# Extraction of Motor Imagery for Operation of UAV Communication Systems

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***Abstract*—This paper presents a novel approach in enhancing Unmanned Aerial Vehicle (UAV) communication systems through the application of reliable Electroencephalogram (EEG)-based Motor Imagery signals. The concept of EEG signals and the active role that Motor Imagery (MI) signals can play in UAV systems is explored, along with the efficiency aspects and algorithmic superiority of the communication system, demonstrating how the EEG information signal is reliable enough to be utilized in a UAV communication system. The results provide a performance evaluation of the CNN model along with a comparison to other learning models, and an analysis of the spatial separation in the brain. The study concludes by suggesting the implications of the findings for UAV communication and AI in future researches.**

## I. Introduction

The advent of Unmanned Aerial Vehicles (UAVs) has brought about a significant transformation in numerous sectors, including surveillance, disaster management, and environmental monitoring. The success of these applications depend heavily on the robustness and reliability of its communication systems. Traditional communication methods, while effective, are not without their limitations. Issues such as latency and signal interference present challenges that need to be addressed.

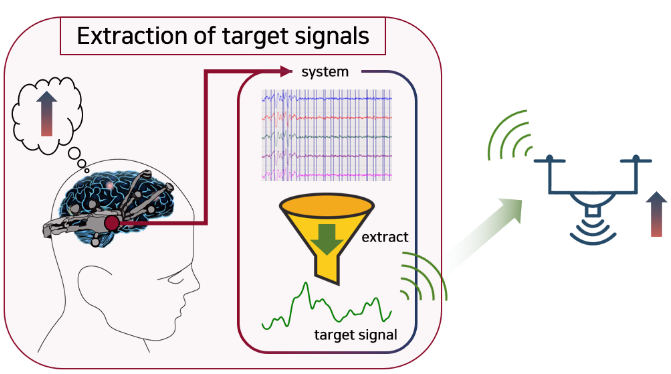


Fig. 1. Utilization of brainwaves in UAV operations

In this context, the application of Electroencephalogram (EEG) signals presents an intriguing frontier. EEG signals, the electrical activities generated by the brain, offer a unique blend of information that can be harnessed to enhance communication systems. Among these, Motor Imagery (MI) signals, generated when an individual imagines performing a specific action, hold particular promise [1].

MI signals are types of EEG that are generated when an individual imagines performing a certain behavior, even without necessarily executing the physical behavior [2]. These signals can be utilized to create a direct link between the user's intent and the control of an external devices. This opens up the opportunity to use MI signals for applications in UAV communication systems.

The use of MI signals in UAV communication systems is not merely a novel approach; it represents a paradigm shift in how we perceive and utilize communication systems [3] By tapping into the brain's electrical activity, we open up a new dimension of intuitive and natural control. This approach also democratizes access to UAV control, extending it to individuals with physical disabilities. Moreover, the use of MI signals can potentially lead to more efficient and responsive UAV systems, as the delay between thought and action can be significantly reduced [4].

Similarly, the issue of signal interference can be mitigated by the unique characteristics of MI signals. Unlike traditional communication signals, which can be affected by external electromagnetic interference, MI signals are generated internally and are therefore less susceptible to such interference. This makes them a reliable source of signals for UAVs [5].

This paper presents a comprehensive exploration of the potential of EEG signals, particularly MI signals, in enhancing UAV communication systems. It provides a detailed overview of the methodology, discusses the challenges currently faced by UAV communication systems, and presents potential solutions based on the use of EEG signals [6]. Fig. 1 illustrates

