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Brain-Controlled Quadrotor Drone

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Abstract:

Paralysis is the result of a block in the information pathway between the brain and the limbs. Patients losing bodily control in this way are unable to move as they need to and are, therefore, unable to look after their own needs. The goal of this paper is to design a functioning quadrotor drone that will respond to a patient's brain activity and accordingly enables them to have normal daily functions. We have designed an innovative brain computer interface (BCI) system to control the drone using only the power of thought. The drone has been designed and built using commercial components. An Emotiv EPOC headset was used to gather brain activity and communicate it to the computer which uses Emotiv software and a translation program to convert the signal pattern into a command that is able to be read by an Open Picus FlyPort module installed on the quadrotor drone. Due to the non-linear nature of the quadrotor, an innovative control law was derived using the Fuzzy Proportional Derivative (FPD) technique. A complete simulation was used to tune the controllers in MATLAB Simulink. The controllers were designed and implemented using on-board microcontrollers and an inertial measurement system. The entire system was tested and verified in an actual flight test. The findings indicate the potential of BCI system for controlling quadrotor, and thus enabling paralyzed people to improve their life and maximize communication capabilities and independence.

INTRODUCTION:

People who cannot use their limbs are, obviously, unable to control objects in their environment. This is often caused by injury to the motor cortex and frequently occurs after a stroke.

Previous investigations have reported that although patients often regain some of their motor function after therapy, most remain chronically disabled. Assistive technologies that translate thought into action can help such people to improve their life and maximize communication capabilities and independence. Recently, there has been much interest in developing a BCI technology to enable disabled people to directly control a drone using their neural signals. The use of this promising technology (AirServer) is more complex and has only recently started to be studied.

AirServer is an intelligent unmanned aerial vehicle (UAV) that automatically responds to a user's brain activity. The drone is smart and autonomous; and it does not need a remote control to fly. It is especially designed for receiving the command from the user's brain by reading electrical signals through the scalp. AirServer requires that the user wears an Electroencephalography (EEG) cap and learns to move a virtual object back, forth, left and right on a computer screen through thinking alone. The BCI system associates those patterns to specific commands and relays them to the AirServer via a Wi-Fi module. An onboard flight controller will receive those commands, and, depending on the type of brain activity detected, guide the drone to the desired location.

FUNCTIONAL MODEL OF THE AIRSERVER SYSTEM:

As shown in Fig. 1, the AirServer combines the use of a brain computer interface and an unmanned aerial vehicle. The unmanned aerial vehicle was built from scratch and has a custom printed circuit board (PCB) attached to its hop. The PCB contains components that are specifically used for receiving, interpreting and processing signals from the BCI system, and

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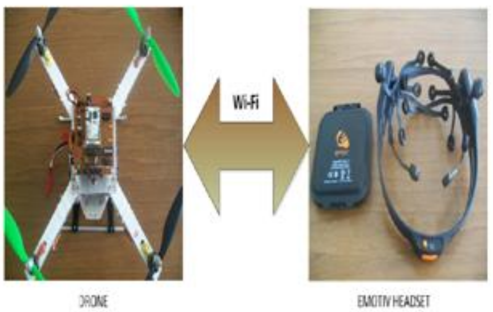
transmitting the correct voltages to the flight controller. The Emotiv headset and customized software are the keys to the BCI system. The software developed to connect the BCI system with the drone was written based on the event-driven and client-server mechanisms. A Wi-Fi connection was used and implemented on a FlyPort module. The server utilizes the signals received from the headset and processes them into usable signals for the drone. Arming/disarming the drone is determined by the position of the user's head. For example, the user can arm the drone by tilting his head left. If the user wishes to disarm the drone, he simply tilts his head to the right. The direction in which the drone moves is determined by the thought of the user.



Structure of the AirServer System

Mind wave sensor (EEG):

Electroencephalography (EEG) is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus on the spectral content of EEG, that is, the type of neural oscillations that can be observed in EEG signals. EEG is most often used to diagnose epilepsy, which causes abnormalities in EEG readings. It is also used to diagnose sleep disorders, coma, encephalopathies, and brain death. EEG used to be a first-line method of diagnosis for tumors, stroke and other focal brain disorders, but this use has decreased with the advent of high-resolution anatomical imaging techniques such as MRI and CT. Despite limited spatial resolution, EEG continues to be a valuable tool for research and diagnosis, especially when millisecond-range temporal resolution (not possible with CT or MRI) is required.

Derivatives of the EEG technique include evoked potentials (EP), which involves averaging the EEG activity time-locked to the presentation of a stimulus of some sort (visual, somatosensory, or auditory). Event-related potentials (ERPs) refer to averaged EEG responses that are time-locked to more complex processing of stimuli; this technique is used in cognitive science, cognitive psychology, and psychophysiological research.

NUMERICAL AND EXPERIMENTAL RESULTS:

We performed several tests to validate the previous finding and test how well the brain commands can control the quadrotor. The controllers as well as the quadrotor’s dynamic model have been first developed in Matlab Simulink. After attaining satisfactory results, the controllers were implemented on a real quadrotor.

