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INVESTIGATING THE PROSPECT OF USING EMOTIV INSIGHT EEG HEADSET IN RECOGNIZING BRAINWAVE MODES

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Abstract

Thanks to its safety, simplicity many consumer-grade EEG hardware have been on-shelf with a wide range of prices and functionalities to realize the prospect of using human brainwaves to communicate with computer interfaces. This research examines the feasibility of using the Emotiv Insight® headset (with only 5 channels) for recognition of EEG patterns; focusing on the accuracy of different pattern recognition methods and sensitivities of 11 mental states.

We use an app written in LabVIEW to collect the EEG signal, then process data and design algorithm in MATLAB environment. In the feature extraction stage, we use Bandpass IIR and FIR digital filters and Discrete Wavelet Transform (DWT) to calculate band energies and channel energies, forming a feature vector of length 26. As for classification algorithms, we investigate Bagged Trees, Support Vector Machine (SVM) and Neural Network. The average accuracies of IIR, FIR and DWT features are 77.86%, 69.27% and 76.72%, respectively. The DWT do not outperform IIR Bandpass filter but require twice the time for computation. Among classification algorithms, Bagged Trees gives an accuracy of 76.47%, SVM 76.33%, and Neural Network 70.04%. Not all states are equally recognizable, for example, imagery tasks Thinking Forward and Thinking Backward have mutual misclassification rates of up to 20%.

The result is satisfactory since an accuracy of nearly 80% is obtained using IIR combined with Bagged Trees or SVM. This opens up the feasibility of using low-cost EEG hardware to perform brain-computer interfaces. For this particular Emotiv Insight headset, we thus propose the scheme of using IIR Bandpass filter combined with Bagged Trees and SVM for brainwave recognition

List of abbreviations

Abbreviations	Meaning
DWT	Discrete Wavelet Transform
EEG	Electroencephalography
FFT	Fast Fourier Transform
FIR	Finite impulse response
ICA	Independent component analysis
IIR	Infinite impulse response
KNN	K nearest neighbors
MLP	Multi-layer perceptron
NB	Naïve Bayes
PCA	Principle component analysis
SVM	Support Vector Machine
WT	Wavelet Transform
AVG	Average
STD	Standard deviation

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1 Introduction

1.1 Motivation

Electroencephalography (EEG) is a noninvasive electrophysiology method for recording brainwaves. This method has long been utilized in medical practices since the 1950s, due to the fact that brainwaves are good indicators of abnormalities in brain activities, such as epileptic attacks. Doctors have observed and tried to recognize EEG patterns, aiming for illness diagnosing and treatments.

The human brain works by means of electrical signals. The nerve impulse, which is technically called an action potential, is actually an inversion in the membrane potential. Its transmission along the axon (a long branch stemmed from the body of a neuron for transferring the signal to other neurons) is maintained by ion channels, the most common of which are Na^+ channel and K^+ channel. When a certain number of neurons fire out together to form a strong enough nerve pulse, it can be transmitted over the skull, to the scalp. The electrical signals at the scalp are typically in the range of 10 to 100 microvolts and special equipment is required to measure them. Thus, the recording of EEG requires really sensitive electrodes sitting on the scalp, and really powerful amplifiers.

Nowadays, many commercial EEG headsets are available, with a wide range of options for users, whether for personal use or academic research. These headsets have various new functionalities compared to the conventional equipment in medical centers. For example, they may have semi-dry sensors and wireless connection, allowing the users to feel comfortable and can still perform free movements. The precision, as well as spatial resolution (number of channels) of the devices, vary with the prices and the companies who provide them. The prices may vary from several hundred dollars for EEG headsets with less than 16 channels to over twenty thousand dollars for headsets with more than 64 channels (Farnsworth, 2017).

Thanks to its safety, simplicity and reasonable price, EEG now is becoming increasingly popular to the public due to its expansion to other fields, apart from medical usages, such as gaming, neuromarketing, and brain-computer interfaces (Abdulkader, Atia, & Mostafa, 2015).

Emotiv Inc. is a bioinformatics company which offers neuroheadsets and software for BCI applications and research. The three hardware headsets that they currently provide come with 5, 14 and 32 channels respectively. The Emotiv Insight is a headset with five channels offered under a price of $299, along with a cost-per-usage of $99 a month for research usage (including license for obtaining the raw data) (the cost-per-usage is lower for longer subscription periods). It uses semi-dry polymer electrodes, is equipped with wireless connection and has a setting up time of only 1 to 2 minutes. The data quality of the Emotiv Insight is self-rated as GOOD, while that is HIGH and HIGHEST for headsets with more channels.

Figure 1: Two commercial Emotiv EEG headsets: EPOC+(left) and Insight(right)

With such a limited number of channels and relatively low cost, our research team finds that it is necessary to investigate the possibility of using the measurements from Emotiv Insight to predict some main types of mental states.

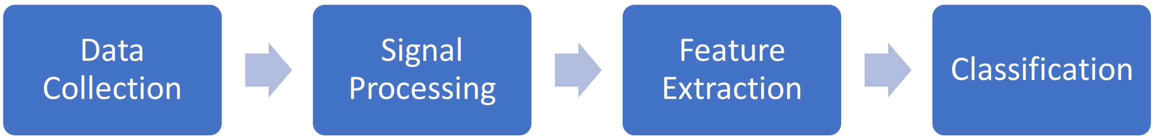
1.2 Objectives

This research aims at accessing the feasibility of using the signals obtained from EEG Insight headset for classification, with the following objectives:

- Survey the utilization of different signal processing and feature extraction schemes for EEG signals.
- Determine the accuracies between conventional classification methods on the EEG data for whether it is good enough to be used in other applications.
- Examine the relative ability of the headset's five channels to extract different activities of the brain, and which types of brainwave are not well represented through these channels.

1.3 Aspects for investigations

In this research, we investigate the use of 5-channel Emotiv Insight headset to classify some mental states and facial expressions. The 7 facial expressions include: normal, open eyes, close eyes, looking left, looking right, raising eyebrows and smiling. The 4 thinking modes are: moving forward, moving backward, turning left and turning right.



In the signal processing stage, we compare the Discrete Wavelet Transform and Digital filter methods. EEG signals are considered to be unstable and appear at low frequencies, thus DWT is may be more favorable to conventional Digital Filter (Sanei & Chambers, 2007).

In the feature extraction stage, we use the band energies and channel energies to form a feature vector with 26 dimensions. We compare the full and partial use of feature vector to give a comparison of accuracy and processing time on computer.

As for classification algorithms, we focus on SVM and Bagged Trees algorithm. Artificial Neural Network is also examined. The accuracy for each method is then compared and the most suitable method for recognizing EEG pattern can be withdrawn.

1.4 Scope of study

This research is a validation on the feasibility of using EEG data with a limited number of channels, from a low-cost commercial hardware, to recognize different modes of brain activities.

The data for research is the raw EEG signal taken from the Emotiv Insight headset. The five channels on the headset are AF3, AF4, T7, T8 and Pz; with reference to the international 10-20 system for locating EEG electrodes.

For signal processing, we use the conventional techniques for bands separation, including Discrete Wavelet Transform and Digital bandpass filters (investigating both IIR and FIR techniques). Median filter for denoising is also investigated.

In the feature extraction stage, the scheme is to use the relative band energies within a channel as wells as relative energies among the five channels.

As for classification algorithms, we utilize the conventional algorithms, including Support vector machine, Bagged Trees and Neural Network.

The Data Collection stage is carried out through an app written in LabVIEW being able to communicate with the EEG headset, with suggesting videos for the subjects and real-time plotting of the recordings.

For convenience, the investigations are conducted within the MATLAB environment, utilizing the function in toolboxes such as Signal Processing Toolbox, Wavelet Toolbox, Statistics and Machine Learning Toolbox, Neural Network Toolbox.

1.5 Scientific Significance and Practical Applications

If positive results are obtained, that is, the EEG headsets with low cost and a limited number of channels can be used to produce good classification result, it will be a motivation for further development in various EEG applications in entertainment, education, etc. with competitive price.

Or even, it will be a driving force for researchers and companies to manufacture better and cheaper EEG headsets.

Although the research's investigation is carried out in MATLAB for convenience. The scheme for classifying the EEG signals can be deployed in platforms and languages other than MATLAB. If the expected accuracy is satisfied, software developers can apply the technique in this research to build desktop or mobile apps to provide prompt use of EEG technology.

2 Background and related works

2.1 Commercial EEG headsets and BCI systems

In recent years, while there appear more and more consumer-grade EEG headsets in the market, researchers have posed the questions whether the results obtained from these devices are reliable or to what extent can those products be effective for BCI systems.

