A SURVEY ON UNMANNED AERIAL VEHICLE REMOTE CONTROL USING BRAINCOMPUTER INTERFACE

Seminar Report

Submitted in partial fulfillment of the requirements for the award of degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

of

APJ ABDUL KALAM TECHNOLOGICAL UNIVERSITY

Submitted By

ASHLAY CYRIAC

Department of Computer Science & Engineering
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CERTIFICATE

This is to certify that the report entitled **A Survey On Unmanned Aerial Vehicle Remote Control Using BrainComputer Interface** *submitted by* ***Mr. ASHLAY CYRIAC****, Reg. No.* ***MAC15CS017*** *towards partial fulfillment of the requirement for the award of Degree of Bachelor of Technology in Computer science and Engineering from APJ Abdul Kalam Technological University for December 2018 is a bonafide record of the seminar carried out by him under our supervision and guidance.*

....	....	....
Prof. Joby George	**Prof. Neethu Subash**	**Dr. Surekha Mariam Varghese**
Faculty Guide	***Faculty Guide***	***Head of the Department***

Date: Dept. Seal

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ABSTRACT

Numerous methods have been developed to gain reliable real-time remote control over pilotless flying aircraft and to perform teleoperation. BCI interface has provided an avant-garde approach to reach this goal. Due to its broad range of application BCI has been the center of attention as a promising candidate for deciphering brain signals into corresponding control commands for various systems. The application of BCI in designing control modules for UAV is described. The brainwave is captured with BCI device and the captured signal is classified after preprocessing, in order to issue corresponding control signal. The issued signal is transmitted to various systems using various transmission methods. Key areas covered are basic configuration of UAVs, Principal components of control systems, BCI categorization and BCI framework. Details will be given on how essential strategies and key techniques regarding feature extraction and classification of data as well as hybrid modality could be applied tin this field to develop a robust system.

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List of Abbreviation

AI	Auditory imagination
AR	Augmented reality
BCI	Brain Computer Interface
AEP	Auditory Evoked potential
EEG	Electroencephelography
MEG	Magnetoencephelography
(f)MRI	(functional)Magnetic resonance imaging
(f)NRIS	(functional)Near-infrared spectroscopy
VEP	Visually evoked potential
RNN	Recurrent neural network
UAV	Unmanned aerial vehicle

Introduction

Developing a direct communication pathway between the human brain and the outside world is a distinguished concept. Technology developed over the past two decades has allowed for the implementation of brain-computer interface (BCI), which is an outstanding innovation for recording and translating brain signals into control commands for robotic systems. Although BCI research is still in its early stages, it has been proven effective in a wide range of applications, and has thus gained significant momentum over the past few years.

An unmanned aerial vehicle (UAV), commonly known as a drone, is an aircraft without a human pilot aboard. UAVs are a component of an unmanned aircraft system (UAS); which include a UAV, a ground-based controller, and a system of communications between the two. The flight of UAVs may operate with various degrees of autonomy: either under remote control by a human operator or autonomously by onboard computers[1].

Unmanned aerial vehicles have experienced a drastic growth over the past decade, which was primarily driven by their vast functionality and their wide range of applications, but is not limited to target tracking, power and pipeline inspection, search and rescue operations, environmental monitoring, and anomaly detection. Drones and other classes of unmanned vehicles share common characteristics in terms of their basic architectures, communications, and also the strategies that could improve their autonomy attributes. However, certain features are associated with drones that make them distinct from their counterparts. Due to their inherently unstable nature, extra degrees of freedom in state space, and also being typically underactuated, designing control modules for UAVs requires rigorous consideration.

This is where the need for BCI control of UAV arises.UAVs are used for numerous applications as of now. As we rely more on them for practical applications the need for reliable control mechanism should also be developed.The existing control mechanisms for the control of UAVs are tiresome and takes time to master.

Brain-computer interfaces (BCI) are systems that allow communication between the brain and various machines.They work in three main steps: collecting brain signals, interpreting them and outputting commands to a connected machine according to the brain signal received. BCI can be applied to a variety of tasks, including but not limited to neurofeedback, restoring motor function to paralyzed patients, allowing communication with locked in patients and improving sensory processing.

An Electroencephalogram (EEG)-based Brain Computer Interface (BCI) system is put forward to implement the continuous control of an Unmanned Aerial Vehicle (UAV) in the indoor 2D space using the motor imagery (MI) tasks. This BCI system utilizes the discriminative time- and frequency-dependent spatial filter to extract the EEG features of MI tasks. The adaptive linear discriminant analysis (LDA) method is utilized to accomplish the classification of these extracted features. The calibration experiment and actual indoor 2D space controlling experiment presented the effectiveness and feasibility of using this BCI system to achieve the indoor 2D space continuous control of UAV.

Related works

As the name suggests BCI stands for deciphering brain signals to control signals that is suitable to control the UAV.For the brain signals to be converted into control signals there numerous methods available.The underlying principle for all the signal extracting methods are the same and each method has its own advantages and disadvantages.Each methods are equipped in fields where their respective advantages are helpful.

The BCI systems are classified into 2 based on the nature of signal collection, Invasive and Non invasive.The systems are further classified in case of both invasive and non invasive based on the technology used to extract brain signals.Namely EEG,MEG,(f)MRI,(f)NIRS,PET.

2.1 Invasive

Invasive Brain Computer Interface devices are those implanted directly into the brain and have the highest quality signals. These devices are used to provide functionality to paralyzed people. As they rest in the grey matter, invasive devices produce the highest quality signals of BCI devices but are prone to scar-tissue build-up, causing the signal to become weaker or even lost as the body reacts to a foreign object in the brain.Electrode grids are implanted to the brain tissue to record the current ongoing inter cranial activity and the recorded signals are safely transmitted to the collecting device.This method is the purest data acquisition method.Examples are ECoG,LFP.

