Application of EEG in wearable brain-computer interfaces

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Abstract—**The Electroencephalography (EEG) based brain-computer interfaces is a convenient way to use brain waves to investigate different emotions and some mental disorders. With the development of research and design, it is even possible to use brain waves to control devices (such as robot arms) to improve the life of the disabled. On this basis, based on the summary of previous research results, this paper focuses on the analog front-end of wearable brain computer interface (especially electrode and amplifier) and its related algorithms. The algorithms are developed on the basis of some classical machine learning algorithms, which are more suitable for EEG signals like common spatial paternal and long short-term memory network. This article may provide some convenience and inspiration for future development of EEG-based brain-machine interfaces.**

Keywords-wearable brain-computer interfaces; analog front-end;electrodes; methods; machine learning.

I. INTRODUCTION

Electroencephalography (EEG) is a traditional non-invasive method for detecting brain wave signals, which can be obtained indirectly through the scalp rather than through surgery. The whole EEG signal detection device consists of electrodes, analog front end (AFE), main processor, data transmission and data storage. They can be used in many fields, especially medicine, and even engineering. In order to collect and apply EEG more conveniently and quickly, the device needs to be lightweight and flexible. So this paper focuses on the application of EEG in wearable brain-computer interfaces (BCI).

The rest part of the paper is organized as follow. The section 2 is about the design and use of EEG acquisition: (1) dry electrode characteristics and general materials, (2) some recent theoretical designs of AFE circuits, and (3) the proper placement of dry electrodes on the scalp for wearable devices. Because of their convenience, dry electrodes are almost the most suitable components for usage on wearable devices. After the EEG signal enters the circuit through the electrode, it first needs to be amplified and filtered by AFE, not only to retain the required bandwidth, but also to minimize the impact of impedance caused by various factors, e.g., the dry electrode and skin, on the waveform. The amplification part should be able to avoid the signal coupling with the environment electromagnetic interference (EMI), and to suppress the interference of mains and high input impedance as much as possible. These two capabilities are also known as common mode rejection ratio (CMRR) and power supply rejection ratio (PSRR) [1]. The section 3 discusses the algorithms used to analyze and utilize the data from EEG, which mainly focus on Deep Neural Network (DNN), Long Short Term Memory networks (LSTM) and Support Vector Machine (SVM). Due to the principles and characteristics of different algorithms, they can be used in different scenarios. Eventually, a brief summary is given in Sec. 4.

II. THE DESIGN OF EEG ACQUISITION

EEG signals collected from the scalp via electrode devices are usually only a few microvolts, typically in a frequency band of 0.5-50Hz. The signals are generated by synchronous neuronal firing activity in the brain [2]. Traditional methods of recording and analyzing often require going to specific locations, spending a lot of time preparing and then getting results. Recording EEG with a BCI, however, can be done anytime, anywhere. Such devices are constantly iterating and evolving as electronics engineers exploit the knowledge of neuroscience. No matter how it develops, a BCI will always consist of an amplifier, filter, ADC, and processor.

A. Dry electrode

Traditional EEG electrode setup uses a medium like a conductive gel to keep the electrode in good contact with the skin, known as the wet electrode. Because of the gel, it takes more time to deploy a wet electrode and it can't be used for long periods of time. As a non-invasive wearable brain computer interface, dry electrodes are generally used to simplify the time and cost of deployment and use. A variety of dry electrode materials are commonly used, such as conductive rubber or gold-plated metal pins [3]. However, due to the loss of conductive gel, the gap between the dry electrode and the skin will produce greater impedance, thus affecting the final effect.

The equivalent model using dry electrodes is shown in Fig. 1. Zs is the skin impedance, which is composed of the epidermis and dermis. The impedance range of this skin layer is approximately 10kΩ to 1MΩ per square centimeter at 1Hz [4]. Resistance between the skin and the dry electrode from obstacles such as sweat or hair is the dry electrode's biggest challenge, which is shown by Zse. The third impedance called Ze, is related to many parameters such as the material, the amount of impurities, the substance added, and the shape and size of the electrode [4]. Besides, the last type of impedance is related to the input impedance of the amplifier and is expressed in terms of the amplifier Zin.