Hairston et al. (2014) made comparisons among

- BioSemi's ActiveTwo (64 channels)
- Advanced Brain Monitoring's B-Alert X10 (9 channels)
- Emotiv' EPOC (14 channels)
- QUASAR's Dry Sensor Interface 10–2 (9 channels)

and focus on system design, usability factors and comfort issues. One of the results drawn out is that some headsets' flexible arms do not adapt well for different head sizes, and result in uncomfortable pressure point to the user, which may eventually decrease the signal quality.

Further research on the usability of 32-channel Biosemi cap, 14-channel Emotiv EPOC, and 8-channel g.Sahara cap was conducted by Nijboer et al. (2015). The paper evaluates off-line classification accuracies and the results are 88.5%, 62.7%, and 61.7% respectively for these three headsets. It can be seen that there is a substantial decrease in accuracy corresponding to the number of sensors. The author also noted that without information about effectiveness, the Emotiv EPOC – the dry headset is preferable within participants, compared to the other two gelled caps.

There is a paper which focuses on comparisons between low-cost consumer-grade EEG devices: Emotiv EPOC (14 channels) and Neurosky MindWave (1 channel) (both of which uses dry flexible arms) of Maskeliunas et al. (2016). It reported the positive result that one of the headsets can achieve a recognition accuracy of over 75% for blinking recognition.

This research on the Emotiv Insight – a new product after the Emotiv EPOC. There are fewer works on its performance since it's quite new and it's is not intended for research. We will focus on its ultimate ability to give the recognition accuracy that is high enough for BCI applications after passed through conventional algorithms.

2.2 Digital Filter and Discrete Wavelet Transform

The EEG signal is considered to be unstable (having frequency components changing with time), having a high noise-to-signal ratio. While Fast Fourier Transform (FFT) and Digital Filter are time-honored methods for giving the frequency spectrum of various signals, Wavelet Transform is preferable since it can give better result on the temporal extent of each frequency component.

There are several reports on the different methods for processing EEG signals. Shaker (2007) proposed a scheme for combining DWT and FFT for classifying major rhythms in EEG waves. Lakshmi et al. (2014) conducted a comprehensive survey on EEG signal processing methods, including ICA, PCA, WT, AR, WPD, and FT.

As valuable as the methodological insights accomplished by these researches, it is still necessary to check for eventual results that different techniques can produce in recognizing brainwave patterns. Furthermore, the Emotiv Insight headset has already incorporated some filters itself and the data taken out may be different from raw signals used in other researches. Our work will compare the classification accuracies among the feature extraction schemes using DWT, IIR, and FIR Digital Filter.

2.3 EEG pattern recognition methods

There are more and more researches focusing on the application of machine learning algorithms for recognizing EEG patterns.

Lotte et al. (2007) gave a review on a wide range of methods including Linear Discriminant Analysis, Support Vector Machine, Neural Networks, Nonlinear Bayesian, Nearest Neighbor, along with the combination techniques: Boosting, Voting and Stacking. The paper provides a guideline for choosing algorithms in combination with the features extracted.

Belkacem et al. (2013) proposed a simple technique for offline – classification of four directions of eye movements from EEG signals. They used a simple tree decision method with thresholding technique and obtained a positive result of 50-85% correct among twenty subjects.

Chatterjee (2016) focused on EEG-based motor imagery with SVM and MLP algorithms. They use the C3 and C4 electrodes for detecting left and right limb movements and got the accuracy of around 85% for both methods.

Amin (2017) used wavelet-based features from a 128-channel dataset for classifiers such as KNN, SVM, MLP, and NB to get very high accuracies, usually over 90% for most feature sets and algorithms.

There is a report on the usability of the Emotiv Insight for human identification by Bashar (2016). The proposed method is an SVM classifier and achieved a remarkable result of 94% on 9 subjects.

These above researches usually use high-quality EEG headsets or are not specific to any hardware equipment. Our research will use Support Vector Machine, Neural Network, and Bagged Trees to classify the EEG data specifically taken from the low-cost Emotiv Insight headset with only 5 channels, aiming for deployment in BCI applications.

3 Materials and Methods

3.1 Collecting EEG signal of Emotiv Insight by a LabVIEW written app

3.1.1 Dataset specification

We investigate several main modes of facial expressions and thinking. The facial expressions include: opening eyes, closing eyes, raising eyebrows, looking left, looking right and smiling. The thinking modes (imagery tasks) are: moving forward, moving backward, turning left, and turning right.

The recordings were conducted on 10 volunteer subjects (all of whom are students) with ages from 19 to 25, using the Emotiv Insight. The signals are sampled at 128Hz with the resolution of 14 bits and the lowest significant bit equals 0.51 microvolt. Notch Filters at 50Hz and 60Hz has already been incorporated into the hardware (the power lines at the laboratory is 50Hz).

Figure 2: A recording of Thinking Forward state

Each subject expresses 11 states, 1 normal, 6 facial, and 4 thinking. Each state is repeated 20 times, with each time lasts for 8 seconds. For 6 facial expressions, there is a mark point indicating when the subject starts to exhibit the expression, which is written along with the signal file.

In all states, the subject sits down comfortably, looking at a screen showing suggesting videos for each state/expression. The sitting next-to instructor controls the collector app (written in LabVIEW) on a laptop, check for the headset working properly with good contact, and remove the signals which are disturbed, interrupted, having poor contacts or showing abnormalities by looking at the real-time plotting.

The description of each state is given below:

- Normal state: The subject sit comfortably in a chair, with eyes open, being calm and avoid any thinking tasks.
- Close eyes: From normal state, the subject is told to close eyes leisurely at about 2 to 4 seconds after the recording starts; and then keep eyes closed for the rest of the recording.
- Open eyes: From normal state, except for the eyes being closed, the subject is told to open eyes leisurely at about 2 to 4 seconds after the recording starts; and then keep eyes open for the rest of the recording.
- Looking left: From normal state, at about 2 to 4 seconds after the recording starts, the subject is told to look to the left and keep that until the recording stops.
- Looking right: From normal state, at about 2 to 4 seconds after the recordings starts, the subject is told to look to the right and continues until the recording stops.
- Raising eyebrows: From normal state, at about 2 to 4 seconds after the recording starts, the subject is told to raise his eyebrow, as if being surprised.
- For 4 thinking modes, throughout the recording, the subject is shown a video recorded from a game playing desktop. The four videos are from a common game, showing basic movements: walking ahead, stepping backward, turning left continuously and turning right continuously; respectively corresponding to thinking forwards, backward, left and right.

3.1.2 LabVIEW environment

The word LabVIEW stands for Laboratory Virtual Instrumentation Engineering Workbench. LabVIEW is a development environment produced by National Instruments, USA. It is based on a graphical language called G, which is known as a programming language profoundly different from conventional languages such as Pascal, C, Java, etc.

LabVIEW allowed users to program applications graphically. It provides visualizations for hardware configurations and data measurement, thus making it very well suited for building hardware interfaces to many scientific products.

This research uses a self-written app in LabVIEW communicating with the Emotiv Insight headset for carrying out the specific recordings described above.

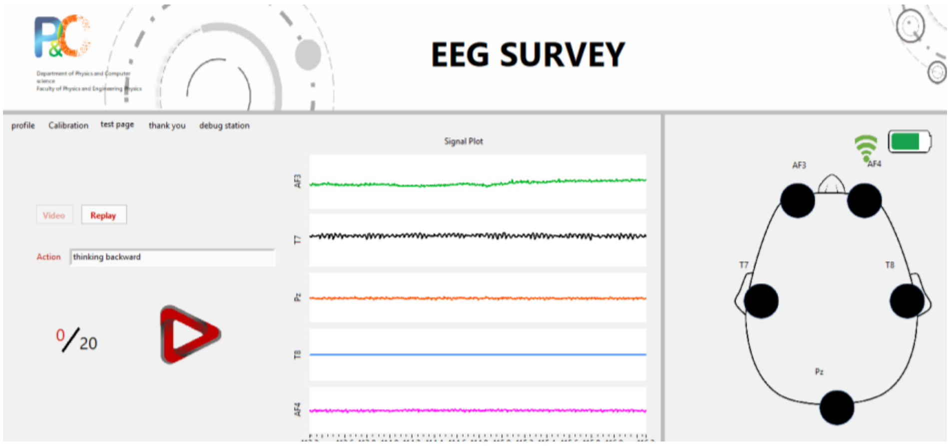


Figure 3: The working screen of the LabVIEW recording app

This app gives details information about the contact quality of each sensor, the battery percentage, etc. There is also a video projected to a separate screen to give suggestions for the subject being recorded. The signals received from the sensors are promptly plotted in the working screen so that some clearly unclean data will be rejected. The recordings are finally named and saved to the computer in the .txt file format.

