Research on Emotional Recognition System of EEG Signals Based on CNN+LSTM

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Abstract. We studied an emotion recognition system based on EEG signals, conducted MATLAB simulation for EEG signal collection, and conducted experiments on EEG signal collection using STM32 microcontroller. We proposed an EEG emotion recognition system based on convolutional neural network (CNN) and short-term memory artificial neural network (LSTM) models. The model used gradient descent algorithm and cross entropy loss function algorithm, and was used the DEAP dataset to verify the accuracy of emotion recognition results, which reached 94.023%, The accuracy of emotion recognition results which is achieved by running the Python trained model on Raspberry Pi reached 98.98%. After compared the data collection information and tested the software and hardware, the experimental results showed that the EEG signal collection system can achieve the functions of EEG signal data collection and improve emotion recognition rate.

Keywords: EEG signals; emotion recognition; convolutional neural network; long and short-term memory artificial neural network; Raspberry Pi.

1. Introduction

Emotion is an interaction of subjective feelings, physiological reactions,and cognition that expresses specific actions.Depression is a common psychological disorder,with significant and lasting depression as the main clinical feature.Depression has a high incidence rate among Chinese teenagers.China has clearly included depression screening into the content of students' health examination.By studying EEG activity,we can gain a deeper understanding of the information processing process in the human brain,as EEG activity is closely related to different brain regions and states,making it a very important source of information.Studying EEG signals [1,2] can reveal the mechanisms of brain activity. Design an emotion recognition system based on EEG signals,analyze and judge the collected signals, and then concentrate on processing and research.This can provide doctors with clinical diagnostic basis for depression,reduce the diagnostic cost of depression, and improve the accuracy of depression diagnosis.At present, there are mainly traditional machine learning and deep learning methods for emotion recognition of EEG signals.Traditional machine learning has disadvantages such as large computational load,overfitting in continuous variable discretization processing,sensitive parameter settings,and insufficient training for large-scale samples.Deep learning has high accuracy and adaptability.Compared to traditional machine learning, deep learning can process large amounts of complex data.Deep learning models can automatically extract features from the data and predict their features.It can also self adjust and adapt to different application scenarios based on different datasets.The main models of deep learning are Convolutional Neural Networks (CNN)[3,4] and Recurrent Neural Networks (RNNs)[5,6].Combining existing models, in order to extract more complete features, in addition to considering the features at the current moment,we also need to consider the relationship between previous and current EEG signals. Therefore, we need to introduce sequence learning methods specifically designed for modeling short-term and long-term memory. Inspired by this, we propose EEG emotion recognition methods based on Convolutional Neural Networks (CNN) and Long Short Term Memory Artificial Neural Networks (LSTM) [7,8] to improve the accuracy of EEG emotion recognition. Considering the performance requirements and portability of hardware devices for deep learning models, the models trained in Python are deployed on the embedded terminal device Raspberry Pi[9,10]to achieve edge deep learning.This article uses the TGAM EEG signal acquisition module to design an EEG signal acquisition system, and uses the DEAP dataset to design emotion recognition based on convolutional neural networks and long short-term memory artificial neural networks.Through STM32 microcontroller EEG signal acquisition experiments and MATLAB software acquisition simulation experiments,functions such as collecting EEG signals, processing EEG signals, and outputting EEG signals are achieved.By simulating in Python and deploying a neural network model on Raspberry Pi,emotion recognition of EEG signals was achieved.The overall system diagram is shown in Figure 1.

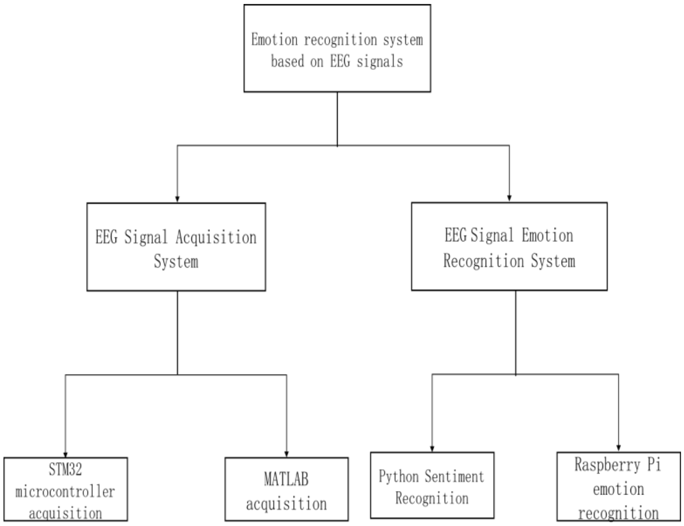
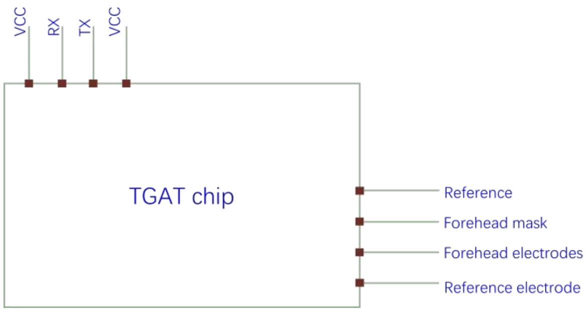


