and peripheral modules.

From the electrical engineering perspective, the challenges can be summarized as follows:

- **Safety**: Both implanted electrodes, stimulation and recording electronics must cause a minimal damage to the brain tissue. This requires the design of the neural interface electronics to have proper input and output impedance, stimulation power density, charge balance and so on;
- **Performance & Reliability**: Performance and reliability are both important for a BMI device. A reliable performance includes a robust signal quality, a reliable wireless data link, reliable electrode connection and electronic assembling, and so on;
- **Interfacing**: The BMI device should provide multiple functional interfaces for neural signal recording, stimulation and various modalities, including body area sensors and supervision. The interface should also include user interface for researchers and investigators to use for experiments and analysis;
- **Wireless communication**: A reliable solution for real-time streaming of multiple-channel signal for recording

neuron activities down to the single neuron level is still highly desirable. The ideal solution would fully consider the trade-offs between the bandwidth and power consumption, with a minimum data corruption;

- **On-chip processing**: On-chip processing is important for reducing the wireless data rate, and more importantly, to support real-time closed-loop operation. With the help of artificial intelligence and deep learning techniques, the on-chip real-time neural signal processing is one of most promising research areas in the next few years;
- **Power consumption**: Low-power is always an important design consideration for BMI devices, for both extending battery life and minimizing the tissue damage caused by the generated heat. Developing low-power circuit design techniques as well as exploring energy harvesting opportunities would be the path to overcome this power challenge;
- **Packaging**: Biocompatible packaging is critical in the developing of implantable BMI devices. The ideal implantable BMI device would be fully sealed with only wireless interfaces for communication, programming and battery recharging.

The key features and specifications of a typical BMI system are listed in Table I. The commonly used neural signal including local field potential (LFP) and action potential (AP). The major building blocks of the recording front-end include low-noise amplifiers, programmable filters, programmable gain amplifiers, and analog to digital converters (ADC). The total input referred noise of the neural recording front-end should be lower than the thermal noise of the electrode or providing a sufficient signal to noise ratio (SNR) for the target signal. The ADC should provide sufficient effective number of bit (ENoB) for the dynamic range requirement of the signal. Filters are important for removal of out-of-the band signal and noise. Online data compression, including compressed sensing and spike detection can be used to reduce the wireless data rate. The stimulator back-end is designed for multi-functional electrical stimulation. A high compliance voltage is required for high impedance electrodes. Biphasic charge balanced stimulation is usually preferred during experiments. A closed-loop controller is also commonly required for on-chip processing. Various body area sensors are to be used to monitor animal behavior and sensory inputs. The battery powered device should be able to support continuous operation over 8 hours, or over 12 hours if experiments during animals sleep are required.

TABLE I
KEY FEATURES OF THE PROPOSED BIDIRECTIONAL BMI

Analog Front-end		**Stimulator Back-end**	
Channel count	16	Channel #	16
Noise rms	$<5\mu$V	Stimlus Curr.	2mA
LFP Bw	1 - 200Hz	Curr. Res.	6 bit
AP Bw	300 - 10kHz	Pulse width	1 - 255μs
AmpGain	1000 - 8000	Time interval	8ms - 2s
ADC res.	10 - 12bit	Compliance volt.	5V
Neural Feature Ex.		**Closed-loop Operation**	
LFP feat.	Energy	Feature Extraction	LFP/AP
AP feat.	Discrim.	CL ctrl	On-chip
Others	Matched filter	Machine Learning	Opt.
Wireless		**Power**	
Protocol	Bluetooth/FSK	Chip power	$<$1mW
Data rate	2Mbps	System power	$<$30mW
Memory	FAT32	Total battery life	$>$12h

II. Design Specifications and Methods

The design specifications and methods are reviewed and summarized in this section. In a neural recording front-end, the key requirements include: low input-referred noise, sufficient dynamic range, high input impedance, high linearity, high common mode rejection ration (CMRR) and power-supply rejection ratio (PSRR). The most commonly used figure-of-merits (FoM) for neural recording amplifier is the noise efficiency factor (NEF). The NEF was first proposed by M. Steyaert et al. in 1987 [6], and was resurrected by R. Harrsion in 2003 [7].

$$NEF = \overline{V_{ni,rms}}\sqrt{\frac{2I_{tot}}{\pi\Phi_t \cdot 4kT \cdot BW}} \quad (1)$$

Topologies for low-noise neural amplifiers can be classified into two types, designs using capacitive gain elements [7], and designs using resistive gain elements [8]. Low-noise transconductance amplifiers (OTA) topologies, including current mirror OTA, Miller OTA, folded cascode OTA, and telescopic OTA have been used as the core. Maximizing the transconductance for a given supply current is important for achieving a good power-noise efficiency [9, 10]. In addition, noise reduction techniques including chopping [11, 12], auto-zeroing, digital assisted trimming, analog and digital filtering have been commonly used.