3.2 Using MATLAB environment for signal analyzing and building algorithms

MATLAB (Matrix Laboratory) is a numerical computing environment widely used in Science and Engineering.

It is based on MATLAB language, a matrix-based language and is an easy to use programming environment which incorporates Numerical computation, Data Visualization, Statistical and Machine Learning, etc.

Many applications are built-into MATLAB toolboxes and graphical Apps. In this research, we will exploit the Statistical and Machine Learning Toolbox and Neural Network Toolbox, which provide quick and powerful functions for classifying EEG patterns.

Besides, the Signal Processing Toolbox and Wavelet Toolbox is also used to process the signals and extract the features from raw EEG for classification.

3.2.1 Classification Learning Toolbox

MATLAB's Statistical and Machine learning Toolbox™ provides functions to create trees and its training methods. Along with that, there are dozens of other common classification algorithms, including:

- Decision trees
- Support vector machine
- K nearest point
- Discriminant analysis
- Bagged Tree and Boosted Tree

3.2.2 Neural Network Toolbox

MATLAB's Neural Network Toolbox™ provides functions with algorithms for creating shallow or deep neural networks and training these nets. After training, the toolbox helps to visualize the training process with confusion matrices, ROC curves, etc.

3.3 Feature extraction with Digital Filter and Discrete Wavelet Transform

There are several main rhythms in brain waves (Sanei & Chambers, 2007).

- Delta waves (0.5-4 Hz): are associated with deep sleep and can be easily confused with muscle artifacts (of neck and jaws).
- Theta waves (4-7.5 Hz): are associated with creative inspiration and deep meditation, or drowsiness. Theta waves are examined for maturational and emotional studies.
- Alpha waves (8-13 Hz): can be detected in all parts of posteriors lobes of the brain, being the most prominent rhythm in the whole realm of brain activities. Alpha waves represent both relaxed and reflecting states. It may be confused with the act of closing the eyes. The amplitude is normally under 50 microvolts.
- Beta waves (14-26 Hz): are associated with active thinking, active attention, high alert, etc. The amplitude of beta rhythms is usually under 30 microvolts.
- Gamma waves (30-45 Hz): appear along with perceptions that combine two different senses, such as eyes and ears.

With the brain waves from 5 channels, we decide to separate each wave into its four sub-band frequencies, along with channel relative energies and one total power of 5 channels. Thus, there are a total of 26 features.

The band frequencies are:

- From 64Hz to 32Hz, corresponding to gamma rhythms
- From 32Hz to 16Hz, corresponding to beta rhythms
- From 16Hz to 8Hz, corresponding to alpha rhythms
- From 8Hz to 4Hz, corresponding to theta rhythms.

3.3.1 Digital Filter

We apply the built-in designfilt function in MATLAB to execute the Bandpass filters and then separate different ranges of frequency corresponding to main brainwave rhythms.

We analyze both the results obtained by IIR filter and FIR filter, both of which are of order 20.

Fundamentally, FIR filters are guaranteed to be stable but sharp filter specifications can lead to long filter lengths and eventually more computations. On the other hand, IIR filters have low computational cost but are potentially punstable (Orfanidis, 2010).

3.3.2 Discrete Wavelet Transform

Frequency analysis of a signal entails the task of separating different frequency bands from the measured signal. The most common method to take out a frequency component from a mixed signal is the Fourier transform, which in principle comparesc the signal with the basic sinusoidal waves. But for EEG signals, which are unstable and have a low frequency range, Wavelet transform is believed to be more suitable.

The reason is that a sinusoidal has a fixed frequency but spreads in all time, that is it is time localized but there is no localization in time. Fourier transform decomposed signals into sine waves, thus may give good results for stable signals (not changing much over time), but for rapidly-changing signals, it is no longer suitable. It may tell the existence of a frequency but the time localization of that frequency is not clear.

Wavelet transform, on the other hand, uses wavelet – a wave packet that has a fixed range of frequency but also lasts for a finite time interval. Thus, using wavelets to decompose the signal give the result which has good resolution in both frequency domain and time domain.

To take out a particular frequency from the original signal, the mother wavelet is stretched or squeezed (scaling) to that frequency and then shifted along the original to make decomposition. For digital signals, we use discrete wavelet transform, in which only a certain number of scaling factor is used, to keep the calculation finite. Furthermore, because low-frequency signals need a longer time to finish a cycle, we need to investigate them for over a longer period. These demands are well satisfied by multiresolution analysis in DWT.

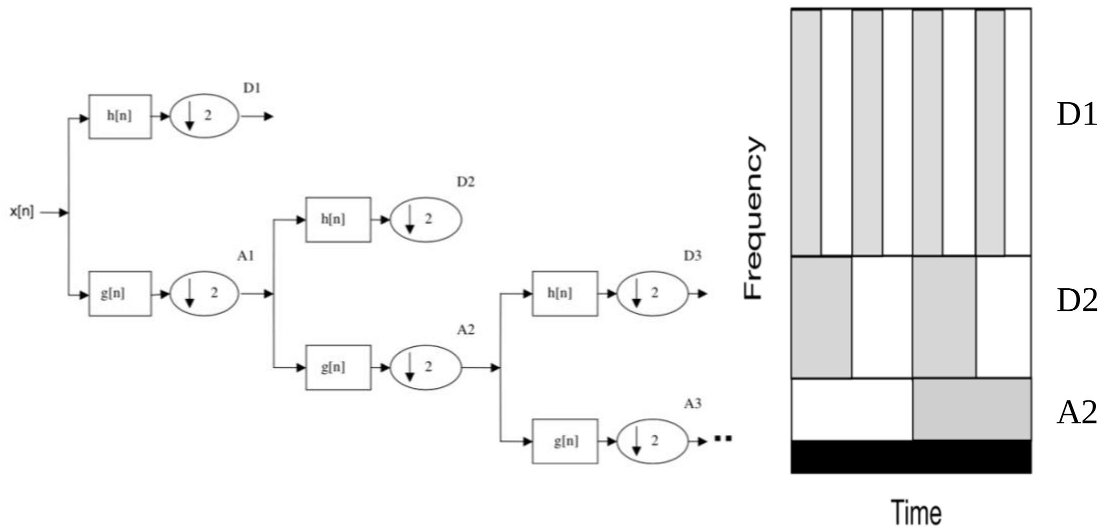


Figure 4: Illustration for multiresolution analysis in DWT

In DWT, the original signal X is passed through a high pass filter h[n] and then down sampled to give the detailed coefficients D1 since half of the frequencies are lost and we need less coefficients to store the signal. X is also passed through a low pass filter g[n] to give approximation coefficients A1, containing the information of the upper half of frequency range. A1 then goes through high pass and low pass to give D2 and A2, the process continues until we stop it or when the signal can no longer be down sampled (Landau, Páez, & Bordeianu, 2015).

The coefficients A and D can be reconstructed to give the frequency components of the original signal. Given f the sampling frequency of our signal, then the frequencies range described by that signal is from 0 to f/2, obeying the Nyquist rule. Then A1 represents the range from f/4 to f/2, A2 from f/8 to f/4 and the list goes on.

In our case, since f=128Hz, we will need to decompose the signal down to level 4 to get A1, A2, A3, and A4.

The MATLAB functions used are wavedec (wavelet decomposition) and wenergy (wavelet energy).

3.4 Classification Algorithms

3.4.1 Bootstrap Aggregating with Decision Trees

Bootstrap aggregating algorithm is considered a powerful one in classification. It can be applied to datasets having both a large number of classes and a large number of variables, and they are extremely resistant to outliers (Steinberg & Colla, 1995) (Sutton, 2005).

In this algorithm, decision trees are built with each node test on one particular attribute of the data and after one sample datum is passed over the tree, the class of that sample is then determined.

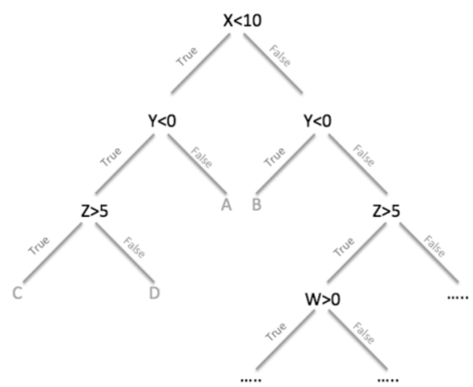


Figure 5: An example of a Decision Tree

Bagged Trees is an ensemble method, which uses many decision trees, each of which is fitted to a subset of the training data, and then using voting between these trees for classification. This method is believed to be able to combine weak learners into a strong learner.