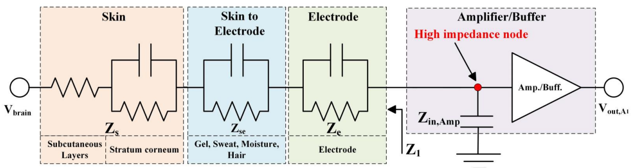

Fig. 1. The theoretical impedance of collecting EEG signals using a dry electrode [4].

The electrodes for the wearable brain-computer interface are usually circular metal plates that can be attached to the scalp. However, according to the usage scenario and needs, some have developed electrodes that can be used as earplugs, which is usually much smaller than common electrodes [5, 6].

The embedded electrodes used for the headphone-form brain-computer interface is made by a titanium (Ti) matrix which covered with iridium oxide (IrO2) [7]. IrO2 is a suitable material with low impedance and pseudo capacitance properties [7]. Past use of IrO2 in biological potential detection suggests that it is suitable as a dry electrode material.

B. *Analog Front-end circuit Design*

After the EEG signal is collected by the electrode, it needs to be processed by an analog front-end (AFE) circuit. The amplifier part of the AFE is mainly discussed here.

The amplifier circuit is the key point of EEG acquisition. Since the human EEG signal is very weak, and there are noise and signal source impedance. The amplifier needs to have high input impedance, high common mode rejection ratio (CMRR), low noise, low drift, appropriate bandwidth and other performance.

Sullivan et al. used TL6010 to construct the AFE circuit with a noise level of 0.28 µVrms and a power consumption of 423 µW [6]. Recently Tao Tang group used a kind of neoteric AFE construction which combine Time Division Multiplexing (TDM) together with chopping stabilization [3], which measured the part of amplifier intrinsic CMRR are 89 dB and system-level AFE CMRR are 82 dB, while the power per channel is only 1.5µW under 1 V supply.

Contemporarily, relatively mature designs have replaced Multi-Chip-Module (MCM) with more integrated System on a Chip (Soc) little by little. The Soc contains AFE and MCU, i.e., the Soc is programmable and more flexible for specific jobs. The basic composition of the Soc is determined by the CMOS process. The more sophisticated the process, the lower the power consumption and the faster the response. At present, 180nm process Soc is mostly used, while 65nm or even 55nm Soc is also used. The internal section topology of a 4-channel AFE from Soc is illustrated in Fig. 2. Nevertheless, due to the complexity and high cost of making specialized Soc, they generally remain in the design. Table I listed some AFE designs of various wearable devices in recent years.

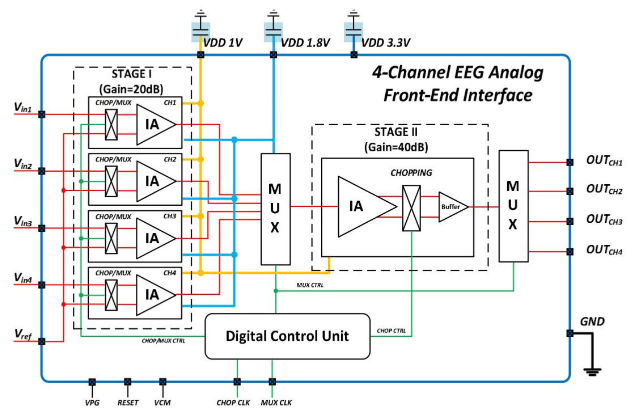

Fig. 2. Block diagram of the 4-channel TDM/chopping EEG AFE [8].

TABLE I
COMPARISON OF SYSTEM ARCHITECTURES OF SOME RECENT DESIGNS OF AFE

Parameters	[3]	[8]	[9]	[10]	[11]	[12]	[13]
Technology(nm)	180	180	180	180	180	350	180
Type	Soc	Soc	ASIC	ASIC	ASIC	ASIC	-
Channel	16	4	1	-	8	-	-
Supply(V)	1	1	1	1.2	-	1.25	1.8
Channel Power (µW)	24	5	1.6	43	-	0.95	108/per
Input referred noise(µVrms)	0.63	0.62	0.61	1.2	1.75	1.5	0.67
Input Impedance(MΩ) @50Hz	560	650	-	720	300	-	6700
AFE CMRR(dB)	89/82	86	85	100	84	-	86
Application	Wearable	Wearable	Wearable	Wearable	Wearable	Wearable	Wearable Ear

