2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

A Brain Biometric-based Identification Approach Using Local Field Potentials

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***Abstract*— Traditional biometrics such as face, iris and fingerprint have been applied widely nowadays. Nevertheless, with more and more potential problems being exposed, such as privacy leak and fabricate attack, it is urgent to find new secure biometrics to meet the needs. Identification based on brain signals is a promising option due to its unique advantages of confidentiality, anti-spoofing, continuity and cancelability. Among various types of brain signals, local field potential (LFP) has long term stability, high signal to noise ratio and high spatial resolution, which is suitable for identification. In this paper, we propose a novel biometric which is extracted from LFP signals with a deep neural network. The proposed biometric can be generated in a task-related manner thus is cancelable. Experiments with ten rats demonstrate that, the proposed biometric achieves a high identification accuracy of 94.47%, and the performance is stable over several days.**

I. INTRODUCTION

Nowadays, traditional biometrics such as fingerprint, face, iris, voice, etc. have been widely applied. However, these biometrics have their own weaknesses [1], and can be easily forged [2], [3]. In addition, these biometrics have a fatal shortcoming that they are noncancelable. This means that if the biometric is stolen, it cannot be replaced because users cannot change their fingerprint, face or iris. For this reason, a biometric that is more secure than any of the above biometrics should meet two criteria: it is more difficult to be stolen and it is cancelable. Identification based on brain signals can meet these two demands.

At present, most of the research uses electroencephalogram (EEG) for identity recognition, which is noninvasive brain signal. EEG signal is acquired through electrodes located at the scalp, which has the characteristics of low signal-to-noise ratio, poor stability and easy to be disturbed. The recognition system based on EEG can achieve 80% to 90% recognition accuracy, which is not high enough to deploy in high security scenes [4]–[7]. In addition, changes in the acquisition environment (such as the number of electrodes, sampling rate, sample size) may reduce the accuracy. However, the electrodes of invasive brain signals (such as ECoG, spike or local field potential) are placed on the cerebral cortex, which eliminates the attenuation and filtering of the signal when transmitted through the skull and scalp [8]–[10]. Nevertheless, in spite of the high information rate of spikes, many researches have proposed that it is hard for long term recording of spikes in BMI applications [11]–[16]. LFP yet has long term stability compared with spikes [17] and has high signal to noise ratio and high spatial resolution compared with ECoG [18], more and more researchers pay attention to the decoding of LFP for motor intention and continuous movement parameters [13], [18]–[20] in BMI.

In this study, we identify ten rats with implanted electrodes using local field potential (LFP). We first calculated the spectral power of LFP as features. Then we utilized a neural network based on a single motor task for classification and the results are unsatisfactory. To improve the identification performance, we exploit a neural network for combination of multiple tasks corresponding to three rat behaviors and achieve 94.47% classification accuracy, which is almost 12% higher than that using the neural network for a single motor task. Furthermore, we find that it is more reliable using the neural network for combination of multiple tasks over long time periods and the classification performance is also acceptable.

II. EXPERIMENTAL SETUP

A. Electrodes Implantation

All surgery and experimental procedures involving rats in this study were strictly complied with the Guide for The Care and Use of Laboratory Animals (China Ministry of Health) and approved by the Animal Care Committee of Zhejiang University, China. We utilized a total of ten adult male Sprague-Dawley rats (300-350g) purchased from Zhejiang Academy of Medical Sciences (Hangzhou, China). All rats were placed in a 12h light/dark cycle and ate food freely, while water was appropriately restricted to 10-15ml per day to prompt the press lever performance of rats.

Rats were anesthetized with propofol (10mg/ml, i.p., 1mL/100g initial dose) and mounted on a standard stereotaxic apparatus (RWD Life Science, China) for brain surgery. The body temperature was retained with a heating pad, with the heart rate (300-400 bpm) and pO2 (> 90%) monitored during the surgery. The state of anesthesia was examinated

*This work was partly supported by the grants from the Key Research and Development Program of Zhejiang Province in China (2020C03004), the National Key Research and Development Program of China (2018YFA0701400), and Natural Science Foundation of China (61906166, U1909202), and the Zhejiang Lab (2019KE0AD01).