This research uses the MATLAB function templateTree and fitcensemble with method Bag to apply Bootstrap aggregating with decision tree classifier. The maximum split for each tree is 219 and the number of learning cycles is set to 30. The scheme to prevent the model's overfitting to the training data is 5-fold cross validation.

3.4.2 Support vector machine

Support Vector Machine is basically a supervised learning method for a binary classification problem. For multiclass problems, this method can be modified using the one-versus-the-rest or one-versus-one approach. That is, multiple classifiers are fitted and then combined to form the final a multiclass classifier (Bishop, 2006).

In this algorithm, each labeled sample is considered a vector in a multidimensional space. The mission is then choosing good hyperplanes that divide the space into regions that well divide the data points of different classes. The criterion for determining a hyperplane is that it is equidistant or farthest from each set of points (Sanei & Chambers, 2007).

In this work, we use the Linear support vector machine method.

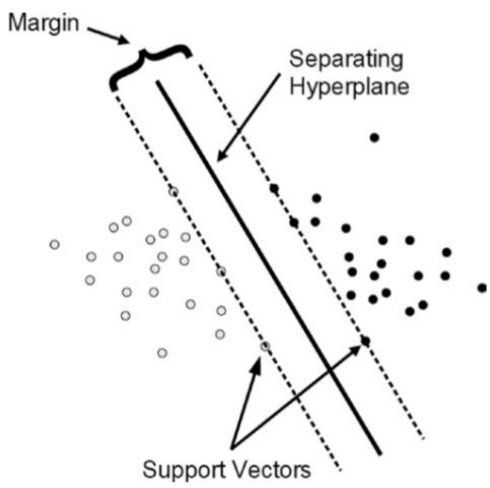


Figure 6: An illustration for Linear Support Vector Machine

After the hyperplanes are drawn out by learning the example data, the model can be applied to predict whether a new point belongs to which class, based on the region it falls on.

For more advanced versions of SVM, the surface separating data points are nonlinear and can be fitted better to the data.

This research uses the MATLAB functions templateSVM and fitcecoc to apply the SVM technique with versions Linear, Quadratic, Cubic, and Medium Gaussian. The scheme for preventing overfitting is 5-fold cross validation.

3.4.3 Artificial Neural Network

Artificial Neural Network is based on the simulation of the function of neurons in human brains. A network's architecture includes three parts: one input layer, one or more hidden layers and one output layer (Nielsen, 2015).

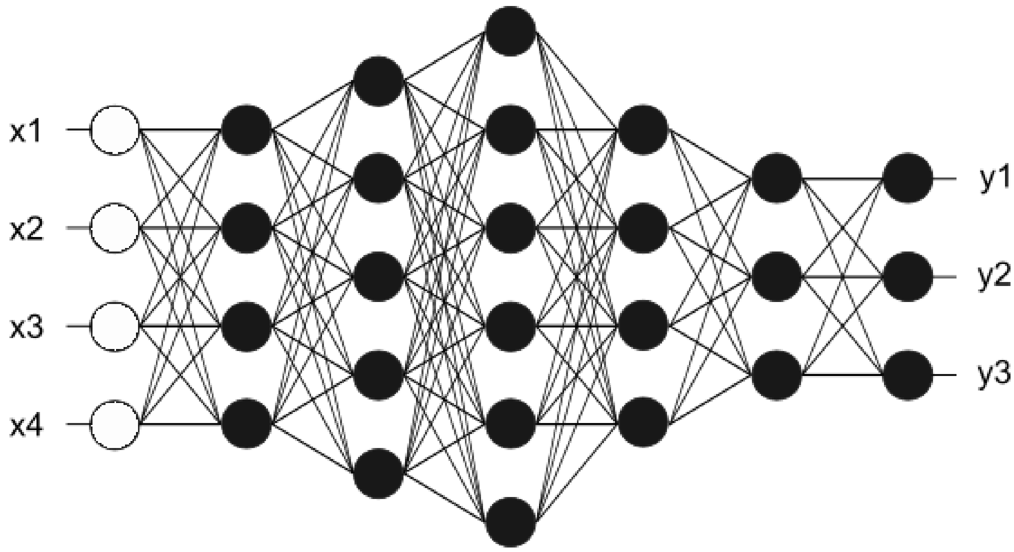


Figure 7: A Neural Network structure with 4 hidden layers

Each node in the network resembles a neuron and is assigned a value. The values of the input layers in this work, for example, are the relative energies between different wavebands and channels. From the input, each node in the next layer will get a value calculated as a linear combination of the previous layers. The coefficients for calculating these linear combinations are fist initialized randomly.

Through the learning process, when sample data are passed through the network, the actual output values and the ideal values representing the classes that we want to achieve are compared. A cost function (also called error function) is built from that comparison and the training stage is actually finding the minimum of that cost function (Bishop, 2006). Then the coefficients are changed to gradually improve the performance of the network.

This research uses MATLAB functions patternnet to create a shallow network with one hidden layer with 16 nodes for classification of a feature vector of size 25 and 11 classes. Fifty percent of the data was kept out for validation to avoid overfitting. The cost function used is crossentropy and the training algorithm is Scaled Conjugate Gradient.

4 Results and Discussion

After collecting 2200 samples (10 people, 11 states per person and 20 samples per state), to extract the features including channel energies and band energies (there are 26 features per sample), we use three different filter methods: IIR band-pass filter, FIR band-pass filter and Discrete Wavelet Transform as stated in Materials and Methods.

For each of these feature tables, we apply three different algorithms to each subject's data and obtain the classìfication rate per individual.

- Bagged Trees and Support Vector Machine (Linear): The data is trained using 5-fold cross validation, and the accuracy referred to is validation accuracy. Each training is repeated 10 times and then averaged.
- Neural Network: The data is trained using 50 percent hold-out validation and the accuracy referred to is accuracy on the hold-out portion of the data. The training is repeated 100 times and then averaged.

The descriptive statistics are presented here for every combination of filtering schemes and classification algorithms. In each of these combinations, we provide a detailed accuracy table of all 10 subjects and a confusion matrix for all 11 states.

Then, we compare the accuracies and also the relative filtering computation times within our different schemes. Since the Emotiv Insight is rather new, and finding a paper that perform similar enough investigations is not easy, we have not yet compared our result with others'.

4.1 The IIR filter

The feature table is extracted by IIR filter with order 20, requiring 7.95 seconds for processing 2200 samples.

Person 6 consistently gets the highest classification accuracy in all the three algorithms, around 9 percent above the average. Person 4 also has the lowest rate of all three methods. The Bagged Trees and Support Vector Machine obtain better results than the Neural Network algorithm (79.28% and 78.59%, respectively, to 72.71%).

As for the sensitivity for different states, the Smile and Raising eyebrows are the most easily recognizable. While the four thinking modes have the lowest rates. The groups of states that are usually misclassified with one another are [Looking Left, Looking Right], [Close Eye, Open Eye] and the four thinking modes [Moving Backward, Moving Forward, Turning Left, Turning Right]; as can be seen from the confusion matrices. The worst case belongs to the pair of [Moving Backward, Moving Forward], with mutual misclassified rates going up to 17 and 18 percent. The Neural Network methods also are substantially weaker in thinking states.