C. Placement method

The first step in using a wearable device is to find the right spots on the scalp to pick up the signal. Before the electrodes are placed, the head of the measured person will be marked in standard positions stipulated by the international 10/20, 10/10 and 10/5 systems in order to collect the desired signal or minimize the factors affecting the effect [14]. Some multi-channel placement methods are exhibited in Fig. 3, where A to D represent signal recording from Oz only, 4-channels, 8-channels and 32-channels respectively. F stands for the frontal lobe, T for the temporal lobe, C for the central lobe, P for the parietal lobe, O for the occipital lobe, and Z for the electrodes placed on the midline.

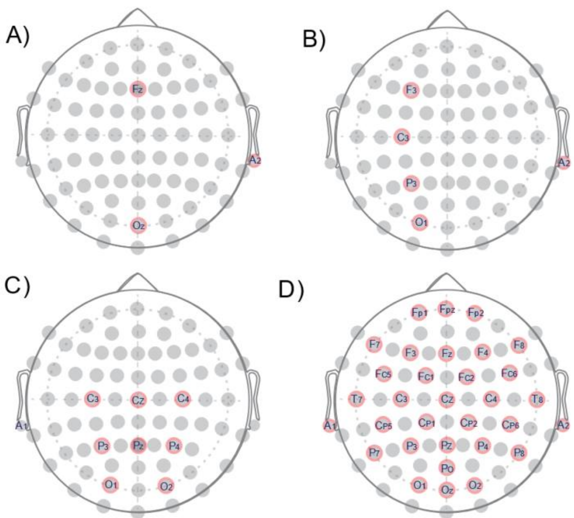

Fig. 3. Electrode placement according to the 10/20 International Positioning System [15].

The 10/20 system was developed with improved resolution for locating signals in the head cortex. In the 10/20 system, additional electrodes are added in the middle position between those electrodes that are 20% of the total distance between the front and rear. To account for these new loci, new points are introduced, such as AF representing the point between Fp and F, and FC representing the point between F and C. Apart from that, signs T3/T4 and T5/T6 were renamed to T7/T8 and P7/P8 [14]. ACNS has accepted this modified combinatorial nomenclature (MCN) system as a standard [14].

Different locations can be selected for collection according to different purposes. To study emotional signals, for example, you can install electrodes in the Fp1, F3, F4 and so on in the prefrontal lobe [16]. Fp1, Fpz, Fp2 and ear electrodes were used as reference electrodes to reduce the impact of statistical noise [16].

III. THE ALGORITHMS USED TO ANALYZE THE DATA FROM EEG

A. Common machine learning

With the development of machine learning and deep learning, relatively mature data recognition and classification algorithms have been developed, which can use to improve the efficiency of EEG signal processing.

1) Deep Neural Network (DNN):

Like the human brain, neural networks are made up of perceptron. DNN can be thought of as a neural network with multiple hidden layers, multiple layers.

DNN is also called a multilayer perceptron (MLP). The internal structure of DNN is mainly composed of three different layers, each of which is composed of a large number of perceptron units. The initial data enters the network from the first input layer, then goes through the hidden layer to process the data into the form you want or more easily to process and classify, and finally visualizes the results through the output layer. For example, you can take an image as input, extract the important features of the image through the computation of the middle hidden layer, and finally the output layer compares and prints the judgment results according to the pre-sorted classes.

In general, complex classification requires the introduction of activation functions in the hidden and output layers. If there is no activation function, no matter how many layers there are in the neural network, the output of each layer will only be the linear value of the initial input value, which is the original perceptron. If the activation function is used, it is equivalent to introducing a non-linear factor into a neural network, so that the network can theoretically approximate any non-linear function, so that the neural network can be used as many non-linear models.

2) Long Short Term Memory networks (LSTM):

LSTM is a temporal recursive neural network (RNN) designed to solve the long term dependence issue of classic RNN.

In all RNN, there is a recursive neural network module in the form of a chain. This repetitive structure module has a very simple structure, such as TANH layer. LSTM has two transfer states, one c^t (cell state) and one h^t (hidden state), whereas RNN has only one transfer state h^t. Where the passed c^t changes slowly, the output c^t is usually the previous state passed c^{t-1} plus some values.