Figure 1 Overall System Block Diagram

2. Microcontroller EEG signal acquisition

2.1 EEG signal acquisition circuit

The EEG signal acquisition system mainly includes an EEG signal acquisition module,a microcontroller module, and a data transmission module. The TGAM module is a high-precision and low-power EEG signal module for portable wearable brain computer interface products,supporting the use of metal electrodes to obtain left and right EEG signals on the forehead.The collected raw EEG signals are filtered and processed in real time,and the raw EEG can be output through the Bluetooth module α、β、γ、δ、θ,Spectral and quantitative EEG analysis features such as focus,left and right brain emotions, brain load stress,fatigue,relaxation,meditation, and other indicators [2].The circuit diagram is shown in Figure 2.



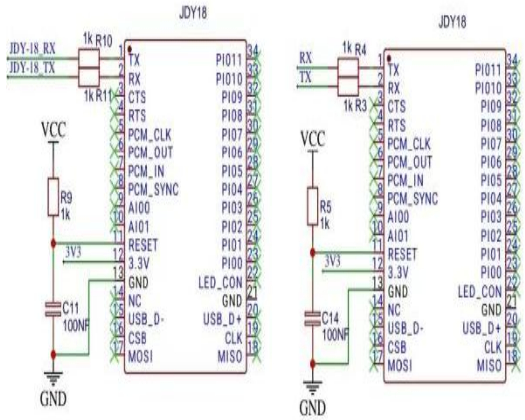
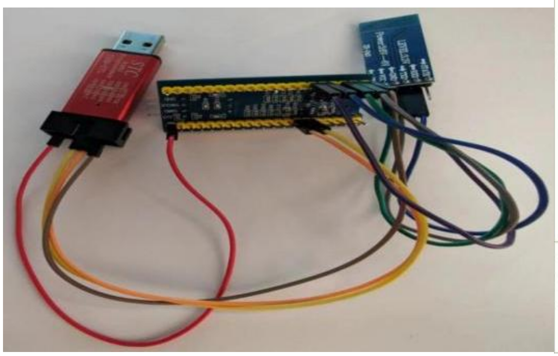


Figure 2 TGAM moduleFigure 3 JDY-18 Bluetooth Module

JDY-18 is a multi chip hybrid integrated RF module based on SRS,using high-performance C8051F060MCU as the main control chip.The main control chip has the characteristics of high performance and low power consumption,with a working voltage of 1.5V to 2.5V.It is equipped with a high-performance and low-power DAC chip DSP1516 for analog signal processing. The module is equipped with an L2CAN controller and a serial communication interface,which can be connected to other Bluetooth devices through the SPI interface.Bluetooth device data can be sent to the server through the serial port,achieving data transmission between the module and the phone, as well as between modules.The circuit is shown in Figure 3.

The physical wiring diagram of the hardware connection between the Bluetooth module and the STM32 microcontroller,as well as the EEG signal acquisition device,is shown in Figure 4.The experimenter wears the TGAM EEG acquisition module,turns on the power switch,waits for the Bluetooth module to automatically connect,opens the serial port reading software,and waits for EEG data collection.



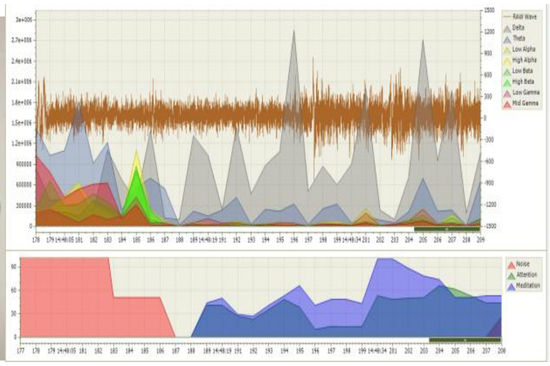


Figure 4 Physical wiring diagram Figure 5 EEG signal acquisition results

2.2 Analysis of experimental results of collecting EEG signals using MATLAB software

The results of EEG signal acquisition are shown in Figure 5.From the figure,it can be seen that the collected data mainly includes nine types:Rawwave, Delta,Theta,Alpha,Beta,Gamma,Noise,Attention,and Meditation.When the experimenter is in a calm state, the collected Rawwave fluctuates within a fixed interval,Delta represents sleep,fatigue,and subconscious state,Theta represents drowsiness,deep relaxation,and subconscious state,Alpha represents wakefulness and quietness,which is the best state for learning and thinking,Beta represents thinking activity,busyness,and tension,Gamma represents advanced cognitive activity.The manifestation of increased neuronal excitability,where Attention represents attention and Meditation represents relaxation.