4.1.1 Bagged Trees

Table 1: Accuracy of Bagged Trees method with IIR filtering

	MEAN	STD	MAX	MIN
Person 1	0.8250	0.0224	0.8591	0.7909
Person 2	0.8064	0.0150	0.8273	0.7864
Person 3	0.7909	0.0159	0.8045	0.7545
Person 4	0.7259	0.0173	0.7636	0.7000
Person 5	0.7855	0.0216	0.8182	0.7500
Person 6	0.8818	0.0113	0.9000	0.8636
Person 7	0.7918	0.0160	0.8136	0.7727
Person 8	0.7845	0.0212	0.8227	0.7545
Person 9	0.7350	0.0159	0.7591	0.7091
Person 10	0.8014	0.0132	0.8136	0.7727
AVG	0.7928	0.0170	0.8182	0.7655

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.8270	0.0085	0.0265	0.0195	0.0100	0.0900	0.0050	0.0100	0.0020	0.0000	0.0015
eyebrow	0.0005	0.9470	0.0045	0.0000	0.0010	0.0050	0.0080	0.0100	0.0130	0.0010	0.0100
eyeleft	0.0395	0.0160	0.8025	0.0495	0.0140	0.0110	0.0095	0.0200	0.0130	0.0110	0.0140
eye right	0.0220	0.0050	0.0735	0.7420	0.0105	0.0270	0.0135	0.0250	0.0380	0.0265	0.0170
normal	0.0045	0.0030	0.0130	0.0090	0.9210	0.0045	0.0150	0.0125	0.0150	0.0000	0.0025
open eye	0.0640	0.0050	0.0235	0.0135	0.0125	0.8620	0.0015	0.0020	0.0050	0.0020	0.0090
smile	0.0035	0.0070	0.0060	0.0085	0.0120	0.0065	0.9285	0.0050	0.0120	0.0080	0.0030
backward	0.0070	0.0160	0.0360	0.0390	0.0145	0.0105	0.0040	0.6075	0.1680	0.0685	0.0290
forward	0.0070	0.0215	0.0175	0.0465	0.0200	0.0160	0.0180	0.1745	0.6080	0.0500	0.0210
left	0.0060	0.0060	0.0205	0.0245	0.0050	0.0075	0.0270	0.0705	0.0635	0.6960	0.0735
right	0.0010	0.0075	0.0090	0.0420	0.0185	0.0015	0.0070	0.0410	0.0340	0.0590	0.7795

Figure 8: Confusion matrix of Bagged Trees with IIR filtering

4.1.2 Support Vector Machine

Table 2: Accuracy of Support Vector Machine method with IIR Filtering

	MEAN	STD	MAX	MIN
Person 1	0.8091	0.0139	0.8364	0.7909
Person 2	0.7909	0.0113	0.8136	0.7773
Person 3	0.8055	0.0102	0.8318	0.7955
Person 4	0.7223	0.0192	0.7636	0.7045

Person 5	0.7864	0.0147	0.8091	0.7636
Person 6	0.8627	0.0056	0.8727	0.8545
Person 7	0.8136	0.0163	0.8364	0.7818
Person 8	0.7714	0.0159	0.7909	0.7455
Person 9	0.7436	0.0176	0.7682	0.7227
Person 10	0.7536	0.0153	0.7818	0.7318
AVG	0.7859	0.0140	0.8105	0.7668

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.7990	0.0015	0.0215	0.0325	0.0090	0.1035	0.0095	0.0050	0.0070	0.0100	0.0015
eyebrow	0.0015	0.8820	0.0005	0.0225	0.0030	0.0050	0.0165	0.0115	0.0320	0.0205	0.0050
eyeleft	0.0150	0.0005	0.8195	0.0710	0.0095	0.0115	0.0120	0.0125	0.0260	0.0115	0.0110
eye right	0.0210	0.0000	0.0685	0.7880	0.0085	0.0005	0.0050	0.0370	0.0265	0.0330	0.0120
normal	0.0080	0.0080	0.0255	0.0145	0.8545	0.0070	0.0225	0.0305	0.0240	0.0055	0.0000
open eye	0.0525	0.0010	0.0210	0.0170	0.0105	0.8690	0.0005	0.0160	0.0050	0.0000	0.0075
smile	0.0015	0.0000	0.0130	0.0150	0.0090	0.0005	0.9100	0.0130	0.0255	0.0115	0.0010
backward	0.0045	0.0090	0.0540	0.0260	0.0105	0.0090	0.0055	0.6025	0.1640	0.0775	0.0375
forward	0.0000	0.0110	0.0150	0.0365	0.0015	0.0115	0.0210	0.1755	0.6290	0.0735	0.0255
left	0.0065	0.0075	0.0175	0.0180	0.0000	0.0035	0.0050	0.0765	0.0605	0.7355	0.0695
right	0.0060	0.0095	0.0205	0.0255	0.0065	0.0090	0.0045	0.0555	0.0360	0.0710	0.7560

Figure 9: Confusion matrix of SVM with IIR filtering

4.1.3 Neural Network

Table 3: Accuracy of Neural Network method with IIR filtering

	MEAN	STD	MAX	MIN
Person 1	0.6671	0.0591	0.8000	0.4818
Person 2	0.7560	0.0494	0.8545	0.6182
Person 3	0.6981	0.0495	0.8000	0.5818
Person 4	0.6629	0.0543	0.7636	0.4818
Person 5	0.7725	0.0388	0.8636	0.6182
Person 6	0.8117	0.0434	0.9000	0.7000
Person 7	0.7251	0.0495	0.8364	0.6182
Person 8	0.7350	0.0450	0.8364	0.6364
Person 9	0.6789	0.0419	0.7636	0.5727
Person 10	0.7635	0.0437	0.8727	0.6364
AVG	0.7271	0.0475	0.8291	0.5945

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.7796	0.0095	0.0379	0.0241	0.0085	0.1068	0.0043	0.0084	0.0050	0.0078	0.0082
eyebrow	0.0044	0.9060	0.0098	0.0088	0.0055	0.0069	0.0108	0.0084	0.0200	0.0104	0.0090
eyeleft	0.0399	0.0124	0.7596	0.0711	0.0133	0.0197	0.0100	0.0244	0.0226	0.0163	0.0107
eye right	0.0296	0.0102	0.0865	0.6849	0.0184	0.0194	0.0182	0.0302	0.0493	0.0311	0.0220
normal	0.0080	0.0029	0.0208	0.0174	0.8626	0.0079	0.0244	0.0257	0.0234	0.0007	0.0063
open eye	0.1217	0.0090	0.0258	0.0183	0.0182	0.7814	0.0029	0.0079	0.0068	0.0024	0.0057
smile	0.0006	0.0115	0.0124	0.0118	0.0224	0.0078	0.8745	0.0099	0.0344	0.0083	0.0065
backward	0.0082	0.0134	0.0447	0.0361	0.0224	0.0130	0.0093	0.4973	0.1839	0.1125	0.0590
forward	0.0062	0.0206	0.0143	0.0500	0.0243	0.0160	0.0229	0.2140	0.5063	0.0894	0.0360
left	0.0092	0.0055	0.0254	0.0247	0.0036	0.0042	0.0123	0.1194	0.0931	0.6104	0.0922
right	0.0072	0.0084	0.0120	0.0336	0.0145	0.0094	0.0053	0.0559	0.0315	0.0896	0.7326

Figure 10: Confusion matrix of Neural Network with IIR filtering

4.1.4 Average confusion matrix

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.8019	0.0065	0.0286	0.0254	0.0092	0.1001	0.0063	0.0078	0.0047	0.0059	0.0037
eyebrow	0.0021	0.9117	0.0049	0.0104	0.0032	0.0056	0.0118	0.0100	0.0217	0.0106	0.0080
eyeleft	0.0315	0.0096	0.7939	0.0639	0.0123	0.0141	0.0105	0.0190	0.0205	0.0129	0.0119
eye right	0.0242	0.0051	0.0762	0.7383	0.0125	0.0156	0.0122	0.0307	0.0379	0.0302	0.0170
normal	0.0068	0.0046	0.0198	0.0136	0.8794	0.0065	0.0206	0.0229	0.0208	0.0021	0.0029
open eye	0.0794	0.0050	0.0234	0.0163	0.0137	0.8375	0.0016	0.0086	0.0056	0.0015	0.0074
smile	0.0019	0.0062	0.0105	0.0118	0.0145	0.0049	0.9043	0.0093	0.0240	0.0093	0.0035
backward	0.0066	0.0128	0.0449	0.0337	0.0158	0.0108	0.0063	0.5691	0.1720	0.0862	0.0418
forward	0.0044	0.0177	0.0156	0.0443	0.0153	0.0145	0.0206	0.1880	0.5811	0.0710	0.0275
left	0.0072	0.0063	0.0211	0.0224	0.0029	0.0051	0.0148	0.0888	0.0724	0.6806	0.0784
right	0.0047	0.0085	0.0138	0.0337	0.0132	0.0066	0.0056	0.0508	0.0338	0.0732	0.7560

Figure 11: Average Confusion matrix of all classifications with IIR filtering

4.2 The FIR filter

The feature table is extracted by FIR filter with order 20, requiring 2.66 seconds for processing 2200 samples.

Person 6 consistently gets the highest classification accuracy in all the three algorithms, around 15 percent above the average. Person 9 also has the lowest rate in all three methods. The Bagged Trees and Support Vector Machine obtain better results than Neural Network algorithm (71.49% and 71.80%, respectively, to 64.52%).

As for the sensitivity for different states, the Smile and Raising Eyebrows are the most easily recognizable. While the four thinking modes have the lowest rates. The groups of states that are usually misclassified with one another are [Looking Left, Looking Right], [Close Eye, Open Eye] and the four thinking modes [Moving Backward, Moving Forward, Turning Left, Turning Right]; as can be seen from the confusion matrices. The worst case belongs to the pair of [Moving Backward, Moving Forward], with mutual misclassified rates going up to 20 and 17 percent.