A. Numerical Results:

The quadrotor dynamic as well as the controller’s models were simulated on a MATLAB/Simulink. Fig. 16 shows the Simulink model of the Fuzzy PD Controller with unity step input. The inputs to the quadrotor model are u1, u2, u3, and u4. The outputs from the same model are the three Euler's angles as well as the position of the quadrotor. Those outputs are used as a feedback input to the FlyPort model_1. The fuzzy controllers (FLCz, FLCphi, FLCtheta, and FLCpsi) were developed using the MATLAB Fuzzy Logic Toolbox. The outputs from the fuzzy system were used to tune the gains of the PD controller. The gains of the conventional PD controller were initially adjusted using the Ziegler-Nichols method. Based on this method, the following gains were obtained: Kp = 0.0122, Kd =0.0093. The nominal values of the quadrotor parameters used for simulation are presented in Table.

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The step input was used to analyze the response of the attitude and altitude control of the quadrotor. The results for the three Euler angles as well as the altitude after running the system are shown in Figiure. It can be observed that the Fuzzy PD controller is able to function correctly and select the most suitable gains in the presence of brain signals.

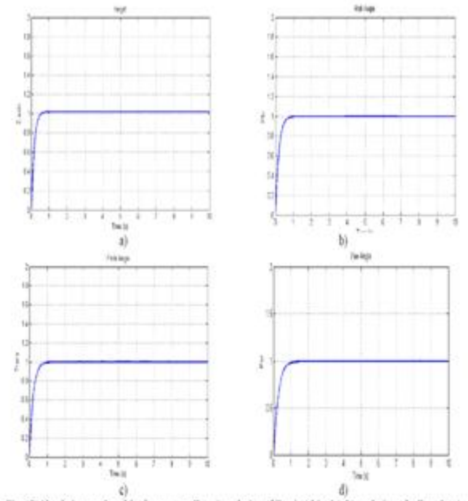
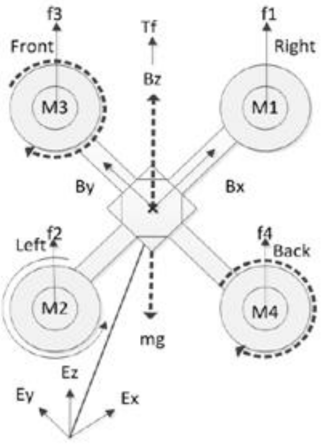


Fig. 17. Simulation results of the fuzzy controller, a) evolution of Z-axis (altitude), b) evolution of roll angle, c) evolution of pitch angle, d) evolution of yaw angle



Quad-rotor schematic including the body and earth frames

Experimental Results:

As shown in Fig. 18, we ran two experiments investigating how the brain signals would control the quadrotor. As an initial step, a healthy participant was seated in front of a computer running all the software required for the experiment and trained to control left, right, pull and push movements of a virtual cube supplied by the Emotiv Company.

Training was done in twelve trials; and each lasted 8 seconds for each action. The trial was considered successful if at least one state was in the required direction during the 8 seconds. After 10 minutes of training, a 52% rate of success was achieved in making an action happen when intended. During training trials, we found that the cognitive suite sometimes produced small outputs that were unintended by the user. We solved this problem by considering the state to be unsuccessful if the participant did not see any movement in the correct direction. We also enhanced the previous step by using Emokey filter, at a certain threshold. During the key mapping, we set a condition greater than the threshold of 30% in order to detect the power of the action. In order not to overwhelm the drone with too many commands, we added the further filtering technique of checking for a new state every 50ms. This technique was implemented by an event-driven mechanism. The training process is shown in Fig. 18a.

The second experiment was designed to test how the quadrotor responds to the fuzzy logic controller. As a starting point, the quadrotor was commanded to maintain a fixed hover position and keep the pitch, roll, and yaw angles within the interval (0, 0, 0). This situation was achieved by instructing the participant to only imagine the push command. Due to the presence of disturbances, such as wind disturbance, it was difficult for the participant to maintain the quadrotor at a constant altitude. This problem was solved by adding an ultrasonic sensor to measure the distance to the ground. The ultrasonic sensor was pointed towards the ground and connected with the FlyPort module via a UART interface. The participant was then instructed to do the experiment again by commanding the drone so that it would take off slowly then proceed until it reached the maximum range of the ultrasonic sensor, Fig. 18b. After reaching the desired altitude, the quadrotor was commanded to pitch-up and then pitch-down.

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a) b)

Snapshots of the AirServer in use a) Emotiv EPOC headset positioned on the test person scalp. b) result of detecting human thoughts

CONCLUSIONS:

The present study shows that it is possible to control the drone with a BCI system. An innovative control law using fuzzy PD was used successfully to stabilize the states of the drone and ensure that the brain waves would not overwhelm the drone with too many commands. A two-input and two-output fuzzy control system was presented. The controller consisted of four fuzzy logic modules designated for the control of the quadrotor height and orientation. The controller was simulated in MATLAB/Simulink and then experimentally tested on our prototype, called AirServer. The source of the control signal was the brain waves recorded from the surface of the scalp using EEG sensors. The cognitive suite received the EEG waves and converted them to commands such as pull, push, right and left. These commands were used to control the AirServer. Simulated results were quite promising and demonstrated the ability of disabled people to steer the drone with the power of thought and use it to look after their own needs. Further study is needed to enhance the movement of the drone.

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