Feature Extraction and Classification of Electroencephalogram Signal

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Abstract

The electroencephalogram (EEG) signal is non-stationary by its nature. Standard approach of frequency analysis seems unsuitable at this point. Instead, in this paper I propose a method of multi-resolution analysis using wavelet transform. It extracts both time and frequency information from each sub-band of EEG signal via orthogonal transformation on the original data set. In particular, the bands of our interests will be scaled with high frequency resolution. The features are then fed to a multi-layer perceptron neural network with at least three hidden layers to produce a three bits output as our control signal.

1 Introduction

The goal of our project is to use EEG wave as control signal to excite some form of actuator; in this case, navigate a flying drone. However, the EEG signal by its nature is random and unpredictable. My job is to process the signal, extract useful information from it, and classify the signal based on user's mental intention. Thus we could pull out the control signal from EEG wave. The proposed method for feature extraction is multi-resolution analysis (MRA) using wavelet decomposition, yet other methods like fast Fourier transform (FFT) and principal component analysis (PCA) will also be discussed and compared in following sections. Furthermore, an artificial neutral network (ANN) serves as our machine learning algorithm to classify EEG signals.

2 Feature Extraction

EEG signal appears just like random noise in time domain, it has barely any pattern. It is very difficult to pull out any useful information by just observing the waveform of the signal. Thus function transformation and mapping become essentially important when it comes to signal processing.

2.1 Fast Fourier Transform

FFT is a very fast and convenient algorithm that transforms a signal from its time domain to frequency domain. One potential use of FFT is to extract the frequency components of signal, select the required components and calculate the power for these components which are considered to be related to user's intention. The useful EEG signal bands, which related to human activities, are typically below 100 Hz, as shown in Figure 1 [1].

However, FFT suffers from a major drawback. Ideally, FFT only makes sense when it is applied to a stationary or periodic signal, but EEG signal is neither stationary nor periodic. Although we could pretend it is periodic over infinite time span, that suggests we have to collect infinite many data points. In any sense, using

FFT to obtain frequency spectrum of EEG signal seems to be inappropriate.

Furthermore, as Robi Polikar points out, FFT only gives the frequency components exist in the signal, but it doesn't provide the time localization of the spectral components [2]. In other words, it doesn't tell when a specific frequency component occurs in the signal. For instance, suppose two signal each consists two frequency components. One of the signals has two components at all times, but for the other signal, the its frequency components rise at different time. Clearly, they all have the same so called spectrum, but they are completely two different signals. This explains why FFT is not an appropriate method to analyze non-stationary signal.

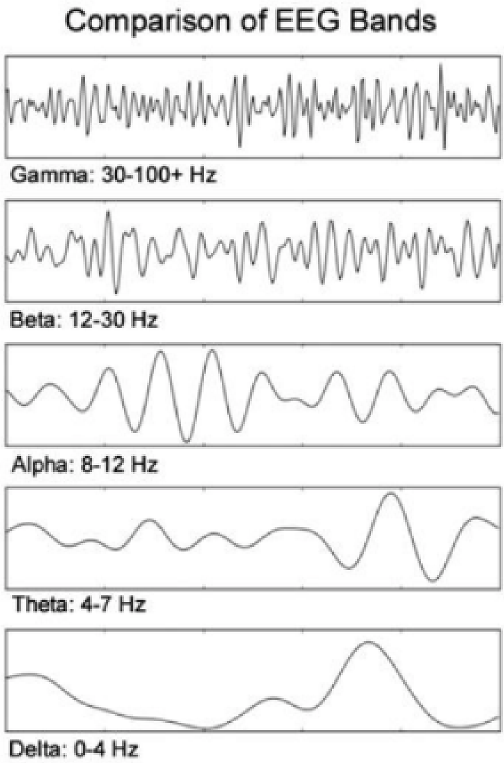

Figure 1: EEG frequency Bands

An alternative way to deal with this time localization problem is to apply a window function to the signal, assuming signal is stationary at that time interval. Then the FFT turns into short time Fourier transform (STFT). However, one can't have both good time resolution and frequency resolution at the same time due to the uncertainty principle [2]. The better the time resolution, the worse the frequency resolution, or vice versa.

2.2 Wavelet Transform

The wavelet transform solves the resolution problem by its unique approach, known as multi-resolution analysis (MRA). It analyzes different frequency components at different resolution. It is the one of most suitable method to analyze EEG signal, since it could have high time resolution and low frequency resolution at high frequency; low time resolution and high frequency resolution at low frequency. Most of useful bands in EEG signal live at low frequency, and we want to capture them carefully. As for high frequency components, they model the rapid change of signal; for those components we are only interested in the time location of the change occurs.