Run the program to obtain the collected EEG signals. The data of the collected local EEG signals are shown in Table 1.From the table,it can be seen that the collected EEG data mainly includes Noise,Attention, and Meditation.The value range of Attention is from 0 to 100,and the larger the value,the more focused the attention is.The value range of Meditation is also from 0 to 100,and the larger the value,the greater the relaxation degree [3].

Table 1 Local EEG data

Noise	Attention	Meditation
200	0	0
95	0	0
0	50	45
0	60	35
0	90	60
0	87	58
0	45	31
200	0	0

3. Research on emotion recognition based on CNN and LSTM

3.1 EEG emotion recognition model based on CNN and LSTM

The model used in this article is a fusion of 4 convolutional layers and 1 LSTM layer,starting with an input layer for preprocessing EEG samples.Then, the convolutional layer and pooling layer together form a local feature extraction module,mainly including the convolutional and pooling processes.The convolution operation is mainly used to obtain local features of EEG signals.After completing one layer of convolution,the activation function acts on the convolution output.This model chooses maximum pooling and only retains larger values in the set pooling window.Adding maximum pooling between consecutive convolutional layers can reduce the number of parameters and computational overload, thereby controlling overfitting of the model.After each convolutional kernel pooling operation is completed,batch normalization will be performed to reduce changes in data distribution. Next is the LSTM layer,which is used to continue searching for useful information from the previous feature maps and learning long-term dependencies in the signal.The LSTM layer can enable the model to learn more complex information in time series signals,thereby improving the accuracy of prediction [5].Finally, there is the fully connected layer,which is used to perform actual classification based on the output of the previous LSTM.For a specific EEG sample,the model can determine depression with a certain probability.

3.2 Simulation of Emotion Recognition in Python Software

The DEAP dataset contains EEG data from 32 participants,which includes 40 individual 2-minute movie clips.Each participant watches these movies and rates them to describe their emotional experiences.These ratings are divided into 5 dimensions, namely valence, arousal, dominance, liking, and familiarity. The ratings for each dimension range from 1 to 9 [14].

For the convenience of research,the collected multimodal information is downsampled to a sampling frequency of 128Hz. The final experimental data is the preprocessed result,containing 32. mat files. S01 to S32 correspond to the physiological information of 32 subjects,respectively. The DEAP dataset is shown in Figure 9.

3.2.1 Program flowchart

Firstly, the EEG information of 32 participants in the DEAP dataset is extracted using DEAP one-dimensional EEG feature values.Then,the extracted one-dimensional DE feature values are transformed into two-dimensional feature maps.Finally,the two-dimensional feature maps are transformed into three-dimensional cubic feature maps and used for emotion recognition using a time dimensional convolutional neural network [16].The flowchart is shown in Figure 10.

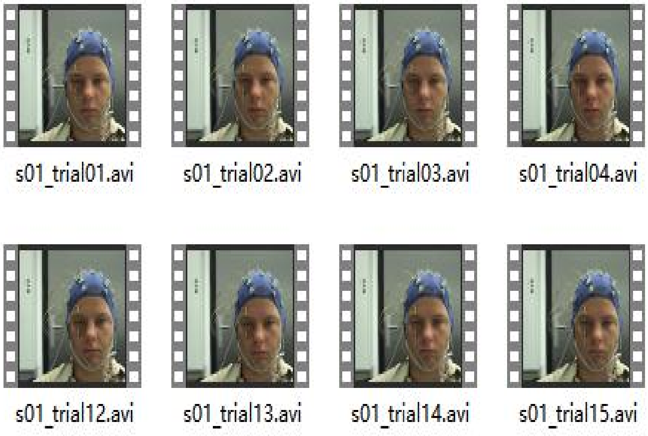


Figure 9 DEAP Dataset

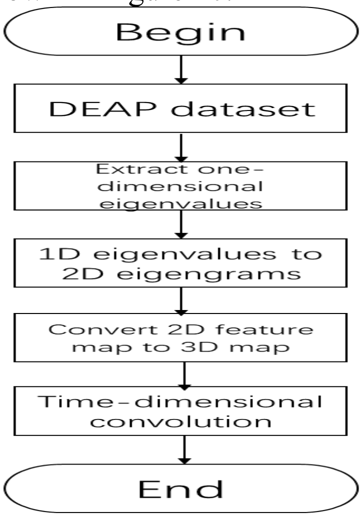


Figure 10 Program flowchart

3.2.3 Analysis of Python software simulation results

Run the program to extract one-dimensional feature values of the DEAP EEG dataset,obtain the one-dimensional feature values of the DEAP dataset EEG data,and save them in the corresponding folder.Then run the program to convert the one-dimensional feature values into two-dimensional feature maps,obtain the two-dimensional feature maps of the DEAP dataset EEG data,and save them in the corresponding folder.Finally,run the three-dimensional cube feature map and time dimension convolutional program to train convolutional neural networks and long short-term memory neural network models,and obtain the accuracy of emotion recognition.