3) Supervised learning Support Vector Machine (SVM):

SVM is a binary classification model in essence. The basic model of SVM is a linear classifier defined in the feature space with the largest interval, which distinguishes it from perceptron.

SVM also includes kernel techniques, which makes it essentially a nonlinear classifier and an optimization algorithm for solving convex quadratic programming.

The primary idea of SVM is to figure out the separation hyper-plane that can correctly segment training data set with the maximal geometric interval.

B. Improvements on EEG data

1) Common spatial paternal (CSP) based DNN:

For the collected EEG signals, spatial filter is very suitable for processing such multi-dimensional signals and data. It can utilize the spatial correlation of EEG signals, eliminate the noise of signals, and realize the localization of local cortical neural activities. Spatial filtering can obtain better processing effect by effectively combining time domain and frequency domain features.

The traditional CSP method uses a single fixed filter bank based on the CSP variance feature and obtains good results. CSP has been widely used in EEG classification. A framework for improving a common spatio-spectral pattern (CSSP) performance is proposed [17]. In CSSP, the FINITE impulse response filter (FIR) coefficients are obtained by applying CSP to the signal and its delay signal. In the CSSP framework, different spectra are calculated for each channel [17].

In the process of motor imagination, the cerebral cortex will produce two kinds of rhythm signals with obvious changes, respectively 8-15Hz μ rhythm signal and 18-24Hz β rhythm. During motor imagination, the neurons are activated. This phenomenon is called Event Related Desynchronization (ERD)/ Event Related Desynchronization (ERS). Based on this relationship, a variety of control instructions can be generated by the human brain actively controlling the amplitude of μ and β rhythms in the left and right brain [16]. CSP is more suitable for motor imagery BCI. So far, the most common areas of motor imagination are left and right, right hand, feet, and tongue.

Kumar et al. used CSP on BCI [17] and pointed out that this framework is better than all other competing methods in reducing the maximum error. The framework can be used to develop BCI systems that use wearables because it is computationally cheaper and more reliable than the best competing methods [17].

He et al. made a relatively complete BCI-based robotic arm control system based on CSP, including electrodes, shielded wires, pre-processing chips, wireless communication, central control system, arm machinery, PC software and mobile APP [18].

2) Long Short Term Memory networks (LSTM):

Hasib et al. used a hierarchical long short-term memory (H-LSTM) model with attention [19]], and the results show that the H-LSTM model is 12.4% higher than the LSTM model and 17.4% higher than the shallow support vector machine model [19]].

Apart from that, the team of Xiaobing Du used a model called Attention-based LSTM with Domain Discriminator (ATDD-LSTM) [20]. They conducted theme-dependent and theme-independent cross-validation experiments on SEED, DEAP and CMEED databases, and the experimental results showed that the proposed ATDD-LSTM model reached the latest level in emotion recognition [20].

In addition, LSTM is more suitable for emotion recognition and diagnosis of some neurological diseases such as Parkinson's disease [19,21].

3) Supervised learning SVM:

The binary linear support vector machine classifier can be used to detect patients with depression [22]. There were significant differences between the patients with depression and the normal control group in θ bands and α bands [22].

The result from [22] shows that patients with depression and healthy subjects can be distinguished by changes in functional connectivity of different frequency bands. Moreover, SVM classifier has the best classification effect on the whole EEG frequency band, without any fitting phenomenon.

IV. CONCLUSION

This paper mainly reviews the simulation front end of wearable brain-computer interfaces and some algorithms by summarizing previous studies in recent years. According to the sequence from sampling to application, this paper first analyzes the principle, some characteristics and standard placement methods of common dry electrodes. Then it introduces most of the pre-amplifier, and lists some new AFE designs through research in recent years. Last but not least, some algorithms suitable for EEG analysis has been reviewed, such as CSP motion algorithm suitable for mechanical control, LSTM algorithm suitable for emotion recognition, SVM suitable for judging depression and other diseases. Of course, many contents are still more theoretical and basic design, which is mainly limited by hardware development. Any excellent design is difficult to be applied and tested due to the problem of manufacturing cost. In the future, more mature filtering technology should be able to gradually solve this problem. It is a good direction for the development of human-computer interaction and biological research. And it's true that there's an increasing number of ideas and technologies that can be applied by extending the EEG brain-machine interface.

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