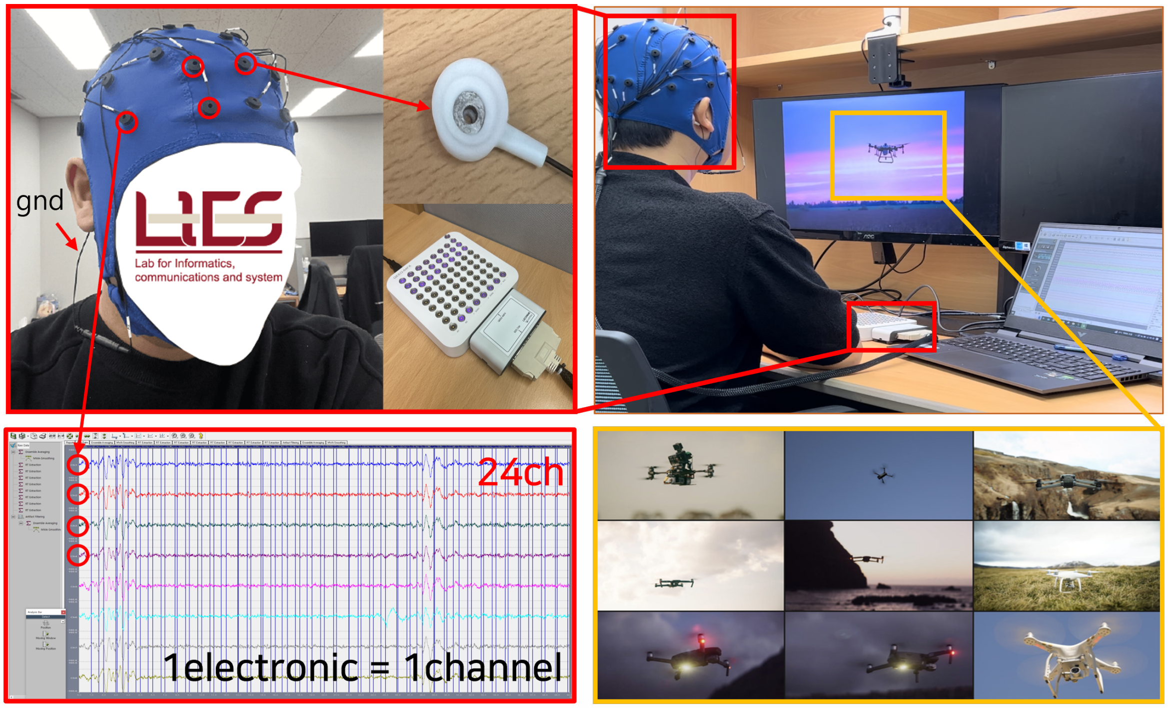


Fig. 2. Experiment setup and dataset construction for EEG extraction

the process of measuring EEG, extracting the desired target signals, and controlling the drone's actions with these signals.

Methods of detailed EEG measurement were a crucial part of this study, which involves the following. Wavelet denoising, eliminating noise from the EEG, was required to preserve the essential features of signals. Fast Fourier Transform (FFT), used to transform the EEG signals from the time domain to the frequency domain, provided a different perspective on the data. Finally, Convolutional Neural Network (CNN)s, a class of deep learning algorithms, were used to automatically and adaptively learn spatial hierarchies of the EEG signal features [7, 8].

## II. Experimentation

### A. Measurement

The first step to utilizing EEG signals is to accurately measure them, which is the process of attaching wet electrodes to the scalp to capture the brain's electrical activity. Medical gel was applied to each of the 24 electrodes to stably attach them to the scalp, which resulted in an average resistance value of 3.8 k$\Omega$ across all channels, adequate for EEG measurement. Fig. 2 shows the EEG measurement setup, which consists of LAXTHA's QEEG-64FX hardware and electrodes. The EEG signals were analyzed and extracted through a total of 24 channels, one channel for each electrode.

The training data was constructed by crawling 2.5-second videos of the drone moving in a specific direction (left/right/up/down/forward). For the EEG measurement, the videos were randomly played to the subjects, while avoiding more than two consecutive videos of the same category, considering the contrast effect of continuous videos and habituation (desensitization to drone videos). The subjects had their EEGs measured for an hour, divided into 10 minute intervals, for the probability of extracting a complete MI signal increases when the subject is concentrating. The two seconds of data immediately after each video was recorded as a single waveform.