2.2 Non-invasive

Non invasive brain computer interface has the least signal clarity when it comes to communicating with the brain (skull distorts signal) but it is considered to be very safest when compared to other types[2]. This type of device has been found to be successful in giving a patient the ability to move muscle implants and restore partial movement. Non-Invasive technique is one in which medical scanning devices or sensors are mounted on caps or headbands read brain signals. This approach is less intrusive but also read signals less effectively because electrodes cannot be placed directly on the desired part of the brain. One of the most popular devices under this category is the EEG or electroencephalography capable of providing a fine temporal resolution. It is easy to use, cheap and portable[3]. Here in case of controlling UAVs also we use non invasive methods since they are easy to use and economical.The different types of non invasive methods are

- Electroencephalography
- magnetoencephalography
- (functional)magnetic resonance imaging
- (functional)near-infrared spectroscopy
- positron emission tomography

2.2.1 Magnetoencephalography

Magnetoencephalography (MEG) is a functional neuroimaging technique for mapping brain activity by recording magnetic fields produced by electrical currents occurring naturally in the brain, using very sensitive magnetometers. Arrays of SQUIDs (superconducting quantum interference devices) are currently the most common magnetometer, while the SERF (spin exchange relaxation-free) magnetometer is being investigated for future machines.Synchronized neuronal currents induce weak magnetic fields. The brain's magnetic field, measuring at 10 femtotesla (fT) for cortical activity and 103 fT for the human alpha rhythm, is considerably smaller than the ambient magnetic noise in an urban environment, which is on the order of 108 fT or 0.1 T. The essential problem of biomagnetism is, thus, the weakness of the signal relative to the sensitivity of the detectors, and to the competing environmental noise[4].

Origin of the brain's magnetic field. The electric current also produces the EEG signal. The MEG (and EEG) signals derive from the net effect of ionic currents flowing in the dendrites of neurons during synaptic transmission. In accordance with Maxwell's equations, any electrical current will produce a magnetic field, and it is this field that is measured. The net currents can be thought of as current dipoles[citation needed], i.e. currents with a position, orientation, and magnitude, but no spatial extent[dubious discuss]. According to the right-hand rule, a current dipole gives rise to a magnetic field that points around the axis of its vector component.

To generate a signal that is detectable, approximately 50,000 active neurons are needed. Since current dipoles must have similar orientations to generate magnetic fields that reinforce each other, it is often the layer of pyramidal cells, which are situated perpendicular to the cortical surface, that gives rise to measurable magnetic fields. Bundles of these neurons that are orientated tangentially to the scalp surface project measurable portions of their magnetic fields outside of the head, and these bundles are typically located in the sulci. Researchers are experimenting with various signal processing methods in the search for methods that detect deep brain (i.e., non-cortical) signal, but no clinically useful method is currently available.

2.2.2 (functional)magnetic resonance imaging

Functional magnetic resonance imaging or functional MRI (fMRI) measures brain activity by detecting changes associated with blood flow. This technique relies on the fact that cerebral blood flow and neuronal activation are coupled. When an area of the brain is in use, blood flow to that region also increases.

The primary form of fMRI uses the blood-oxygen-level dependent (BOLD) contrast, discovered by Seiji Ogawa. This is a type of specialized brain and body scan used to map neural activity in the brain or spinal cord of humans or other animals by imaging the change in blood flow (hemodynamic response) related to energy use by brain cells.Since the early 1990s, fMRI has come to dominate brain mapping research because it does not require people to undergo shots nor surgery, to ingest substances, nor to be exposed to ionising radiation. This measure is frequently corrupted by noise from various sources; hence, statistical procedures are used to extract the underlying signal. The resulting brain activation can be graphically represented by color-coding the strength of activation across the brain or the specific region studied. The technique can localize activity to within millimeters but, using standard techniques, no better than within a window of a few seconds. Other methods of obtaining contrast are arterial spin labeling and diffusion MRI. The latter procedure is similar to BOLD fMRI but provides contrast based on the magnitude of diffusion of water molecules in the brain.

2.2.3 (functional)near-infrared spectroscopy

fNIRS is a non-invasive imaging method involving the quantification of chromophore concentration resolved from the measurement of near infrared (NIR) light attenuation or temporal or phasic changes. NIR spectrum light takes advantage of the optical window in which skin, tissue, and bone are mostly transparent to NIR light in the spectrum of 700900 nm, while hemoglobin (Hb) and deoxygenated-hemoglobin (deoxy-Hb) are stronger absorbers of light. Differences in the absorption spectra of deoxy-Hb and oxy-Hb allow the measurement of relative changes in hemoglobin concentration through the use of light attenuation at multiple wavelengths. Two or more wavelengths are selected, with one wavelength above and one below the isosbestic point of 810 nm at which deoxy-Hb and oxy-Hb have identical absorption coefficients. Using the modified Beer-Lambert law (mBLL), relative concentration can be calculated as a function of total photon path length. Typically the light emitter and detector are placed ipsilaterally (each emitter/detector pair on the same side) on the subject's skull so recorded measurements are due to back-scattered (reflected) light following elliptical pathways.