Through simulation,it is shown that using convolutional neural networks and long short-term memory networks for emotion recognition models,the convolutional neural network automatically extracts features,and the long short-term memory network is trained in sequence with an average accuracy of 94.023%.The experimental data is shown in Table 2.

3.3 Result Analysis of Raspberry Pi

After completing the Raspberry Pi configuration environment,the actual product is shown in Figure 11.

Figure 11 Raspberry Pi 4B physical image

Importing the Python trained model into Raspberry Pi and running it,experiments have shown that the average accuracy of the emotion recognition model combined with convolutional neural networks and long short-term memory networks is 98.980%.The experimental data is shown in Table 3.

Table 2 Accuracy of Convolutional Neural Networks and Long Short Term Memory Neural Networks

	Simulation		Raspberry PI	
	Accuracy	average value	Accuracy	
1	95.0%	94.023%	99.125%	98.980%
2	91.625%		98.0%	
3	98.0%		99.125%	
4	99.0%		98.25%	
5	95.625%		99.0%	
6	94.125%		99.5%	
7	97.125%		99.625%	
8	91.625%		99.5%	
9	95.5%		98.625%	
10	92.25%		99.25%	
11	97.25%		98.375%	
12	98.0%		99.625%	
13	76.875%		99.5%	
14	97.25%		99.0%	
15	93.375%		99.25%	
16	96.5%		99.75%	
17	90.875%		98.25%	
18	96.5%		99.75%	
19	93.0%		98.875%	
20	92.625%		99.25%	
21	91.625%		99.5%	
22	94.875%		95.75%	
23	93.75%		99.75%	
24	95.0%		99.0%	
25	91.625%		99.0%	
26	98.0%		98.625%	
27	99.0%		98.75%	

simulation debugging in Python and simulation debugging in Raspberry Pi,the accuracy of emotion recognition is inconsistent.The main reason for this result is that for the same dataset and deep learning model,the weight initialization adopts the default form, that is,there is no manual setting for weight initialization,and the system randomly sets it.That is to say,the initial value weight is different every time.Its advantage is that due to the different initial values,it eventually converges to different extreme points, and one of these may be the true best advantage.If you want consistent training results each time,you only need to manually set a random seed (seed).

4. Conclusion

Taking EEG signals as the research object,the TGAM module was first used to design an EEG signal acquisition system.Then,an EEG signal acquisition experiment was conducted based on the STM32 microcontroller.Through serial communication software,the waveforms of 9 types of EEG data,including Raw wave,Delta, Theta, Alpha, Beta, Gamma,Noise, Attention,and Medication, can be clearly seen. By analyzing the collected EEG data,the brain activity status of the experimenter in different scenarios can be determined.Then, MATLAB software was used to conduct EEG signal acquisition experiments,obtaining three types of EEG data: Noise, Attention,and Medication.By analyzing the collected EEG signal data, the experimenter's attention and relaxation level can be seen.Based on the convolutional neural network and long short-term memory neural network models,a Python simulation debugging of EEG signal emotion recognition was conducted using the DEAP dataset.The emotion recognition accuracy was 94.023%. Finally,the proposed convolutional neural network and long short-term memory neural network models were deployed in the embedded terminal device Raspberry Pi.Through experiments, it was shown that the emotion recognition accuracy of this model,which is fused with four convolutional layers and one LSTM layer,is 98.980%.It can meet the initial emotion recognition requirements and can be used as a new type of depression diagnosis and treatment method, reducing the diagnostic cost of depression and improving the accuracy of depression diagnosis.2022 Gansu Provincial University Innovation Fund Project,2022A-162,Research on multi-modal emotion recognition method and its application system.2023 Lanzhou Institute of Technology Youth Science and Technology Innovation Project,Research and System Design of Multi object Detection and Tracking Methods for Complex Scenes.Lanzhou Talent Innovation and Entrepreneurship Project 2021-RC-27, Gansu Province Education and Technology Innovation Industry Support Plan Projects 2021CYZC-34 and 2021CYZC-35, Gansu Province Key Science and Technology Research and Development Plan 21YF11GA012

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