The collected signals were converted and processed into a format that could be used to train the learning model. Since blinking or head movement causea spikes in all 24 channels, a pre-processing was required before the process of a noise filtering algorithm.

### B. Algorithm

The signals then undergo a series of transformations before motion classification, as illustrated in Fig. 3. The first of these is wavelet denoising. EEG signals can be contaminated with various types of noise, including muscle artifacts, power line interference, and other external electromagnetic waves. Wavelet denoising works by decomposing the signal into different frequency components using wavelets and then thresholding the wavelet coefficients to remove noise. The result is a cleaner signal that retains its essential features.

Following the denoising process, the FFT transforms it from the time domain to the frequency domain. This frequency domain representation provides insight into the power distribution of the various frequency bands of the EEG signal. This is important for feature extraction, especially since certain frequency bands, such as beta waves, are associated with specific cognitive tasks or motor imagery behaviors. With this

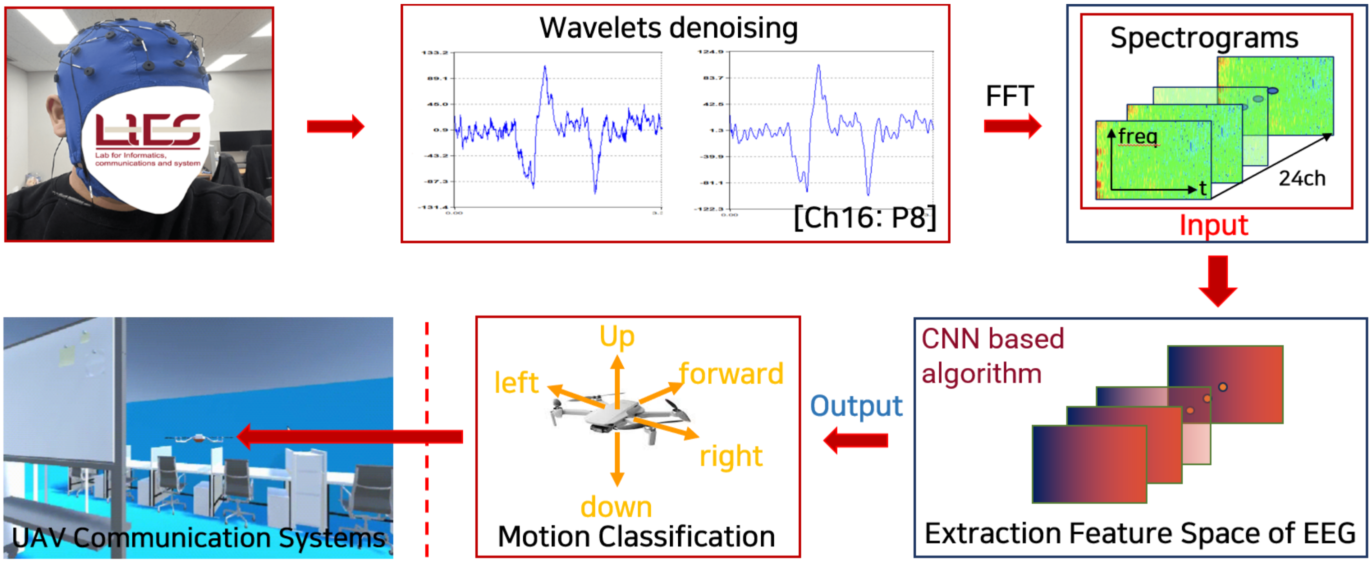


Fig. 3. CNN architecture for EEG spectrograms classification

conversion to the frequency domain, we can extract more accurate features for a specific task [8, 9].