2.2.4 positron emission tomography

Positron-emission tomography (PET) is a nuclear medicine functional imaging technique that is used to observe metabolic processes in the body as an aid to the diagnosis of disease. The system detects pairs of gamma rays emitted indirectly by a positron-emitting radionuclide, most commonly fluorine-18, which is introduced into the body on a biologically active molecule called a radioactive tracer. Three-dimensional images of tracer concentration within the body are then constructed by computer analysis. In modern PET-CT scanners, three-dimensional imaging is often accomplished with the aid of a CT X-ray scan performed on the patient during the same session, in the same machine.

If the biologically active tracer molecule chosen for PET is fludeoxyglucose (FDG), an analogue of glucose, the concentrations of tracer imaged will indicate tissue metabolic activity as it corresponds to the regional glucose uptake. Use of this tracer to explore the possibility of cancer metastasis (i.e., spreading to other sites) is the most common type of PET scan in standard medical care (representing 90 percentage of current scans). Metabolic trapping of the radioactive glucose molecule allows the PET scan to be utilized[5]. The same tracer may also be used for PET investigation and diagnosis of types of dementia. Less often, other radioactive tracers, usually but not always labeled with fluorine-18, are used to image the tissue concentration of other types of molecules of interest.One of the disadvantages of PET scanners is their operating cost

Proposed method

The proposed system is a BCI controller for unmanned aerial vehicle which is based on Electroencephalography.In practice, a teleoperation is performed through controlling drones state vector that normally consists of three position coordinates, three components of the velocity vector, and anywhere between three and nine parameters that describe the vehicles attitude. A typical drone control system comprises two submodules: A low-level, inner-loop, onboard control system and a high-level, outer-loop, offboard control system . For major radio communications these two submodules are typically equipped with a transceivera multipurpose device that consists of both a transmitter and a receiver and is used for sending/receiving the commands to/from UAV. Together, the aircraft and its control system could be considered.

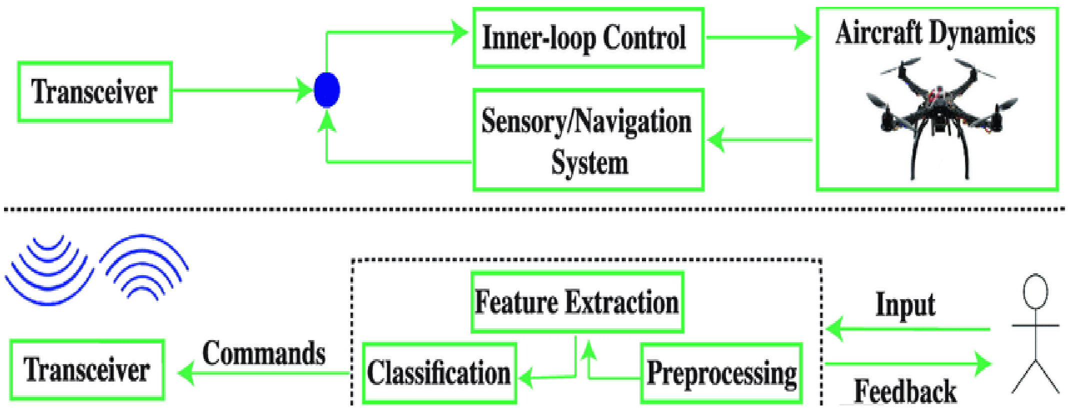

Fig. 3.1: Schematic of the basic configuration of brain-controlled Unmanned Aerial vehicles

The figure 3.1 explains the basic work flow of a standard BCI device.The pilot wears a device which is used to record brain signals.As of the proposed system we are considering a non invasive EEG based brain signal capturing device.The device will be mounted on top of the pilot's head in order to record signal.The BCI device consists of mainly 3 stages the raw signal from the brain is recorded by the EEG device and is sent to the processing unit in order to turn it into useful control signal[6].The raw signals received from the EEG device will first undergo preprocessing followed by feature extraction and classification.After classification the control signals will be issued which will move towards transmitter.All these parts are collectively known as high level system.The transceiver is a collection of radio transmitter and receiver where the transmitter is usually placed in the high level control system and the receiver is situated at the low level control system[7].The high level control system is responsible to issue corresponding control signals to complete a desired mission.Where the low level system is responsible to follow the signals accordingly.The transmitted signal is received by the on-board receiver and the inner loop/low level control system controls the UAV accordingly.

3.1 Control essentials

In practice, a teleoperation is performed through controlling drones state vector that normally consists of three position coordinates, three components of the velocity vector, and anywhere between three and nine parameters that describe the vehicles attitude. A typical drone control system comprises two submodules: A low-level, inner-loop, onboard control system and a high-level, outer-loop, offboard control system

3.1.1 Low-level control system

The onboard, inner-loop control system has two main tasks:

- engaging the guidance system to generate the trajectory that UAV needs to follow in state space in accordance with the receiving reference commands issued by the outer-loop control
- operating the UAV to follow the generated trajectory and stabilizing the airframe using available sensor inputs. Global navigation satellite systems, which also include GPS and inertial navigation systems alongside with other onboard sensors, are essential components at the core of most UAV guidance-navigation systems, and are used to enhance the estimation of the vehicle state.

The seminal role of the inner-loop control is even more evident, when the aircraft is required to operate in a shared-control mode with high levels of autonomy.

3.1.2 High-Level control System

The outer-loop control system, which is typically located in the ground station, gives the pilot the ability to deliver a desired mission, such as following a trajectory, to the UAV. This can be done through transmitting a simple set of navigational commands via a telemetry link. Employing a high-level control system is indispensable in aircraft that operate in the first or second autonomous mode, as these systems rely on external instructions to function. Therefore, designing a robust outer-loop control system is essential in developing brain-controlled UAVs.