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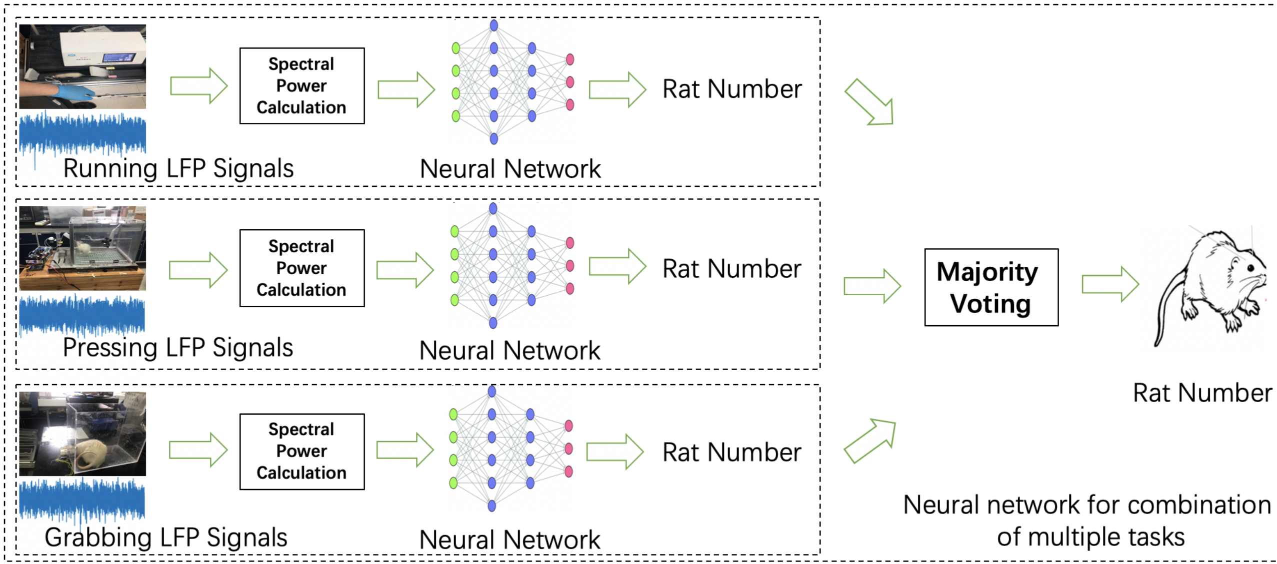

Fig. 1. Deep network-based brain biometric learning.

by toe-pinch test at regular intervals. Additional dose of propofol (10mg/ml, i.p., 0.6ml) was injected if necessary.

A 16-channel (2×8) handmade microelectrode array (35μm nichrome) was implanted of which the anterior 2×4 electrodes were in rostral forelimb area (RFA) and posterior 2×4 lied in ipsilesional caudal forelimb area (CFA) with a depth of 1.2-1.5mm, while the electrodes were attached to the skulls with tiny screws and dental cement.

B. Behavioral Task

Rats were trained to perform three different behavioral tasks: run, press and grab. For run task, Rats were trained to run on a treadmill with the speed of 10 km/h. For press task, rats were trained to press the lever down over a threshold given with the water as reward. For grab task, rats were trained to grab the food crossing an infrared device to record the exact movement time.

The rats were recovered for three to four weeks before training and routine experiments. The signal acquisition lasted for two weeks. For each session, rats were restricted to run for 10 minutes, press and grab respectively for 20 minutes.

C. Data Collection

All data were recorded using a commercial multi-channel neural signal acquisition system (Plexon TM, OmniPlex/128) with amplification of 1750 and a notch filter of 50Hz. Here we collected the signal of 10 rats for two weeks for each behavior.

III. METHODS

As shown in Fig. 1, we first calculated the spectral power of LFP as features. Then we utilized a neural network based on single behavior for classification. Furthermore, we employed the neural network for combination of multiple tasks and adopted majority voting rule to determine the most likely number of the rat.

A. LFP Spectral Analysis

We firstly preprocessed LFPs with a 0.5-500Hz bandpass filter (2-order Butterworth) to extract features from the LFPs of CFA and RFA and then matched the LFP signals with each behavior.

The power of following six different frequency bands for each trial were calculated by applying 512-point windows with overlap to provide one sample every 100ms: delta (δ, 0.5-4Hz), theta (θ, 4-8Hz), alpha (α, 8-12Hz), beta (β, 12-30Hz), gamma1 (γ1, 30-120Hz), gamma2 (γ2, 120-200Hz).

Hanning window followed by a fast Fourier transform to each window was used for power calculation. The log transform was computed as follows:

$$Power(m) = log \sum_{\lambda \in m} p(\lambda) \tag{1}$$

where m stood for each sub-frequency band, p(λ) was the power of frequency belonging to the band. Thus ultimately we obtained a 96-dimension feature for each sample.

B. Deep Neural Network Based Brain Biometric Learning

1) Structure of the Neural Network for a Single Motor Task: We attempted to classify with these features using a fully-connected neural network. The neural network contains an input layer, three hidden layers and an output layer. The input layer has 96 neurons and the hidden layers have 1024, 512 and 20 neurons respectively, while the output layer has 10 neurons, which is the same as the quantity of the rats.

For each behavior, we gathered features of total rats as input for neural network with respective labels. We employed cross entropy loss function and Adam optimization to train our network with learning rate 0.0001 after 40,000 iterations of training. In addition, we used 80% of the samples as training data and the remaining samples as test data.

