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Fusion of EEG and EMG Signals for Home Automation Based on Convolutional Neural Networks with Portable devices

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***Abstract*—Society's advancement is marked by improved quality of life, but challenges faced by individuals with limited mobility due to injuries cannot be overlooked. These challenges, coupled with potential safety risks like unattended gas stoves leading to fires, highlight the need for solutions. To address this, this paper proposed an innovative smart home system for controlling LED light by detecting specific real-time EEG and EMG signals from portable devices. The system uses Bluetooth to transfer the real-time signals of EEG attention and EMG gestures and a convolutional neural network for binary classifications. Through analyzing real-time EEG attention and EMG gestures, our approach enables seamless control of smart devices. By merging technology with EEG and EMG analysis, our project empowers limited mobility individuals for an enhanced quality of life.**

Keywords-components: smart home control, EEG, EMG, CNN

I. INTRODUCTION

In today's society, as people experience an overall improvement in their quality of life, it's important to consider the challenges faced by individuals with disabilities, such as those who have limited mobility due to broken hands or legs. These challenges can greatly hinder their daily activities, such as operating household switches, ultimately affecting their overall well-being. Additionally, these difficulties can pose risks that may even expose the disabled to safety hazards. A prime example would be potential fires that are caused by leaving gas stoves on. In statistics reported by NFPA, an annual average of 172,900 reported home structure fires are caused by this reason, leading to an average of 550 civilian fatalities, and causing approximately 4,820 civilian injuries annually. [1] Therefore, the situation will just be worse for disabled individuals. And a responsive smart home system can make a significant difference under this kind of circumstance. Our project addresses this need by developing a smart home system that utilizes EEG data collected from NEUROSKY's headset which is shown in the figure 1 and EMG data collected by the BiostampRC. The goal is to establish a connection between the headset and a computer via Bluetooth. By analyzing EEG data to detect attention levels and interpreting EMG signals to recognize gestures and body movements, we can achieve real-time control of smart home devices. Unlike conventional methods like remote controllers or applications, our approach eliminates the need for complex user interfaces, reducing the learning curve and making it more accessible for a wider range of individuals.

Figure 1 NEUROSKY's headset

However, this project does come with its challenges. One of the key hurdles is effectively processing the EEG and EMG data. Since our group is using a single electrode setup, the collected data tends to be noisy and lacks precision. Despite this challenge, we successfully gathered the data and employed Bluetooth technology to transmit it to a computer. This data is then utilized as input for a convolutional neural network, which performs binary classifications to distinguish between an open palm and a closed palm gesture. There are many machine learning methods used to process EEG and EMG signals, most researchers use support vector machines to do binary classification. SVM is a supervised machine learning model which can be used for binary classification.[2] But in this case, we use a convolutional neural network. A convolutional neural network(CNN) is based on the mathematical operation called convolution which is an operation to combine two functions to produce a third function that can represent the characteristics of the two functions.[3] The reason we use CNN in this project is because its ability to directly process raw EEG and EMG signals without artificial feature extraction.[4] CNN is

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especially effective at identifying local and global dependencies within various frequency bands in EEG data, which records complicated temporal and spatial patterns. Similar to this, CNN can successfully identify unique muscle activation patterns in EMG data. CNN can extract useful features due to their multi-layer architecture, which eliminates the need for manual feature engineering. [5] In this case of doing a binary classification, the use of SoftMax as the activation function in the final layer of our CNN architecture allows the final output result to be considered as the probability of that category since SoftMax converts a vector of numbers into a vector of probabilities, with each value's probability determined by its relative scale in the vector.[6] By doing so, we enhance the interpretability, accuracy, and convergence of our EEG and EMG classification model.

By merging EEG and EMG data analysis with advanced technology, the team is working towards creating a smart home system that empowers individuals with limited mobility to enhance their quality of life. This approach stands out for its rapid response, minimal learning curve, and absence of complex interfaces, making it a valuable solution for those who need it most.