3.2 Training and feedback

Training is a sine qua non for BCI users, and in particular for brain-controlled UAV operators. The crucial importance of training could be viewed from two aspects. First, users can learn how to modulate their brain activity patterns, based on the system feedback, in order to gain a dexterous control over the aircraft. Second, the system can learn how to avoid future errors by co-adaptation via machine learning strategies. In a typical BCI, users go through an offline training phase prior to running the experiment; however, coadaptive algorithms, offered by state-of-the-art classification, make it possible to fulfill the training online. Another determining factor in the training phase is BCI paradigm for systems based on induced potentials that requires a more rigorous training compared to those using evoked potentials.

Training brain-controlled UAV operators can be done either in a virtual or real environment or both. Since the underlying idea behind most MI-based BCI controllers is similar, controlling a cursor is a putative means for training pilots prior to performing teleoperation in the real world. Fig. is a demonstration of such a training sequence. Providing feedback for a brain-controlled UAV operator is different from other BCI-based devices, since during teleoperation having a direct visual contact with the aircraft is not feasible. Therefore, a visual interface is needed to present the recorded footage by the onboard camera and provide feedback for the pilot. In an attempt to minimize pilots training time, Kosmyna et al. proposed a co-learning based BCI; using an ad hoc bi-directional feedback channel, the operators could validate the BCI output by providing an affirmative feedback to the system

3.3 Control strategies

Depending on the BCI design, the brain-controlled UAV operator can either control the aircraft directly or indirectly. In the former approach, the pilot uses BCI to directly actuate the aircraft in the state space (i.e., navigating the aircraft to right/left, up/down, forward/backward, etc.) .The low level system blindly follows the commands given from the pilot in this method.Here the pilot has more work load and level if automation is very less.In the indirect approach, the operator controls the aircraft through specifying its future trajectory and/or destination. The inner-loop onboard control system is responsible for the continuous adjustment of the aircraft states.This is done with the help of future trajectory received from the pilot and the input obtained from the array of sensors mount on the UAV.An intelligent decision making agent equipped on-board generates the decision what cahnges should be made to the UAVs position vectors.

3.4 Preprocessing

Pre-processing techniques help to remove unwanted artifacts from the EEG signal and hence improve the signal to noise ratio. A pre-processing block aids in improving the performance of the system by separating the noise from the actual signal.preprocessing might vary case by case. The simplest and most widely used method to remove artifacts and extract the desired frequency band is filtering. The most common filters include high-pass, low-pass, band-pass, and notch filter, which can be combined with other computational techniques such as independent component analysis (ICA) or common average reference to remove artifacts and improve signal to noice ratio.

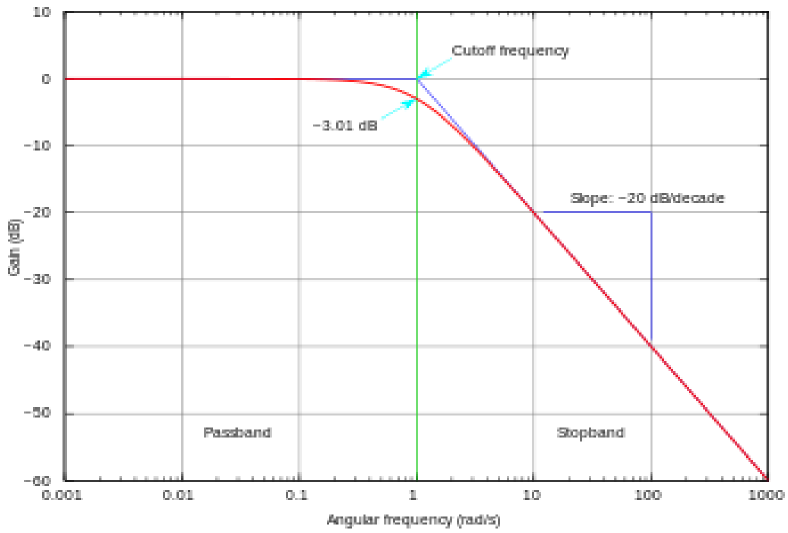

Fig. 3.2: Low pass filter

3.4.1 Low pass filter

A low-pass filter (LPF) is a filter that passes signals with a frequency lower than a selected cutoff frequency and attenuates signals with frequencies higher than the cutoff frequency. Figure 3.2 shows the relation between cut off frequency and the frequencies preserved. It shows the output of a signal after it is passed through low pass filter The exact frequency response of the filter depends on the filter design. The filter is sometimes called a high-cut filter, or treble-cut filter in audio applications. A low-pass filter is the complement of a high-pass filter.

Low-pass filters exist in many different forms, including electronic circuits such as a hiss filter used in audio, anti-aliasing filters for conditioning signals prior to analog-to-digital conversion, digital filters for smoothing sets of data, acoustic barriers, blurring of images, and so on. The moving average operation used in fields such as finance is a particular kind of low-pass filter, and can be analyzed with the same signal processing techniques as are used for other low-pass filters. Low-pass filters provide a smoother form of a signal, removing the short-term fluctuations and leaving the longer-term trend.