2) Structure of the Neural Network for Combination of Multiple Tasks: To improve the identification performance, we utilized the neural network for combination of multiple tasks and adopted majority voting rule to determine the most likely number of the rat. If the predicted numbers of three neural networks were all distinct, then the vote was invalid and a new vote using new signals began.

IV. RESULTS

To evaluate the effectiveness of the neural network for combination of multiple tasks, we compared the classification performance of the neural network for a single task with that of the neural network for combination of multiple tasks. In addition, to testify the reliability of the identification performance over long time periods, we also analyzed the classification accuracy during 7 days with the neural network for a single task and the neural network for combination of multiple tasks.

A. Identification Using a Single Motor Task and Combination of Multiple Tasks

As shown in Table I, the classification accuracy of three neural networks for a single task is 82.08%, 82.30%, 83.10% respectively. With the neural network for combination of multiple tasks, the classification accuracy achieves 94.47%, which is nearly 12% higher than that of neural network for a single task. In addition, we also attempted to utilize a neural network using total three motion data for identification and the classification is 82.72%, which demonstrates that the neural network for combination of multiple tasks is more reliable and effective to identify the rats.

TABLE I

CLASSIFICATION ACCURACY USING NEURAL NETWORK FOR A SINGLE MOTOR TASK AND COMBINATION OF MULTIPLE TASKS

Network	Classification Accuracy
Single Grab Motion	82.08%
Single Press Motion	82.30%
Single Run Motion	83.10%
Three Mixed Motion	94.47%

B. Identification Over Long Time Periods

To testify the reliability of the identification performance over long time periods, we utilized the samples of first 7 days as training data to train neural network and the remaining samples of last 7 days as test data. We calculated the classification accuracy of each day. As shown in Fig. 2, the difference of the classification accuracy of the first few days is relatively small with the neural network for a single task and the neural network for combination of multiple tasks. Nevertheless, the gap increases as time passed. At day 6 and day 7, the classification accuracy of the neural network for combination of multiple tasks is at least 10% higher than that of neural network for a single task, which shows that the neural network for combination of multiple tasks is more reliable and effective.

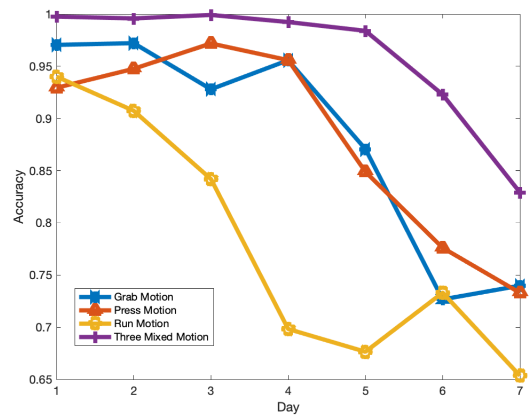

Fig. 2. Classification accuracy during 7 days with neural network for a single motor task and combination of multiple tasks.

C. Identification Using Different Training Sizes

To recognize the ability of the neural network for combination of multiple tasks using various number of samples, we chose the number of training day from 1 to 7, and the day after training days is chosen to be the test day. As shown in Fig. 3, the classification accuracy of the neural network for combination of multiple tasks is always higher than that of neural network for a single task, which is more than 95% throughout. In addition, when using only 1 training day, the classification accuracy of the neural network for combination of multiple tasks achieves 98.92%, which demonstrates that the neural network for combination of multiple tasks is also effective with small samples.

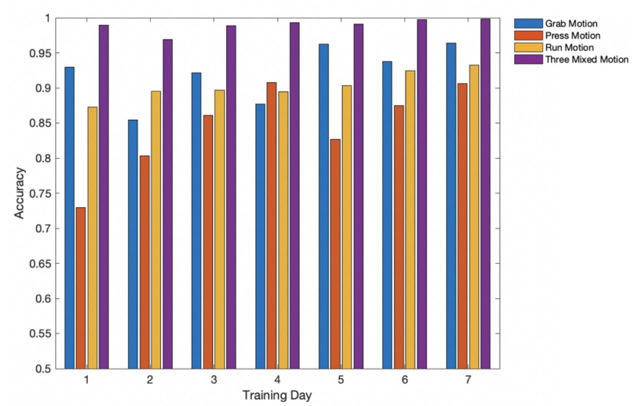

Fig. 3. Classification accuracy using different training days.

V. CONCLUSIONS

In this study, we identify 10 rats with implanted electrodes using local field potential (LFP). With the neural network for combination of multiple tasks, we achieve 94.47% classification accuracy. Furthermore, we find that it is more reliable using the neural network for combination of multiple tasks over long time periods and the classification performance is also acceptable. In future work, we intend to optimize the structure of the neural network and obtain higher identification performance.

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