II. Convolutional Neural Network

Using the convolutional neural network to build a classification model for EEG and EMG signals is a popular topic and a lot of academic papers related to this topic have been published. By reviewing these articles, our team was allowed to develop a better model by carefully analyzing the drawbacks of the previous papers and avoiding making the same mistakes in our paper. We propose a convolutional neural network (CNN) based system that harnesses the power of deep learning to attain a condensed and distinctive feature representation, enhancing accuracy. Employing fundamental architectural elements like input, output, and hidden layers, our model incorporates numerous parameters. Comprising three convolutional layers and one fully connected layer, the network is carefully designed by adding a pooling layer after each convolutional layer. Except this, by introducing an additional fully connected layer, the model's capacity for non-linear expression is enhanced. This augmentation involves an increase in the neuron count, resulting in heightened model complexity. Consequently, the learning capability of our model has been enhanced.

The architecture of our CNN model is displayed in Figure 2. We use max pooling as the pooling layer and through the utilization it, we can acquire a condensed representation of distinctive characteristics present in the input data. This serves to counteract the influence of minor positional fluctuations in the input's features, as the pooled feature map guarantees their alignment. Employing max-pooling is strategic, as it exclusively captures the highest element within the filter-covered region of the feature map. This results in an output feature map from the max-pooling layer, embodying the most salient attributes from the preceding map [7]. We use ReLU as the activation function for convolutional layers [8]. The main purpose of employing an activation function in convolutional layers is to enhance the model's capacity for nonlinear expression. Without the activation function, neurons would solely engage in linear transformations using the input data. Consequently, a neural network reliant on linear transformations would possess diminished effectiveness, lacking the capability to learn complex patterns within the dataset. Despite considering additional layers initially, their incorporation did not yield the expected accuracy increase; instead, it introduced susceptibility to overfitting, particularly evident when training accuracy reached 100%. To circumvent the risk of overfitting, dropout regularization is applied. The dropout technique involves randomly deactivating the output of hidden neurons with a 50% probability [9]. This prevents the neurons from influencing the forward pass and contributing to back-propagation [10]. Consequently, each neural network layer features a distinct architecture, yet with shared weights. We adopted Google's existing dropout algorithm, integrating it into our model through TensorFlow. In the hardware aspect, our model's performance evaluation employs a computer equipped with an Intel Core i7 processor and 32GB of RAM. This hardware configuration ensures robust testing and assessment of the model's capabilities.

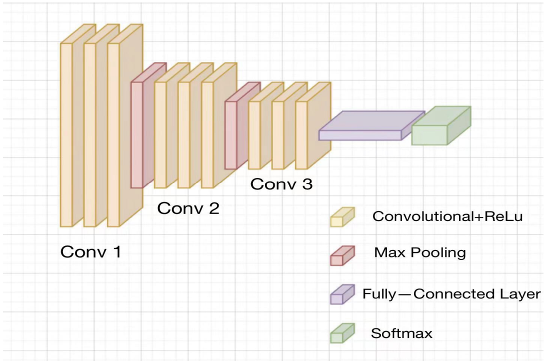

Figure 2 Architecture of CNN model

III. Method

A. Hardware

In this paper, we utilize the commercial-available EEG and EMG devices to record and recognize human attention and behaviors, respectively. For attention measurements, a single channel EEG setup from NeuroSky, released by NeuroSky, Inc. is chosen, as it is low cost, portable, user-friendly with an acceptable accuracy. It records the electrical activity along the scalp, namely the wearer's brain activity, compared to the reference node at the ear as a time-series data at 100Hz. To capture the musculation of people with forearm amputee, surface electromyography (EMG) data were acquired using the BiostampRC device, positioned over the biceps brachii muscle. The placement location was consistent with SENIAM guidelines, specifically, it was located at a point that is one-third of the distance between the cubital fossa and the medial acromion [11].

B. Pre-Processing

In this study, the utilization of the NeuroSky device must be considered within the context of its intended applications for entertainment purposes, and it's essential to acknowledge that its accuracy and complexity are not on par with medicalgrade EEG devices typically employed in clinical settings. Consequently, to extract meaningful information related to human attention and hand gestures from the device's data, we performed several preprocessing steps within MATLAB.

