System-on-a-Chip Brain-Machine-Interface Design - a Review and Perspective

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***Abstract*—Brain-Machine-Interface (BMI) is a system that builds artificial pathways between different parts of the neural system. Due to different application scenarios, a BMI system may consist of a neural signal acquisition, electrical neural stimulation, signal processing, wireless communication, and power management. This paper reviews the state-of-art development in system-on-a-chip BMI design technology from application to circuit design details. A perspective on the future trend is also included.**

***Index Terms*—Brain-Machine-Interface, integrated circuit design, neural signal acquisition, electrical stimulation, closed-loop BMI**

I. Introduction

A Brain-Machine-Interface (BMI) is a system which establishes an artificial pathway between the human brain and/or body and external hardware. By extracting user intent from the acquired electrophysiological signals, such as slow cortical potentials, P300 potentials, electromyograph, commands can be generated using a wearable non-invasive BMI device [1].

Taking advantage of the development of CMOS technology and nano fabrication, the volume size of BMI has shrank dramatically in the past two decades, which enables the operation of various clinical practices that require an invasive BMI device. An invasive BMI device enables the acquisition of mu or beta rhythms recorded from the scalp, and/or cortical neuronal activity recorded by implanted electrodes. The development of invasive BMI devices bring hope to patients suffering from brainstem stroke, spinal cord injury and various neuromuscular disorders, i.e. Parkinson's disease, Huntington's disease, etc. An implanted BMI device enables a way to rebuild the injured pathway and/or function of the human body. Pacemaker and cochlear implant were the earliest prosthesis that have improved the life quality of many people.

In 1999, [2] first reported a real-time control of a robot arm using neural signal directly acquired from the brain motor cortex of a trained rat. In the reported experiment, the rat has trained to obtain water by pressing a level. The concept of controlling prosthesis using user intent extracted from neuron activities of the user's brain becomes realistic [3, 4]. Encouraged by the practices performed on animal objects [2, 5], medical researchers began the clinical experiments on human objects. [5–8] implanted electrode arrays in the brain for the extraction of thought to control a computer cursor. Several tens of channels of neural signals have been captured simultaneously for further signal processing. A utilization of a BMI to control the movement of the object's arm, as well as to generate artificial tactile sensing signal to brain was reported later [9]. In [10], the feeling of touch restored from skin-like sensors was successfully transferred to human neural system by using electric stimulations. The implanted BMI enables the user to "feel" the touch from a prosthetic hand.

In addition to the research and development of BMI based prosthetics, promising results have been reported recently on bridging the transected spinal cord using implant BMI devices. [11, 12] show a recovering of the motor function of the spinal cord transected rat by applying epidural spinal stimulation. More recently, a fully implanted, wireless closed-loop BMI for the cure of spinal cord transected rat was demonstrated [13].

There is no doubt that BMI provides a promising method for a better understanding of brain function, as well as for new therapies for patients suffering from neural diseases. However, there are challenges lays in front of engineers, such as device size, power consumption, battery solution, biocompatibility and biosafety. In the follows, the authors will review the state-of-art hardware implementation of BMI.

II. Hardware Implementation of BMI

A. System Overview

As illustrated in Fig.1, a typical BMI system consists of neural signal acquisition module, neural stimulation module, neural data processing module, data transmission module and power management module. Multiple channel analog front end circuits are usually integrated in the neural signal acquisition module, which usually consists of a low noise amplifier and programmable gain stage. A multiplexer is utilized for the timing management of the shared analog-to-digital convertor (ADC). For the neural stimulation module, a digital-to-analog convertor (DAC) is shared by all the channels for the pulse generation. An analog back end is used as the output stage. On-chip neural data processing, which typically consists of feature extraction and neural coding, is optional for a closed-loop operation. For invasive BMI system implementation, wireless data and power transmission is critical for the optimization of the device size. Wireless transceiver and power management modules are therefore widely used in invasive device designs. ISM band FSK, FM, UWB, and backscattering are commonly used.

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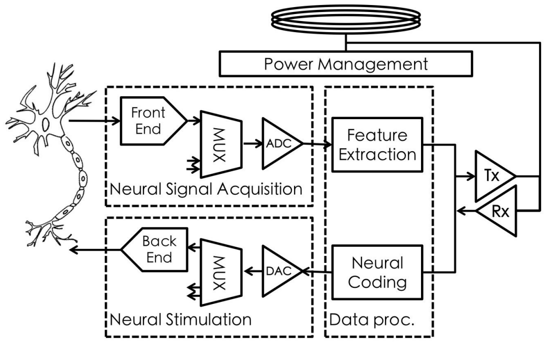

Fig. 1. Typical architecture of a BMI system, consisting of 1) neural signal acquisition module, 2) neural stimulation module, 3) neural data processing module, 4) data transmission module and 5) power management module. An on-chip signal processing unit may also be utilized for closed-loop operation.

B. Design of Neural Signal Acquisition Module

The neural signal acquisition module integrates an analog front-end (AFE) which amplifies the raw neural signal before digitization. The design challenge of the AFE comes from the nature of the neural signal. The amplitude of the raw signal varies from sever micro-volt to milli-volt. Thus, a low noise amplifier is required. Both capacitor mode amplifier [14–18] and resistor mode amplifier [19, 20] have been widely used in AFE design for a BMI. In addition, the neural signal of the researchers' interests typically lays in the frequency band from near DC to kHz range. Chopping is commonly used to improve the noise performance in the lower frequency band. Different design methods focusing on the improvement of the performance has been reported in the literature. [21] proposed a method to optimize the power and area with the considering of channel numbers. [22] proposed neural recorder circuit design working under low voltage supply (0.5V). Table I compares the performance of some selected work in literature.