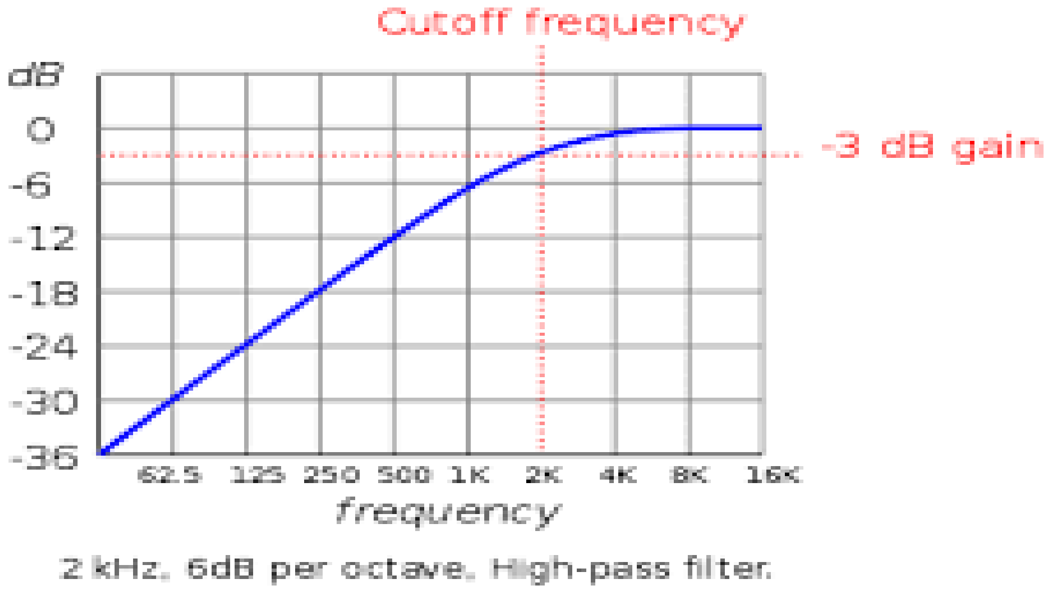

Fig. 3.3: High pass filter

3.4.2 High pass filter

A high-pass filter (HPF) is an electronic filter that passes signals with a frequency higher than a certain cutoff frequency and attenuates signals with frequencies lower than the cutoff frequency. Figure 3.3 shows the relation between cut off frequency and the frequencies preserved.It shows the output of a signal after it is passed through high pass filter. The amount of attenuation for each frequency depends on the filter design. A high-pass filter is usually modeled as a linear time-invariant system[8]. It is sometimes called a low-cut filter or bass-cut filter. High-pass filters have many uses, such as blocking DC from circuitry sensitive to non-zero average voltages or radio frequency devices. They can also be used in conjunction with a low-pass filter to produce a bandpass filter.

3.4.3 Notch filter

In signal processing, a band-stop filter or band-rejection filter is a filter that passes most frequencies unaltered, but attenuates those in a specific range to very low levels[9]. It is the opposite of a band-pass filter. A notch filter is a band-stop filter with a narrow stopband (high

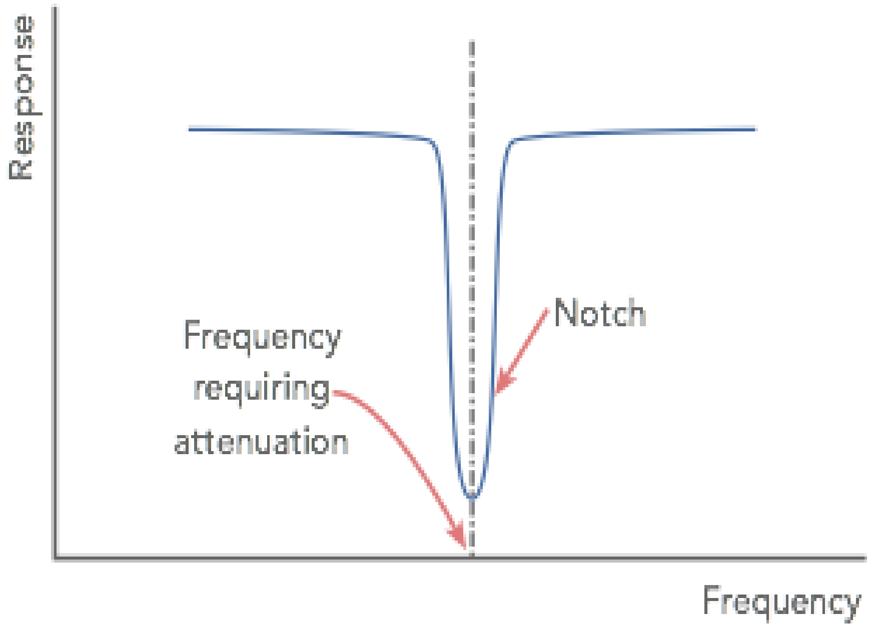

Fig. 3.4: Notch filter

Q factor).The output obtained after the filter is plotted in the figure 3.4.

Narrow notch filters (optical) are used in Raman spectroscopy, live sound reproduction (public address systems, or PA systems) and in instrument amplifiers (especially amplifiers or preamplifiers for acoustic instruments such as acoustic guitar, mandolin, bass instrument amplifier, etc.) to reduce or prevent audio feedback, while having little noticeable effect on the rest of the frequency spectrum (electronic or software filters). Other names include ’band limit filter’, ’T-notch filter’, ’band-elimination filter’, and ’band-reject filter’.Typically, the width of the stopband is 1 to 2 decades (that is, the highest frequency attenuated is 10 to 100 times the lowest frequency attenuated). However, in the audio band, a notch filter has high and low frequencies that may be only semitones apart.

3.5 Feature extraction

feature extraction block helps to retrieve the most relevant features from the signal. These features will aid the decision making mechanism in giving the desired output.In machine learning feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is a dimensionality reduction process, where an initial set of raw variables is reduced to more manageable groups (features) for processing, while still accurately and completely describing the original data set.

When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

3.5.1 Power spectral density value

The power spectrum of a time series x(t) describes the distribution of power into frequency components composing that signal. According to Fourier analysis, any physical signal can be decomposed into a number of discrete frequencies, or a spectrum of frequencies over a continuous range. The statistical average of a certain signal or sort of signal (including noise) as analyzed in terms of its frequency content, is called its spectrum.