From equation 1 [2], we can see that the wavelet coefficient is obtain by taking the inner product of the signal against finite support and scalable wavelet function $\psi(t)$, which can be slided along time axis. The bigger the scale factor s, the longer the support length of $\psi(t)$ is. In other words, the window becomes wider, the frequency resolution becomes higher, and time resolution drops.

$$\Psi_x^{\psi}(t,s) = \frac{1}{\sqrt{s}} \int x(\tau)\psi(\frac{\tau - t}{s})d\tau \tag{1}$$

In our application, we will use Discrete Wavelet Transform (DWT) to decompose EEG signal into to multiple levels until we obtain the frequency bands of our interest (under 100 Hz). One could apply DWT on a signal to get detail space (high frequency) and approximate space (low frequency). This process could be performed repeatedly on approximate space at each level until one obtain desired frequency bands. This is effectively applying low pass and high pass filters on signal. This whole process can be visually perceived in Figure 2.

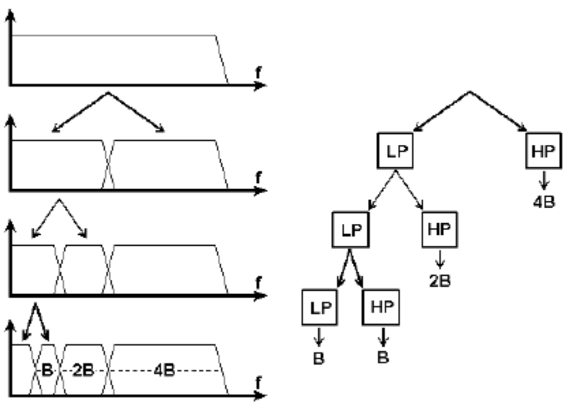

Figure 2: EEG signal decomposition [3]

In our project, the EEG signal will be sampled at least 200 Hz to keep enough information according to Nyquist-Shannon sampling theorem. At sampling rate of 200 Hz, the frequency bandwidth of the signal can go up to 100 Hz, which covers the desired EEG bands. This suggests that we need to decompose the signal at least into 5 levels to get the information from the delta band. The coefficients

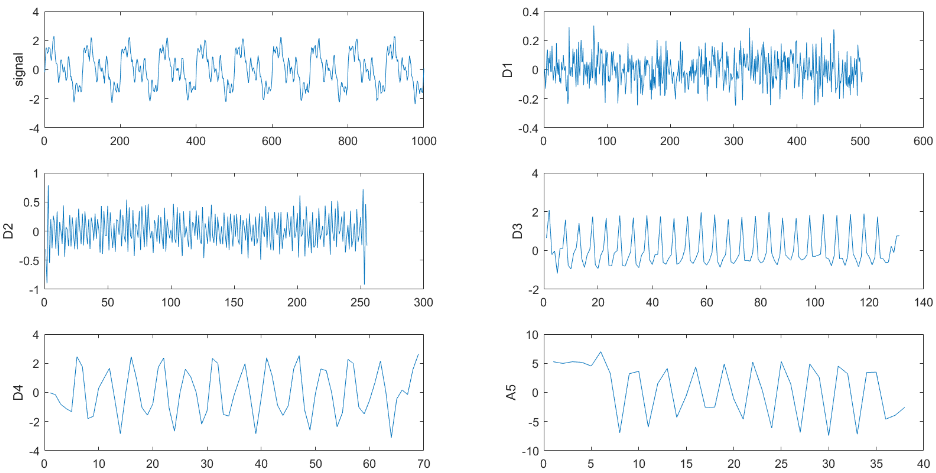

Figure 3: Wavelet Decomposition at Different Subspace

of the sub-detailed spaces will be used as the features for our EEG signal in this case; specifically, the coefficients in each EEG bands. Moreover, the Daubechies 4 wavelet will be used for the mother wavelet, because it is most suitable to process biomedical signal [3]. Daubechies 4 wavelet is implemented in finite impulse response (FIR) filter, thus it is internally stable. Moreover, it has advantage of computational simplicity over other wavelet functions.

Figure 3 shows the original signal generated at random, and its corresponding approximate coefficient and detail coefficients. At sampling rate of 200 Hz, each subspace corresponds to particular EEG signal band. The details are list in Table 1 [3].

2.3 Principal Component Analysis

Principal component analysis (PCA) is a statistical process to covert a set of variables possibly correlated into a set of linearly independent variable via orthogonal transformation [4]. Its operation can be thought of as revealing the internal structure of data in a way that best explains the variance in the data [5].