4.2.1 Bagged Trees

Table 4: Accuracy of Bagged Trees with FIR filtering

	MEAN	STD	MAX	MIN
Person 1	0.7059	0.0163	0.7318	0.6773
Person 2	0.7150	0.0152	0.7455	0.6955
Person 3	0.7132	0.0189	0.7364	0.6818
Person 4	0.6773	0.0190	0.7136	0.6591
Person 5	0.6895	0.0195	0.7273	0.6591
Person 6	0.8964	0.0036	0.9000	0.8909
Person 7	0.7077	0.0227	0.7364	0.6727
Person 8	0.7077	0.0170	0.7318	0.6864
Person 9	0.6186	0.0175	0.6500	0.5909
Person 10	0.7177	0.0241	0.7409	0.6727
AVG	0.7149	0.0174	0.7414	0.6886

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.7670	0.0130	0.0490	0.0235	0.0075	0.0920	0.0085	0.0185	0.0100	0.0040	0.0070
eyebrow	0.0150	0.8935	0.0270	0.0070	0.0025	0.0080	0.0055	0.0115	0.0170	0.0035	0.0095
eyeleft	0.0455	0.0240	0.7855	0.0420	0.0060	0.0405	0.0060	0.0230	0.0105	0.0095	0.0075
eye right	0.0205	0.0155	0.0535	0.7145	0.0200	0.0340	0.0335	0.0245	0.0365	0.0310	0.0165
normal	0.0090	0.0100	0.0120	0.0360	0.8060	0.0175	0.0280	0.0185	0.0415	0.0105	0.0110
open eye	0.0765	0.0085	0.0170	0.0110	0.0175	0.8110	0.0260	0.0135	0.0040	0.0035	0.0115
smile	0.0095	0.0275	0.0090	0.0350	0.0435	0.0165	0.7945	0.0165	0.0170	0.0150	0.0160
backward	0.0125	0.0410	0.0315	0.0330	0.0125	0.0225	0.0220	0.4970	0.1765	0.0915	0.0600
forward	0.0155	0.0230	0.0170	0.0570	0.0435	0.0105	0.0320	0.2075	0.5175	0.0410	0.0355
left	0.0150	0.0105	0.0305	0.0260	0.0135	0.0065	0.0390	0.0985	0.0540	0.5935	0.1130
right	0.0080	0.0115	0.0290	0.0235	0.0190	0.0065	0.0130	0.0545	0.0415	0.1095	0.6840

Figure 12: Confusion matrix of Bagged Trees with FIR filtering

4.2.2 Support Vector Machine

Table 5: Accuracy of SVM with FIR filtering

	MEAN	STD	MAX	MIN
Person 1	0.7136	0.0190	0.7455	0.6773
Person 2	0.6936	0.0081	0.7091	0.6864
Person 3	0.7305	0.0125	0.7455	0.7045
Person 4	0.6777	0.0190	0.7091	0.6500
Person 5	0.7232	0.0196	0.7545	0.6955
Person 6	0.8809	0.0139	0.9091	0.8591
Person 7	0.7523	0.0150	0.7818	0.7318
Person 8	0.6909	0.0190	0.7227	0.6636
Person 9	0.6195	0.0101	0.6364	0.6045
Person 10	0.6977	0.0185	0.7227	0.6682
AVG	0.7180	0.0155	0.7436	0.6941

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.7550	0.0095	0.0455	0.0195	0.0060	0.1080	0.0035	0.0125	0.0220	0.0095	0.0090
eyebrow	0.0085	0.8505	0.0235	0.0115	0.0000	0.0145	0.0145	0.0350	0.0330	0.0090	0.0000
eyeleft	0.0245	0.0150	0.7980	0.0400	0.0000	0.0295	0.0055	0.0505	0.0185	0.0050	0.0135
eye right	0.0250	0.0065	0.0615	0.7680	0.0020	0.0105	0.0145	0.0345	0.0320	0.0340	0.0115
normal	0.0120	0.0160	0.0390	0.0345	0.7200	0.0160	0.0515	0.0200	0.0475	0.0235	0.0200
open eye	0.0445	0.0060	0.0170	0.0090	0.0110	0.8480	0.0105	0.0205	0.0240	0.0000	0.0095
smile	0.0030	0.0190	0.0145	0.0485	0.0115	0.0185	0.7960	0.0380	0.0320	0.0120	0.0070
backward	0.0165	0.0130	0.0355	0.0275	0.0055	0.0175	0.0200	0.5535	0.1420	0.1030	0.0660
forward	0.0110	0.0155	0.0275	0.0490	0.0120	0.0150	0.0450	0.1935	0.5260	0.0720	0.0335
left	0.0220	0.0100	0.0200	0.0265	0.0075	0.0005	0.0185	0.0870	0.0765	0.6370	0.0945
right	0.0115	0.0085	0.0230	0.0510	0.0040	0.0105	0.0130	0.0915	0.0475	0.0935	0.6460

Figure 13: Confusion matrix of SVM with FIR filtering

4.2.3 Neural Network

Table 6: Accuracy of Neural Network with FIR filtering

	MEAN	STD	MAX	MIN
Person 1	0.6018	0.0634	0.7455	0.4455
Person 2	0.5749	0.0537	0.7000	0.4364
Person 3	0.5985	0.0502	0.7091	0.4727
Person 4	0.6516	0.0522	0.8091	0.5182
Person 5	0.6795	0.0536	0.8000	0.5000
Person 6	0.7952	0.0378	0.8818	0.7000
Person 7	0.6402	0.0633	0.7818	0.5182
Person 8	0.6943	0.0473	0.7909	0.5455
Person 9	0.5493	0.0632	0.6727	0.1455
Person 10	0.6663	0.0492	0.7727	0.5364
AVG	0.6452	0.0534	0.7664	0.4818

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.7194	0.0217	0.0532	0.0216	0.0125	0.1106	0.0060	0.0201	0.0166	0.0103	0.0081
eyebrow	0.0171	0.8082	0.0300	0.0220	0.0083	0.0344	0.0254	0.0211	0.0194	0.0072	0.0068
eyeleft	0.0486	0.0326	0.6860	0.0785	0.0067	0.0384	0.0201	0.0348	0.0194	0.0153	0.0197
eye right	0.0331	0.0253	0.0792	0.6259	0.0225	0.0233	0.0443	0.0302	0.0445	0.0318	0.0399
normal	0.0182	0.0130	0.0300	0.0324	0.7480	0.0155	0.0426	0.0220	0.0496	0.0092	0.0195
open eye	0.1266	0.0219	0.0247	0.0262	0.0248	0.7188	0.0109	0.0139	0.0196	0.0048	0.0080
smile	0.0049	0.0426	0.0239	0.0465	0.0266	0.0143	0.7572	0.0175	0.0362	0.0160	0.0144
backward	0.0298	0.0358	0.0399	0.0331	0.0215	0.0223	0.0303	0.4110	0.2018	0.1059	0.0684
forward	0.0195	0.0258	0.0236	0.0513	0.0478	0.0207	0.0340	0.2063	0.4319	0.0919	0.0472
left	0.0150	0.0116	0.0280	0.0280	0.0049	0.0067	0.0315	0.1117	0.0887	0.5470	0.1270
right	0.0119	0.0108	0.0299	0.0437	0.0135	0.0108	0.0161	0.0630	0.0468	0.1161	0.6375

Figure 14: Confusion matrix of Neural Network with FIR filtering

4.2.4 Average confusion matrix

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.7471	0.0147	0.0492	0.0215	0.0087	0.1035	0.0060	0.0170	0.0162	0.0079	0.0080
eyebrow	0.0135	0.8507	0.0268	0.0135	0.0036	0.0190	0.0151	0.0225	0.0231	0.0066	0.0054
eyeleft	0.0395	0.0239	0.7565	0.0535	0.0042	0.0361	0.0105	0.0361	0.0161	0.0099	0.0136
eye right	0.0262	0.0158	0.0647	0.7028	0.0148	0.0226	0.0308	0.0297	0.0377	0.0323	0.0226
normal	0.0131	0.0130	0.0270	0.0343	0.7580	0.0163	0.0407	0.0202	0.0462	0.0144	0.0168
open eye	0.0825	0.0121	0.0196	0.0154	0.0178	0.7926	0.0158	0.0160	0.0159	0.0028	0.0097
smile	0.0058	0.0297	0.0158	0.0433	0.0272	0.0164	0.7826	0.0240	0.0284	0.0143	0.0125
backward	0.0196	0.0299	0.0356	0.0312	0.0132	0.0208	0.0241	0.4872	0.1734	0.1001	0.0648
forward	0.0153	0.0214	0.0227	0.0524	0.0344	0.0154	0.0370	0.2024	0.4918	0.0683	0.0387
left	0.0173	0.0107	0.0262	0.0268	0.0086	0.0046	0.0297	0.0991	0.0731	0.5925	0.1115
right	0.0105	0.0103	0.0273	0.0394	0.0122	0.0093	0.0140	0.0697	0.0453	0.1064	0.6558

Figure 15: Average Confusion matrix of all classification algorithms with FIR filtering

4.3 The Discrete Wavelet Transform

The feature table is extracted by FIR filter with order 20, requiring 14.16 seconds for processing 2200 samples.