The spectrograms of the signals, which are representations of the spectrum of frequencies of a signal as it varies with time, are then used as input for the CNN. The CNN applies convolution and Rectified Linear Unit (ReLU) operations to the input. In the context of a CNN, the convolution allows the network to process features which are crucial for understanding the patterns in the EEG signals. ReLU introduces non-linearity into the network, aiding it to learn from the complex patterns in the data.[10, 11] The signals are then pooled to decrease the computational complexity of the network, making it more efficient. Moreover, pooling helps in extracting the dominant features of the EEG signals, which are crucial for the classification task.[12]

Finally, the signals are passed through a Softmax function. The function outputs a vector that represents the probability distributions of potential outcomes. This process allows motion classification, distinguishing the motions of the drone based on the processed EEG signals. The output of the Softmax function can be interpreted as the probability that the EEG signal corresponds to a particular motor imagery task, which can be used to command the drone's movements.

## III. Simulation Results

The simulation results presented in Fig. 4 are the result of the experimenter imagining the movement of the drone and the algorithm judging the extracted signals. The spatial activation of the brain is shown when the user imagines the drone moving left or right. The left and right-hand sides of the brain in the parietal and occipital lobes were activated when imagining the drone flying in either direction. This result confirms a key premise of our approach: spatial segregation of the brain during different motor imagery tasks.

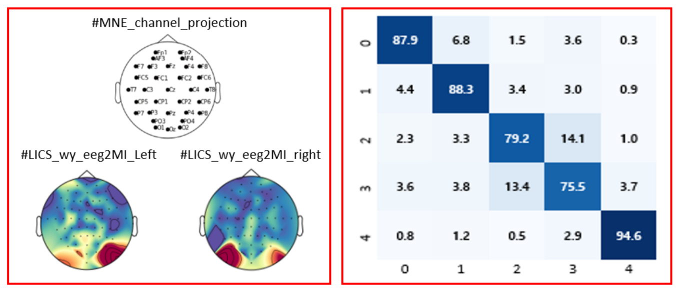


Fig. 4. Spatial activation and confusion matrix

The confusion matrix provides additional insight into the performance of the system. This matrix shows the predicted and actual classifications for each of the five categories. Zero through 4 correspond to the categories (left/right/up/down/forward). We can see that the system achieves high accuracy in the 'left' and 'right' categories, with 88% accuracy each. The 'forward' category also achieves a high accuracy of 94%. These results suggest that our system can effectively interpret the user's intentions based on the user's EEG signals.

However, the 'up' and 'down' categories were relatively more difficult to classify. One possible explanation for this phenomenon is the spatial distribution of brain regions involved in these tasks. The parietal and occipital lobes, which are primarily responsible for processing visual and spatial information, are more activated when subjects imagine a left or right movement. The 'up' and 'down' movements, on the other hand, can involve a wider range of brain regions, making it more difficult to distinguish between these two categories based on EEG signals.

Overall, the simulation results show that our proposed EEG-based UAV control communication system is reliable, and that the it achieves a reasonable accuracy in classifying different motor imagery tasks, confirming the feasibility of using EEG signals for drone control.

## IV. Conclusion

This study presents a novel approach for controlling drones using EEG signals, with a particular focus on MI tasks. The proposed system leverages the power of CNN to classify the EEG signals into different categories, corresponding to the intended direction of the drone's movement.

The simulation results demonstrate the effectiveness of the proposed system. High accuracy rates were achieved for the 'left', 'right', and 'forward' categories, confirming the system's ability to accurately interpret the user's intention based on their EEG signals. These results underscore the potential of EEG-based systems for controlling drones and other external devices.

However, the study also revealed challenges in classifying the 'up' and 'down' categories. This observation could be attributed to factors such as the spatial distribution of the brain regions involved in these tasks and the inherent variability in the way individuals perceive and interpret 'up' and 'down' movements. Addressing these challenges will be a key focus of future works.

In addition to improving the classification accuracy, future research should also explore the potential of distributing the computational load between the transmitter and receiver ends. This approach, which involves transmitting the characteristic space of the brain waves over the communication link, could lead to improved power consumption and computational efficiency.

In conclusion, this study represents a significant step forward in the field of EEG-based drone control. The proposed system, with its high accuracy rates and potential for improved efficiency, offers a promising direction for future research and development in this area.

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