Potentially, we could apply PCA on the collected data sequence to obtain the feature of the data, the directional vector pointing to the maximum variation. The

Table 1: Frequency range corresponding to different levels of wavelet decomposition with a sampling rate of 200 Hz

Decomposed signal	Frequency Range(Hz)
D1	50-100
D2	25-50
D3	12.5-25
D4	6.25-12.5
D5	3.125-6.25
A5	0-3.125

detailed steps are following [5]:

- reduce the dimension of data by blocking
- compute the covariance matrix for each block of data
- sum them up and perform singular value decomposition on resulting matrix

Unlike WT and FFT, it is very difficult to visualize how would PCA fits to EEG signal analysis. Furthermore, PCA cannot retain the data sequence order and adjacency information. Yet we will leave PCA as our second option in turns of feature extraction tools after WT.

3 Classification

Once the features of the EEG signal are obtained, the next question is how to classify them, since there are always some degree of variations in those features.

3.1 Statistical Approach

One easy way to classify data is just to do statistical analysis; for instance we could calculate the variance of the features. Since we have labeled data, we would know the input associated with specific variance if the variance converges with enough sample data. Then we could implement the least square method to make decision upon variance of the features.

However the downside of this approach is the variance might not converge at all due to the non-stationarity of the EEG signal. Or in other extreme case, two total different features might have very similar variance. In other words, this method is not scalable, as it works fine with only limited feature.

3.2 Support Vector Machine

Support vector machine (SVM) is one of most efficient machine learning algorithm, which is widely used in pattern recognition such as image recognition, speech recognition, text categorization, and face detection [6].

The underlying principle behind SVM is actually very simple. In two-dimensional case, it draws lines to separate different sets of data based on their features. In higher dimensional case, it finds hyper-surfaces to classify data. One can always go higher dimension, because the higher the dimension is the more freedom one has to draw the separation lines or surfaces.

Although it is extremely simple algorithm, and works well in principle, it has a disadvantage of requiring tons of data. The higher dimension one goes, the more data one needs to fill up the space, and the memory requirement on machine is demanding.

For our specific EEG project, we can only collect very limited sample data from our group members. Therefore, SVM will not be considered as our classification method.

3.3 Artificial Neural Network

Artificial neural networks (ANN) are computing systems made up of large number of simple, highly interconnected processing elements (called nodes or artificial neurons) that abstractly emulate the structure and operation of the biological nervous system. One example neural network is shown in Figure 4 [3]. The proposed architecture of ANN for our project is multilayer perceptron neural network

(MLPNN). This ANN will consist at least three hidden layer, and three outputs corresponding to three bits control signal that is fed to our drone. The number of inputs depends on the number of features we capture from previous stage. Ideally, we would like to have multiple level extraction to capture higher level features, thus reducing the inputs of neural network, simplifying the overall structure of the network as well. Here we suggest that the detail coefficients and approximate coefficient from different levels of wavelet decomposition will serve as our inputs for the neural network.

The determination of appropriate number of hidden layers is one of the most critical tasks in neural network design. A neural network with too few hidden layer would be incapable of differentiating complex pattern, while too many layers would cause training extremely time-consuming [3]. Therefore, the actual number of hidden layers would be determined through trial and error.

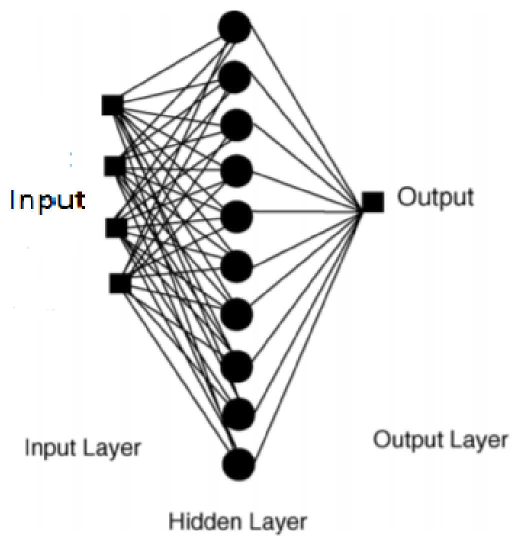

Figure 4: Artificial Neural Network

In addition, back-propagation algorithm will be used to train the neural network in conjunction with Levenberg—Marquardt optimization method. Back-propagation along suffers from lots of problems. Since it use gradient descent to search minimum surface, it might stuck at local minimum, and back-propagation normally has slow convergence rate [3].

4 Data Acquisition

As mentioned before, the useful EEG signal bands are under 100 Hz, therefore each sample data will be recorded at least 2-5 seconds. Moreover, we estimate at least 200 samples for each feature are required based on the results of previous studies [3] [5].

Furthermore, since we only have four people in our group and we probably can't collect data from people other than ourselves, we would only be collecting data consistently from one person. Doing so would reduce the data variation, but the setup would only work for just one person. For future development, in order to adapt our setup to a wider scope of people, we need to gather data from a large group of subjects.

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