Person 6 and Person 2 hold the two highest classification accuracies in all the three algorithms. Person 4 and Person 9, on the contrary, have the lowest rates. The Bagged Trees and Support Vector Machine obtain better results than Neural Network algorithm (78.64% and 78.61%, respectively, to 72.90%).

As for the sensitivity for different states, the Smile and Raising Eyebrows are the most easily recognizable. While the four thinking modes have the lowest rates. The groups of states that are usually misclassified with one another are [Looking Left, Looking Right], [Close Eye, Open Eye] and the four thinking modes [Moving Backward, Moving Forward, Turning Left, Turning Right]; as can be seen from the confusion matrices. The worst case belongs to the pair of [Moving Backward, Moving Forward], with mutual misclassified rates going up to 22 and 17 percent.

4.3.1 Bagged Trees

Table 7: Accuracy of Bagged Trees with DWT

	MEAN	STD	MAX	MIN
Person 1	0.7882	0.0144	0.8091	0.7591
Person 2	0.8309	0.0151	0.8545	0.8091
Person 3	0.7868	0.0180	0.8136	0.7545
Person 4	0.7018	0.0165	0.7273	0.6818
Person 5	0.8050	0.0143	0.8227	0.7818
Person 6	0.8423	0.0119	0.8545	0.8136
Person 7	0.7891	0.0211	0.8182	0.7545
Person 8	0.8000	0.0202	0.8227	0.7727
Person 9	0.7564	0.0282	0.7909	0.7091
Person 10	0.7636	0.0170	0.7955	0.7318
AVG	0.7864	0.0177	0.8109	0.7568

Actual Class \ Predicted Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.8290	0.0000	0.0325	0.0215	0.0105	0.0775	0.0145	0.0090	0.0020	0.0020	0.0015
eyebrow	0.0040	0.9610	0.0090	0.0005	0.0030	0.0015	0.0080	0.0015	0.0055	0.0010	0.0050
eyeleft	0.0355	0.0110	0.7885	0.0675	0.0170	0.0115	0.0070	0.0205	0.0225	0.0115	0.0075
eye right	0.0285	0.0055	0.0670	0.7320	0.0210	0.0240	0.0180	0.0250	0.0375	0.0215	0.0200
normal	0.0065	0.0025	0.0135	0.0180	0.9020	0.0075	0.0135	0.0125	0.0150	0.0005	0.0085
open eye	0.0660	0.0035	0.0285	0.0120	0.0125	0.8440	0.0060	0.0075	0.0040	0.0030	0.0130
smile	0.0035	0.0065	0.0075	0.0110	0.0140	0.0035	0.9255	0.0020	0.0165	0.0080	0.0020
backward	0.0085	0.0135	0.0435	0.0340	0.0115	0.0155	0.0085	0.5810	0.1755	0.0635	0.0450
forward	0.0045	0.0150	0.0170	0.0435	0.0165	0.0035	0.0145	0.1970	0.6040	0.0610	0.0235
left	0.0035	0.0030	0.0200	0.0380	0.0050	0.0050	0.0120	0.0805	0.0725	0.7075	0.0530
right	0.0060	0.0045	0.0120	0.0350	0.0180	0.0035	0.0125	0.0525	0.0250	0.0550	0.7760

Figure 16: Confusion matrix of Bagged Trees with DWT

4.3.2 Support Vector Machine

Table 8: Accuracy of SVM with DWT

	MEAN	STD	MAX	MIN
Person 1	0.8082	0.0140	0.8273	0.7818
Person 2	0.8377	0.0191	0.8818	0.8182
Person 3	0.7877	0.0241	0.8227	0.7455
Person 4	0.7450	0.0149	0.7591	0.7136
Person 5	0.7732	0.0118	0.7864	0.7545
Person 6	0.8345	0.0084	0.8500	0.8182
Person 7	0.7923	0.0098	0.8045	0.7727
Person 8	0.7950	0.0172	0.8182	0.7727
Person 9	0.7418	0.0164	0.7682	0.7182
Person 10	0.7455	0.0119	0.7591	0.7227
AVG	0.7861	0.0148	0.8077	0.7618

Actual Class \ Predicted Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.8195	0.0000	0.0365	0.0125	0.0125	0.0835	0.0090	0.0085	0.0040	0.0080	0.0060
eyebrow	0.0015	0.9000	0.0035	0.0185	0.0085	0.0010	0.0125	0.0105	0.0325	0.0045	0.0070
eyeleft	0.0265	0.0030	0.7940	0.0580	0.0125	0.0220	0.0060	0.0230	0.0270	0.0150	0.0130
eye right	0.0195	0.0000	0.0605	0.8020	0.0145	0.0000	0.0030	0.0290	0.0360	0.0150	0.0205
normal	0.0100	0.0105	0.0075	0.0325	0.8660	0.0095	0.0095	0.0175	0.0205	0.0135	0.0030
open eye	0.0390	0.0000	0.0235	0.0265	0.0160	0.8530	0.0055	0.0205	0.0030	0.0010	0.0120
smile	0.0000	0.0110	0.0080	0.0160	0.0105	0.0020	0.8915	0.0055	0.0260	0.0150	0.0145
backward	0.0040	0.0060	0.0425	0.0225	0.0095	0.0165	0.0055	0.6370	0.1550	0.0555	0.0460
forward	0.0000	0.0150	0.0145	0.0300	0.0165	0.0005	0.0155	0.2380	0.5795	0.0630	0.0275
left	0.0075	0.0040	0.0130	0.0130	0.0010	0.0035	0.0050	0.0885	0.0610	0.7420	0.0615
right	0.0135	0.0090	0.0060	0.0335	0.0165	0.0060	0.0015	0.0705	0.0235	0.0575	0.7625

Figure 17: Confusion matrix of SVM with DWT

4.3.3 Neural Network

Table 9: Accuracy of Neural Network with DWT

	MEAN	STD	MAX	MIN
Person 1	0.6933	0.0571	0.8091	0.5636
Person 2	0.7933	0.0425	0.8818	0.7091
Person 3	0.6810	0.0596	0.7909	0.5273
Person 4	0.6791	0.0394	0.7636	0.5818
Person 5	0.7561	0.0410	0.8455	0.6182
Person 6	0.7853	0.0508	0.8909	0.6091
Person 7	0.7316	0.0549	0.8455	0.5818
Person 8	0.7480	0.0449	0.8636	0.6455
Person 9	0.6859	0.0469	0.7909	0.5273
Person 10	0.7368	0.0445	0.8182	0.6000
AVG	0.7290	0.0482	0.8300	0.5964

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.7919	0.0080	0.0406	0.0258	0.0087	0.0970	0.0033	0.0093	0.0015	0.0057	0.0080
eyebrow	0.0020	0.9116	0.0091	0.0124	0.0071	0.0052	0.0114	0.0048	0.0163	0.0062	0.0138
eyeleft	0.0471	0.0124	0.7342	0.0750	0.0131	0.0230	0.0172	0.0248	0.0249	0.0145	0.0139
eye right	0.0365	0.0043	0.0843	0.6891	0.0251	0.0196	0.0143	0.0259	0.0559	0.0213	0.0236
normal	0.0087	0.0033	0.0147	0.0203	0.8593	0.0158	0.0196	0.0228	0.0267	0.0019	0.0068
open eye	0.1194	0.0057	0.0290	0.0241	0.0194	0.7711	0.0038	0.0107	0.0058	0.0047	0.0063
smile	0.0027	0.0100	0.0060	0.0134	0.0156	0.0070	0.8864	0.0088	0.0310	0.0089	0.0100
backward	0.0066	0.0142	0.0419	0.0290	0.0225	0.0162	0.0122	0.5120	0.1924	0.0993	0.0536
forward	0.0074	0.0197	0.0143	0.0553	0.0335	0.0088	0.0244	0.2158	0.5030	0.0805	0.0375
left	0.0087	0.0043	0.0228	0.0175	0.0055	0.0074	0.0126	0.1124	0.1012	0.6223	0.0851
right	0.0134	0.0063	0.0117	0.0340	0.0197	0.0077	0.0103	0.0573	0.0285	0.0751	0.7359