When the energy of the signal is concentrated around a finite time interval, especially if its total energy is finite, one may compute the energy spectral density. More commonly used is the power spectral density (or simply power spectrum), which applies to signals existing over all time, or over a time period large enough (especially in relation to the duration of a measurement) that it could as well have been over an infinite time interval. The power spectral density (PSD) then refers to the spectral energy distribution that would be found per unit time, since the total energy of such a signal over all time would generally be infinite. Summation or integration of the spectral components yields the total power (for a physical process) or variance (in a statistical process), identical to what would be obtained by integrating $x^2(t)$.

3.5.2 Phase coherency

The spectral coherence is a statistic that can be used to examine the relation between two signals or data sets. It is commonly used to estimate the power transfer between input and output of a linear system. If the signals are ergodic, and the system function linear, it can be used to estimate the causality between the input and output.

3.5.3 Common spatial pattern

Common spatial pattern (CSP) is a mathematical procedure used in signal processing for separating a multivariate signal into additive subcomponents which have maximum differences in variance between two windows

3.6 Classification

classification is the problem of identifying to which of a set of categories (sub-populations) a new observation belongs, on the basis of a training set of data containing observations (or instances) whose category membership is known.. The five general classes of classifiers are as follows: linear classifiers, nonlinear Bayesian classifiers, neural networks, nearest neighbor classifiers

3.6.1 Linear classifier

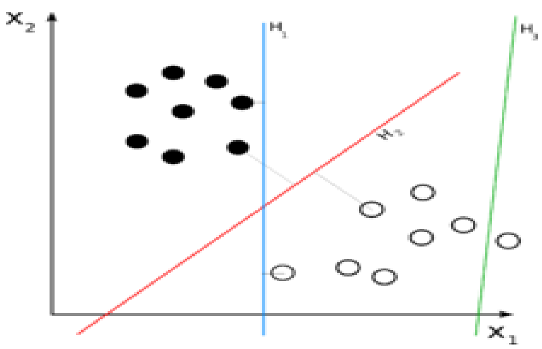

Fig. 3.5: Linear classifier

In the field of machine learning, the goal of statistical classification is to use an object's characteristics to identify which class (or group) it belongs to. A linear classifier achieves this by making a classification decision based on the value of a linear combination of the characteristics. The classification space is visualized in figure 3.5. An object's characteristics are also known as feature values and are typically presented to the machine in a vector called a feature vector. Such classifiers work well for practical problems such as document classification, and more generally for problems with many variables (features), reaching accuracy levels comparable to non-linear classifiers while taking less time to train and use. linear methods can only solve problems that are linearly separable (usually via a hyperplane).

3.6.2 Nonlinear classifier

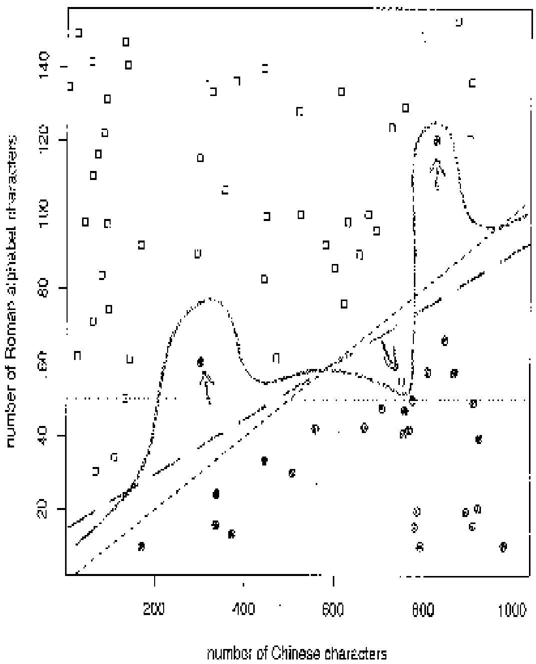

Fig. 3.6: Non Linear classifier

non-linear classifier when data is not linearly separable. Under such conditions, linear classifiers give very poor results (accuracy) and non-linear gives better results. This is because non-linear Kernels map (transform) the input data (Input Space) to higher dimensional space(called Feature Space) where a linear hyperplane can be easily found.The classification boundary is depicted with figure 3.6.