Feature extraction is an important technique to transform the raw data into a representation that can be effectively understood. Neural feature extraction allows one to acquire qualitative and quantitative information from the neural signal, which can be used for pattern recognition, motor decoding [13], detecting epilepsy [14], Parkinson's disease [15], depression, and so on. The feature extraction can be performed in different domains, including: i) time domain, ii) frequency domain, iii) wavelet domain, iv) statistics domain, and so on. The commonly used neural features for real-time, closed-loop BMI including: energy in multiple frequency bands, features of different brain states, synchronization between electrodes, action potential detection and sorting, action potential fire rate, and so on.

Neurostimulation is a method for modulating the nervous system's activity using non-invasive means. The essential process during an electrical stimulation is the charge transfer and redistribution across the electrode and electrolyte interface [16]. An ideal stimulator triggers the desired neural response with minimum injected charges, and leaves no residual charges. Commonly used stimulation methods include i) voltage-regulated stimulation [17], ii) current-regulated stimulation [18], and iii) charge-regulated stimulation [19]. In summary, voltage-regulated stimulation usually provides the highest efficiency, current-regulated stimulation gives the best controllability, and the charge-regulated stimulation can achieve both high efficiency and controllability, at the price of circuit complexity and silicon area. Charge balance is critical in stimulation since residue charges might cause toxic effects and lead to permanent brain tissue damage. Commonly used methods for achieving charge balance including matching [20], calibration, passive and active discharge.

One of the primary challenges in a bidirectional neural interface design is the stimulation artifact [21]. Stimulation artifact blanks the recording front-end, and corrupts the evoked neural response. Several techniques have been proposed in the literature to attenuate or remove the stimulation artifacts, including recording front-end blanking, symmetrical electrode placement [22], temporary frequency shifting [23], real-time signal processing [24].

III. Animal Experiments

Behavioral and *in-vivo* animal experiments have been used through the history of biomedical research. The study of neural modulation and closed-loop control also requires a custom designed wearable or implantable BMI device to perform on-chip signal processing, feature extraction, classification, machine learning, neuromodulation, and mapping [25–28]. In this session, animal experimental methods and typical results are presented.

The most commonly used neural signal includes local field potential (LFP) and action potential (AP). AP is the individual neuron activity and LFP is the summed activities from multiple nearby neurons. Fig. 2 (a) shows a 10-sec recording of LFP from a Rhesus macaque. Fig. 2 (b) shows the on-chip neural feature extraction in a certain frequency band (β band: 10-30 Hz). Fig. 2 (c) shows the power spectrum of a 17-hour continuous recording in the Rhesus macaque.

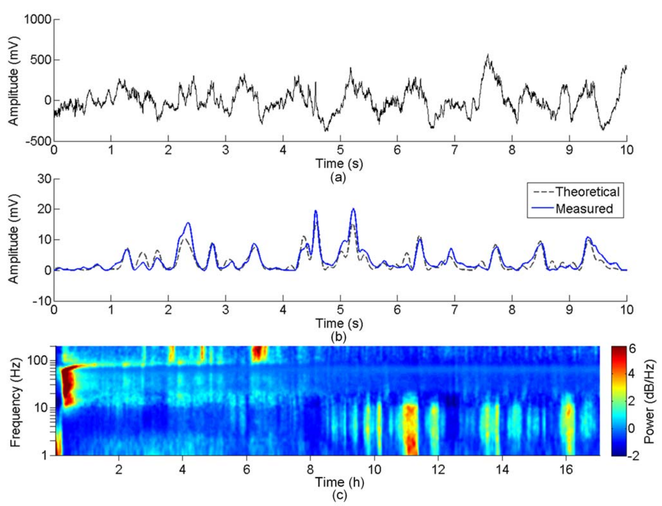

Fig. 2. (a) A 10-sec recording of local field potential signal, (b) on-chip neural feature extraction in a programmable frequency band, (c) the power spectrum of neural recording in a 17-hour period.

Fig. 3 shows a 1-sec typical recording of the action potential signal from a Long-Evans rat. The detection action potentials are marked by the red triangles. There are two neurons nearby the recording electrode. A cluster analysis was used to identify them. Normalized maximum and minimum amplitudes are calculated and used as two features for the analysis. Fig. 4 (a) shows the analysis result in the feature domain, which clearly shows that the two clusters are well separated. A K-means clustering was used to separate the two neurons. Fig. 4 (b) shows the action potentials plotted with color coding based on the classification results.