To mitigate the inherent noise in the collected data, we initiated the preprocessing by applying a rolling average with a window size of 100 data points. This smoothing process was essential to handle sudden fluctuations introduced by the device. To further enhance data quality and minimize interference from the electrical system's frequency (typically 60Hz), we employed the Fast Fourier Transform (FFT) to transform the signals. Subsequently, we meticulously removed components falling within the narrow frequency range of 59.8Hz to 60.2Hz, ensuring that our subsequent analyses were not affected by this external interference. This data cleaning procedure can be visualized in Figure 3, where the red circles highlight the sections of data earmarked for subsequent analysis.

Following the data cleaning stage, we proceeded to extract relevant features based on the refined dataset. To establish a structured framework for feature extraction, we segmented the data into intervals of size 100. Notably, our study encompassed a total of 10 features drawn from both EEG and EMG data. In the case of EEG, we meticulously selected nine features from both spatial and temporal domains, exemplified by the inclusion of features such as delta (0.53 Hz), theta (4-7 Hz), low alpha (8-13 Hz), high alpha (14-17 Hz), low beta (13-23 Hz), high beta (24-34 Hz), low gamma, and mid-gamma. Each of these channels represented one of the extracted features.

Moreover, our study categorized the combined actions into three distinct groups, and subsequently, the generated dataset underwent shuffling and was divided into a training set and a validation set in an 8:2 ratio. These meticulously preprocessed and segmented datasets were then fed into our custom-built convolutional neural network for further analysis.

In summary, the theoretical foundation of our approach rests on recognizing the limitations of the NeuroSky device, the necessity for data preprocessing to ensure data quality, and the structured feature extraction process to discern meaningful insights related to human attention and hand gestures from the collected data. This methodology lays the groundwork for the subsequent application of machine learning techniques, such as convolutional neural networks, in our analysis. give me a new version of these paragraphs through adding detailed formulas to corresponding places