3.6.3 Neural networks

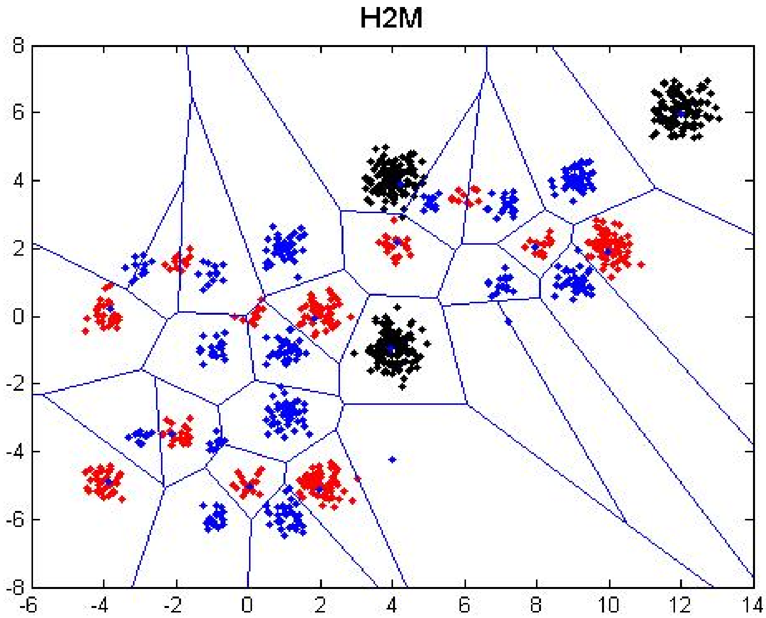

Fig. 3.7: Neural network classifier

Artificial neural networks are relatively crude electronic networks of neurons based on the neural structure of the brain. They process records one at a time, and learn by comparing their classification of the record (i.e., largely arbitrary) with the known actual classification of the record. Basic block diagram is depicted in figure 3.8. The errors from the initial classification of the first record is fed back into the network, and used to modify the networks algorithm for further iterations[9]. The neural netwrok classifies datas that are alike the one visualised in the figure 3.7. A neuron in an artificial neural network is

1. A set of input values (xi) and associated weights (wi).

2. A function (g) that sums the weights and maps the results to an output (y).

Neurons are organized into layers: input, hidden and output. The input layer is composed not of full neurons, but rather consists simply of the record's values that are inputs to the next layer of neurons. The next layer is the hidden layer. Several hidden layers can exist in one neural network. The final layer is the output layer, where there is one node for each class. A single sweep forward through the network results in the assignment of a value to each output node, and the record is assigned to the class node with the highest value.

Training an artificial neural network

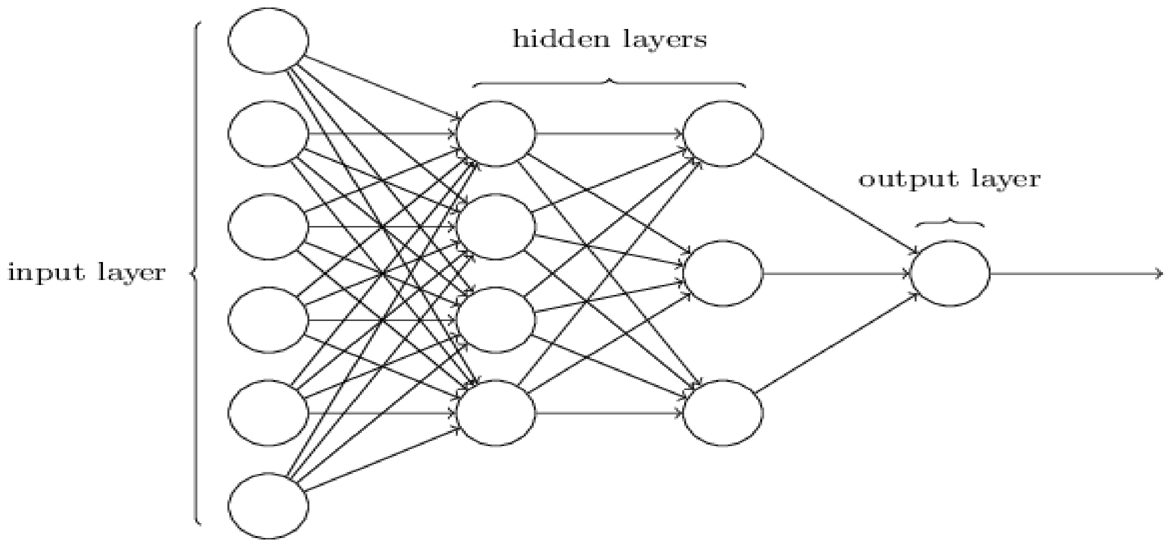

Fig. 3.8: Neural network block diagram

In the training phase, the correct class for each record is known (termed supervised training), and the output nodes can be assigned correct values – 1 for the node corresponding to the correct class, and 0 for the others. (In practice, better results have been found using values of 0.9 and 0.1, respectively.) It is thus possible to compare the network's calculated values for the output nodes to these correct values, and calculate an error term for each node (the Delta rule). These error terms are then used to adjust the weights in the hidden layers so that, hopefully, during the next iteration the output values will be closer to the correct values.

The iterative learning process

A key feature of neural networks is an iterative learning process in which records (rows) are presented to the network one at a time, and the weights associated with the input values are adjusted each time. After all cases are presented, the process is often repeated. During this learning phase, the network trains by adjusting the weights to predict the correct class label of input samples. Advantages of neural networks include their high tolerance to noisy data, as well as their ability to classify patterns on which they have not been trained. The most popular neural network algorithm is the back-propagation algorithm proposed in the 1980s.

Once a network has been structured for a particular application, that network is ready to be trained. To start this process, the initial weights (described in the next section) are chosen randomly. Then the training (learning) begins.

The network processes the records in the Training Set one at a time, using the weights and functions in the hidden layers, then compares the resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights for application to the next record. This process occurs repeatedly as the weights are tweaked. During the training of a network, the same set of data is processed many times as the connection weights are continually refined.

Note that some networks never learn. This could be because the input data does not contain the specific information from which the desired output is derived. Networks also will not converge if there is not enough data to enable complete learning. Ideally, there should be enough data available to create a Validation Set.

Feedforward, Back-propagation

The feedforward, back-propagation architecture was developed in the early 1970s by several independent sources (Werbor; Parker; Rumelhart, Hinton, and Williams). This independent co-development was the result of a proliferation of articles and talks at various conferences that stimulated the entire industry. Currently, this synergistically developed back-propagation architecture is the most popular model for complex, multi-layered networks. Its greatest strength is in non-linear solutions to ill-defined problems.