Figure 18: Confusion matrix of Neural Network with DWT

4.3.4 Average confusion matrix

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.8135	0.0027	0.0365	0.0199	0.0106	0.0860	0.0089	0.0089	0.0025	0.0052	0.0052
eyebrow	0.0025	0.9242	0.0072	0.0105	0.0062	0.0026	0.0106	0.0056	0.0181	0.0039	0.0086
eyeleft	0.0364	0.0088	0.7722	0.0668	0.0142	0.0188	0.0101	0.0228	0.0248	0.0137	0.0115
eye right	0.0282	0.0033	0.0706	0.7410	0.0202	0.0145	0.0118	0.0266	0.0431	0.0193	0.0214
normal	0.0084	0.0054	0.0119	0.0236	0.8758	0.0109	0.0142	0.0176	0.0207	0.0053	0.0061
open eye	0.0748	0.0031	0.0270	0.0209	0.0160	0.8227	0.0051	0.0129	0.0043	0.0029	0.0104
smile	0.0021	0.0092	0.0072	0.0135	0.0134	0.0042	0.9011	0.0054	0.0245	0.0106	0.0088
backward	0.0064	0.0112	0.0426	0.0285	0.0145	0.0161	0.0087	0.5767	0.1743	0.0728	0.0482
forward	0.0040	0.0166	0.0153	0.0429	0.0222	0.0043	0.0181	0.2169	0.5622	0.0682	0.0295
left	0.0066	0.0038	0.0186	0.0228	0.0038	0.0053	0.0099	0.0938	0.0782	0.6906	0.0665
right	0.0110	0.0066	0.0099	0.0342	0.0181	0.0057	0.0081	0.0601	0.0257	0.0625	0.7581

Figure 19: Average confusion matrix of all classification algorithms with DWT

4.4 Overall comparison

It can be seen from the accuracy table below that the features extracted using IIR filter and Wavelet Transform give considerably better result than FIR filter, up to 7 percent higher on average. Furthermore, the standard deviation is larger in FIR accuracies, indicating that the brainwave patterns are as clearly expressed as in other filters.

Table 10: Average accuracies of all combinations of filters and classification algorithms

		IIR	FIR	Wavelet	AVG
Bagged Trees	Accuracy	0.7928	0.7149	0.7864	0.7647
	STD	0.0437	0.0703	0.0397	0.0512
SVM	Accuracy	0.7859	0.7180	0.7861	0.7633
	STD	0.0404	0.0675	0.0351	0.0477
Neural Network	Accuracy	0.7271	0.6451	0.7290	0.7004
	STD	0.0498	0.0706	0.0427	0.0543
AVG	Accuracy	0.7686	0.6927	0.7672	
	STD	0.0446	0.0694	0.0392	

The Bagged Trees and Linear SVM algorithms give nearly the same result with all three filters, while Neural Network gives 6 percent lower result.

Table 11: Different time intervals needed for three filters

Filters	IIR	FIR	Wavelet
Time (s)	7.9514	2.6575	14.1636

Accounting also for the discrepancy in the time needed to perform different filters, which is lowest in FIR and highest in Wavelet Transform; we propose the scheme of using IIR filter for feature extraction and Bagged Trees or SVM for classification. The Wave Transform being credited as well-suited for brain signals, does not outperform in this particular case. The reason may lie in the fact that the signal taken out from the headset is not pure since it's has incorporated some filters itself.

There is a consistency between classification methods that some subjects' samples have higher accuracy and some states are more easily recognizable than others. This may result from another problem which is so-called BCI illiteracy. That is, not all people can equally exert the clear patterns from their brain to communicate computer interfaces.

As for the different sensitivities (true positive rates) between the states, some groups of states are usually highly mutually misclassified, as seen from the confusion matrices.

Notable examples are [Looking left, Looking Right], [Close Eyes, Open Eyes], the four thinking modes, and particularly the pair [Thinking Backward, Thinking Forward].

One of the reasons may be that feature vectors containing just energies of bands and channels may not be able to present enough information to differentiate between them. Since energy has positive value, two waves with opposite sign will have the same energy.

For Thinking Backward and Thinking Forward states, additional reasons such as BCI illiteracy, and the density of electrodes should be considered. Since the misclassification rates are up to 20% between these two states, compared to about 7% in other cases, it is probable that Emotive Insight is not suitable for Thinking Backward and Thinking Forward. On the other hand, Thinking Left and Thinking Right still gets acceptable accuracies.

Predicted Class

Actual Class	close eye	eyebrow	eyeleft	eye right	normal	open eye	smile	backward	forward	left	right
close eye	0.8135	0.0027	0.0365	0.0199	0.0106	0.0860	0.0089	0.0089	0.0025	0.0052	0.0052
eyebrow	0.0025	0.9242	0.0072	0.0105	0.0062	0.0026	0.0106	0.0056	0.0181	0.0039	0.0086
eyeleft	0.0364	0.0088	0.7722	0.0668	0.0142	0.0188	0.0101	0.0228	0.0248	0.0137	0.0115
eye right	0.0282	0.0033	0.0706	0.7410	0.0202	0.0145	0.0118	0.0266	0.0431	0.0193	0.0214
normal	0.0084	0.0054	0.0119	0.0236	0.8758	0.0109	0.0142	0.0176	0.0207	0.0053	0.0061
open eye	0.0748	0.0031	0.0270	0.0209	0.0160	0.8227	0.0051	0.0129	0.0043	0.0029	0.0104
smile	0.0021	0.0092	0.0072	0.0135	0.0134	0.0042	0.9011	0.0054	0.0245	0.0106	0.0088
backward	0.0064	0.0112	0.0426	0.0285	0.0145	0.0161	0.0087	0.5767	0.1743	0.0728	0.0482
forward	0.0040	0.0166	0.0153	0.0429	0.0222	0.0043	0.0181	0.2169	0.5622	0.0682	0.0295
left	0.0066	0.0038	0.0186	0.0228	0.0038	0.0053	0.0099	0.0938	0.0782	0.6906	0.0665
right	0.0110	0.0066	0.0099	0.0342	0.0181	0.0057	0.0081	0.0601	0.0257	0.0625	0.7581

Figure 20: Average confusion matrix of all combinations of filters and classification algorithms

5 Conclusion

5.1 Usability of the Emotiv Insight

The achieved accuracy of 79.28% (IIR combined with Bagged Trees) for differentiation between up to 11 states is satisfactory since the headset is new to all the subjects. Furthermore, the number of samples for training is small and may be prone to many outliers. If there is longer interacting time, the performance is expected to be better.

The Wavelet Transform give nearly the same accuracy as the IIR filter, while requiring twice the time for computation. The FIR filter has the computation time just one-third of the time for IIR but unfortunately, its accuracy is about 7% lower than the other two.

The Bagged Trees and SVM priove to perform better than shallow Neural Network, up to 6% higher. The variation between Bagged Trees and SVM is less than 1%.

It can be concluded that Emotiv Insight is not well-suited for recognizing the states [Thinking Forward, Thinking Backward]; on the other hand, [Thinking Left, Thinking Right] still give acceptable results.

Thus, for the particular case of the Emotive Insight headset, we propose the combination of IIR filter for feature extraction and Bagged Trees or SVM for classification.

5.2 Limitations

This research has limitations in some respects. Since this work is done by two students within less than two months, the new knowledge in signal processing and machine learning, which constitute a large proportion of the report has to be learned in haste. Besides, a large amount of time was spent on EEG signal recording.

The signal quality may be not secured since the headset does not fit with some subjects and this caused the sensors to have poor contact with the scalp. This also results in the longer time needed for recording and the subjects’ fatigue.

On the other hand, the signal filtering and classification algorithms investigated are the built-in MATLAB functions with little modifications, thus there is a lack of flexibility in methodology.

5.3 Future developments and applications

On the continuation of this work, we will inquire into better techniques of feature extraction and make apply modifications to the classification algorithms for better results. In the signal processing stage, we will apply new techniques such as ICA and PCA to remove noise from EEG signals.

Because the metal states chosen for the first time was quite intuitive and with little experience, it is necessary that more mental states will be recorded and studied.

At the high advancement of this work, real-time signal processing and pattern recognition will be conducted because that is the eventual application of the current research.

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