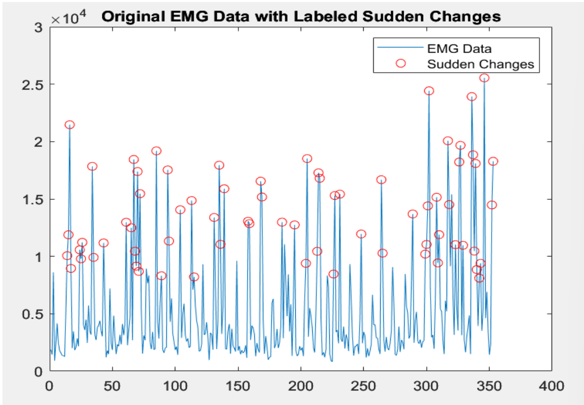

Figure 3. Partial EMG data that has been cleaned

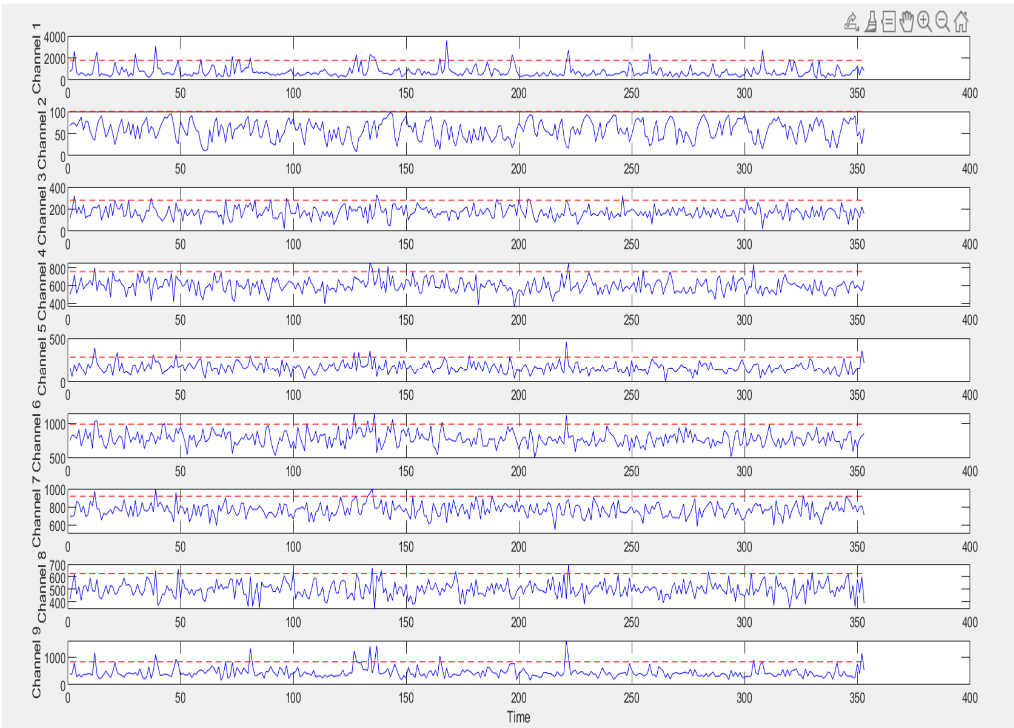

Figure 4 Overview of EEG data in 9 channels

C. Experiments

Two healthy subjects (one female and one male, both aged 16 years) provided their informed consent, volunteering to participate in the study for dataset collection. Participants were seated in a relaxed chair, with their right elbow bent at a 90-degree angle and their upper arm positioned vertically next to their body. Figure 5 illustrates a portion of the experiment setup. The forearm was maintained in a neutral position to restrict any rotation movements [12].

For the application of home automation control, we combined the attention and hand gestures and divided them into three groups, namely:

1) A person pays 100% attention to things around him and makes a fist;

2) A person pays 100% attention to things around him, keeping hands relaxed;

3) A person keeps calm and his hand relaxed;

In each experiment, we measured 1000 data at a time, when the volunteer tried to keep the selected action group and for each action, 35 experiments were performed. After pre-processing of the data, for example, the filtering and the feature extraction introduced in section II, we obtained the final labeled dataset with a size of 1050.

Figure 5 A volunteer who is doing the experiment

IV. Conclusion

Our purpose for this research is to let disabled people especially the deaf to control the household's appliances by doing three different actions since those kinds of disabled people cannot control the appliances by voice. This paper introduces a multi-layer CNN model designed to classify specific movements and mental states, which can be used for smart home control like turning on the lights as mentioned above. The entire process consists of three phases. First and foremost, we use the Neurosky headset and the BiostampRC to record the raw EEG and EMG data. Then, we use Matlab to pre-process these data in order to allow our convolutional neural network can learn and classify these data in a specific manner. After this, the multi-layer CNN will be used to determine and learn the features of the input EEG and EMG data that have been cleaned and labeled. This method is tested on a validation dataset and achieves similar outcomes, averaging an accuracy rate of 90.1 percent to make sure that the CNN is able to classify similar data in a broader case. Further research on this work can be done, for example, within the range of improving the accuracy and usefulness of the data from the data-collecting process.

V. Discussion

Innovations in our study are multifaceted. Firstly, we established groups of individuals based on their brain activity data and hand gesture control, addressing a crucial accessibility issue. By doing so, we aimed to provide an alternative control mechanism for smart home devices, catering to individuals with disabilities such as hearing impairment, who may face challenges with sound-based control. Our approach shifted the paradigm towards concentration-based control, a method accessible to a broader demographic.

Moreover, our experimental design introduced a fresh perspective. We recorded both hand gestures and concentration levels at 10-second intervals, alongside EEG and EMG signal acquisition. This granular approach allowed us to collect precise data, subsequently cleaned and labeled for analysis. To further refine our data, we implemented a specialized data filtering method and tailored feature extraction techniques, transforming the data from the time domain into the frequency domain.

However, it's important to acknowledge the limitations of our initial setup. The single-channel EEG measurement device introduced challenges, including suboptimal electrode-brain contact, signal delays, and noise formation. To enhance accuracy, future experiments will incorporate multiple channels, ensuring better signal fidelity. Additionally, EEG signals' inherent fluctuations and noise necessitated extensive processing using MATLAB's nine-channel capabilities to obtain clean, actionable data.

Furthermore, data scarcity, stemming from a limited pool of participants, underscored the need for broader data variation. To address this, future endeavors will involve a more extensive participant pool, enriching our dataset and enhancing the robustness of our findings. These advancements collectively pave the way for a more inclusive and effective smart home control solution, particularly for individuals with disabilities.

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