The typical back-propagation network has an input layer, an output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers but typically there are just one or two. Some studies have shown that the total number of layers needed to solve problems of any complexity is five (one input layer, three hidden layers and an output layer). Each layer is fully connected to the succeeding layer.

The training process normally uses some variant of the Delta Rule, which starts with the calculated difference between the actual outputs and the desired outputs. Using this error, connection weights are increased in proportion to the error times, which are a scaling factor for global accuracy. This means that the inputs, the output, and the desired output all must be present at the same processing element. The most complex part of this algorithm is determining which input contributed the most to an incorrect output and how must the input be modified to correct the error. (An inactive node would not contribute to the error and would have no need to change its weights.)

To solve this problem, training inputs are applied to the input layer of the network, and desired outputs are compared at the output layer. During the learning process, a forward sweep is made through the network, and the output of each element is computed by layer. The difference between the output of the final layer and the desired output is back-propagated to the previous layer(s), usually modified by the derivative of the transfer function. The connection weights are normally adjusted using the Delta Rule. This process proceeds for the previous layer(s) until the input layer is reached.

3.6.4 Nearest neighbour classifier

k-nearest neighbors algorithm (k-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression.In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.In k-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbors.

k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms.Both for classification and regression, a useful technique can be used to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where d is the distance to the neighbor.The neighbors are taken from a set of objects for which the class (for k-NN classification) or the object property value (for k-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.A peculiarity of the k-NN algorithm is that it is sensitive to the local structure of the data

3.7 Control singals

Considering the fact that in choosing the best classification algorithm, there is a trade-off between robustness and computational cost on the one hand, and the analysis speed on the other. Linear classifiers are generally the preferred class for developing brain-controlled UAVs. Linear discriminate analysis and support vector machine (SVM) are the main two types that have been widely used in previous prototypes. To the best of our knowledge, the only exception in this trend is the study by Kosmyna et al., where they reported developing an ad hoc, co-learning-based BCI using recurrent neural network (i.e., a nonlinear classifier)[10]. In prototypes that use basic MI-based BCI, the pilot imagines right/left hand movement to actuate the aircraft to right/left, and therefore the system needs a binary classifier to distinguish between the two classes. However, in pursuit of increasing degrees of freedom, the majority of developers used multiclass classifiers to map complex MI tasks into several output control commands for the aircraft.

3.8 Performance evaluation

Despite the significant progress that has been made in the field of BCI, the lack of a widely accepted platform for evaluating and comparing the performance of different BCI systems is being felt. Several key factors can be enumerated, whose variability is considered as the main impediment on the way of reaching a common ground for assessment within the BCI community; subjects, data acquisition methods, experiment protocols and tasks, and evaluation metrics are among these factors. Nevertheless, performance evaluation and comparison are feasible on the basis of a particular parameter such as speed and accuracy, ITR, or receiver operating characteristic (ROC) curve

Several ad hoc strategies have been used in previous studies to evaluate the performance of developed brain-control UAVs[10] LaFleur et al. used ITR metric based on Shanons work, customized for asynchronous BCI. In many of these studies, performance assessment is task specific and is measured intrinsically for each subject. A universal framework for assessing the performance of brain-controlled UAVs is yet to be established

Regardless of their underlying configuration, the basic principle that governs different hybrid BCIs remains the same; one of the engaged modalities is counterbalancing limitations of the other and vice versa. In these systems, the grand hierarchy determines [10]. whether different components are engaged concurrently or sequentially. In the first case, recorded signals from different sources are processed in parallel and subsequently mapped to control commands. The simultaneous use of different input modalities could significantly improve the BCI bit-rate and the information throughput. On the other hand, in sequential hybrid BCIs, the output of one modality serves as the input for others. The practical merit of sequential hybrid BCIs is twofold. First, they could be designed in a way that enables the operator to selectively initiate/terminate other control processes, e.g., a sequential ERS-based brain switch could be used to turn ON/OFF an SSVEP BCI. Second, by the same token, a sequential hybrid BCI could enable the operator to rectify, reinforce, or cancel the issued control commands and, therefore, reduce the overall false positive rate of the system. Numerous studies were dedicated to review the design and application of the hybrid BCI[10].

Conclusion

The intriguing idea of deciphering brain signals into direct,indirect, and implicit control commands for different devices has been the greatest motivation for numerous scientists around the globe to orient their research on developing BCI-based systems. These early efforts set the stage for others to engage BCI for controlling various robotic systems, and in particular flying robots.

A successful design and implementation of a brain-controlled UAV require a great deal of knowledge and expertise in both involved technologies (i.e., BCI and UAV). The key point in engineering integrated systems, such as braincontrolled UAVs, is to consider the involved components as parts of the entire ensemble and not as an independent, secluded entities. Choosing proper techniques for implementation of different elements is highly influenced by the entire systems configuration. From this standpoint, the architecture of the employed BCI in a brain-controlled UAV is different from other robotic systems, for they demonstrate an inherently unstable nature. In addition, controlling an aircraft in real-time is a continuous task that requires a high Infromation transfer rate; this poses a technical challenge on developing BCI-based control systems for drones. Using efficient control strategies is another essential consideration in these systems. Controlling a drone by executing the MI task is an exhausting procedure that can restrict pilots capability to maneuver the aircraft. Path planning or target selection, on the other hand, are indirect control approaches that provides more degrees of freedom for the BCI operator

Previous research on brain-controlled UAVs has paved the way for successful implementation of these systems. From the very first developed prototype, brain-controlled UAVs have experienced considerable improvement. However, significant progress is still needed to enhance their fidelity and robustness in order to see the application of these systems transcends just laboratories, and finds its way into our daily life.

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