In addition, while the resolution of the electrode array is increasing, on-chip data compression is one of the demanded functions in BMI systems. Neural recorder integrated linear slope predict[23], or compressed sensing [24–26], or spike detection [27] have been reported in literature.

C. Design of Neural Stimulation Module

Different types of electrical stimulation methods, such as voltage-controlled [32], current-controlled [33–35], and charges-controlled [36] have been reported in literature. The voltage-controlled stimulation method features the highest efficiency, but it is difficult to control the total amount of the injected charges [37]. The charges-controlled stimulation limits the total amount of the inject charges by discharging a series of capacitors, but the capacitors require a large area and the discharging time cannot be precisely controlled. The current-controlled stimulation enables a high controllability of the charge injection, thus is the most widely used method. However, the power efficiencies in conventional designs are usually lower than the other methods.

Biosafty is one of the critical issues in electrical neural stimulation design. The accumulation of carries may cause tissue destruction. During the procedure of electrical stimulation, there are two types of charge transfer, polarizable and non-polarizable, occur at the interface between the physiological medium and the electrode [31]. The irreversible non-polarizable charge transfer will cause damaging chemical species and dissolve electrodes. Typically, charge balance is achieved by applying reversed stimulus current as illustrated in Fig.2. A stimulation procedure that consists two phases with different current direction is denoted as biphasic stimulation. However, due to process voltage and temperature variation in circuit design, the ideal net-zero charge of biphasic stimulation is seldom realized. [38] proposed to reduce the charge error by applying feedback control of an adaptive driving voltage, which enables a constant low operating voltage for the entire active circuits. In addition, the accumulated charges on the blocking capacitor was used for further stimulation. An efficiency improvement of 51% is experimentally demonstrated. [39] proposed an active charge balance method, which enables a 100% charge compensation in monophasic mode and a 36% amplitude correction in biphasic mode.

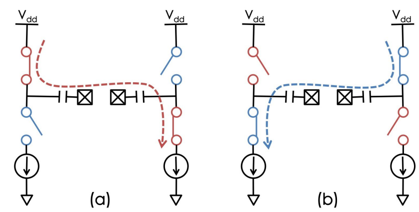

Fig. 2. Operation principle of biphasic stimulation.

D. Design of a Closed-loop BMI

As mentioned earlier, the goal of BMI is to build an artificial pathway to replace the function of an injured neural pathway. In order to realize this goal, a closed-loop operation between the raw acquired neural signal and the neural stimulation is required [13, 27, 40–45]. Feature extraction, such as action potential detection and spectral processing, is widely used for the analysis of the user intent. Neural coding is used to organize the output pattern of the electrical stimulations. For example, [40] presents a 4-channel bidirectional BMI which extracts spectral features from field potentials in the analog domain. At the system level, a neurostimulator is included for closed-loop applications. In [41], detected action potentials are used to trigger stimulation using a 4-channel closed-loop BMI.

In addition to the integration of specified a feature extraction module, more general closed-loop feedback control methods, such as programmable proportional-integral-derivative (PID) controller [42] or proportional-integral (PI) controller [43] has been used in reported closed-loop BMI chip designs. Such a general-purpose PID controller calculates the difference between a preset target value and the extracted neural feature as an error signal. The extracted neural feature can be action potential of single neuron, neural spectral feature, energy, and etc. A weighted sum of the original, the derivative and

TABLE I
COMPARISON WITH BIDIRECTIONAL NEURAL INTERFACE DESIGNS

Reference	[15]	[28]	[29]	[30]	[43]	[23]
CMOS technology	$0.8\mu m$	$0.5\mu m$	$0.5\mu m$	65nm	180nm	$0.35\mu m$
ch # of rec./stim.	-	64 / -	9 / -	64 / -	4 / 2+8	3 ECG / 4 EEG / 1 DOT
AFE noise	$0.98\mu V_{rms}$	$8\mu V_{rms}$	$4.58\mu V_{rms}$	$1.2\mu V_{rms}$	$6.3\mu V_{rms}$	$1.46\mu V_{rms}$
AFE NEF	4.6	-	2.83	4.76	3.76	3.31
Bandwidth (Hz)	0.05 - 100	<100 - 10k	0.178 - 6.92k	ECoG	0.64 - 6k	0.2 - 250
ADC ENOB	-	-	-	-	5.6	9.3
Front-end pwr./ch	<2μW	225μW	13.98μW	2.3μW	61.25μW	525nW
Feature extraction	-	Spike detection	-	Bandpass filter	Energy detect PI controller	Linear slope predict
Wireless	-	OOK	TDM-FM	-	Backscatter	-

the integral of the error signal is output from the controller and further used to modulate an actuator, i.e. configurable parameters of the stimulator.

III. CONCLUSION

We have witnessed a dramatic development in system integration of BMI in the last two decades. Nowadays, the emerging compact, ultra-low power-consumption, invasive BMI devices are pushing the frontier of medical researches on brain function as well as clinical practice on various neural diseases. A BMI with simultaneous processing capability of tens of channels is relatively mature and available in research labs. However, electrode and/or electrode arrays with higher density is greatly required for the recording of neuron action potentials and/or local field potentials. [46, 47] have reported high density neural probe designs integrating hundreds of recording channels, which enables a larger scale neural activity recording with less damage to the brain tissue. The increasing resolution places challenges for BMI device design in terms of power consumption and data transmission.

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