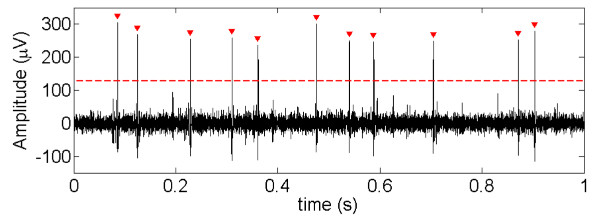

Fig. 3. A 1-sec typical recording of the action potential signal. The detected spikes are marked by red triangles.

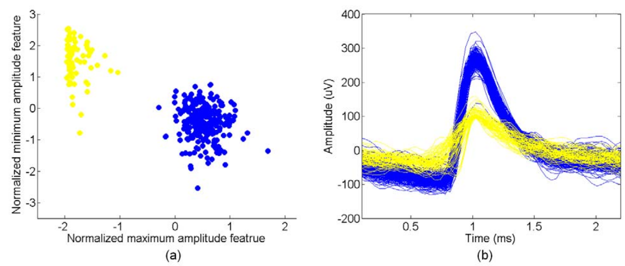

Fig. 4. A cluster analysis of the action potentials. (a) Normalized maximum and minimum amplitudes are calculated and used as two features for the analysis. (b) The action potentials are labelled with different colors according to the classification results.

Fig. 5 (a) shows the measured compliance voltage of a stimulation pulse train in a rat. Fig. 5 (b) shows the measured compliance voltage of a single stimulation pulse. It is a current regulated stimulation with equal amplitude in the stimulation and reversal phases.

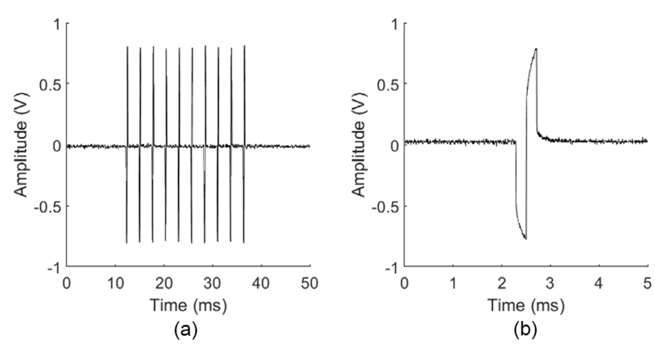

Fig. 5. (a) The measured compliance voltage of stimulation pulse train in a rat. (b) The measured compliance voltage of a single stimulation pulse.

The experimental result of a stimulation artifact is shown in Fig. 6. The testing was performed in a female Long-Evans rat, with a bipolar electrode pair implanted in the sensory cortex and a monopolar electrode implanted in motor cortex. LFP was recorded in the motor cortex and stimulation was performed in the sensory cortex. Fig. 6 (a) shows that the recording electrode saturates from a stimulation current of 2mA, while Fig. 6 (b) shows the result of artifact reduction method, including highpass frequency corner shifting and electrode discharging.

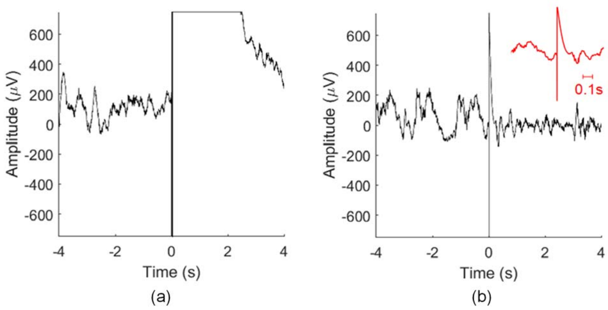

Fig. 6. The stimulation artifact in neural recording. (a) the recording electrodes' saturation with a stimulation current of 2mA. (b) the same stimulus current with stimulation artifact reduction by discharging stimulation electrodes and shifting highpass frequency corner after the stimulation.

IV. Conclusion

This work presents the review of brain-machine interface system for neuroscience research and neuroprosthetics development. The background and overall system are first reviewed. The design specifications and methods of the important building blocks of a BMI are summarized. The animal experimental methods and typical results are presented in the end. With further improvements in performance, reliability, and range of applications, the BMI technology will revolutionize the neuroscience research and eventually benefit a larger and larger population.

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