A COMPARISON OF ACCURACIES OF VARIOUS CLASSIFIERS TO PROCESS EEG SIGNALS FOR PROSTHESIS CONTROL USING VARIATIONAL MODE DECOMPOSITION

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Abstract - Modern prosthetics use electroencephalogram (EEG) signals to receive signals from individual's muscles to control the prosthesis. The prosthetic of an amputee which cannot accurately detect the brain signals is a dead investment for him. This paper tries to maximize the classification accuracies of these signals so as to improve prosthetics by comparison between two main algorithms namely using Naïve Bayes and Part rule algorithms. The EEG dataset for the conditions using 27 different subjects with four different hand movements viz., finger open (fopen), finger close (fclose), clock wise wrist rotation (cw) and counter clock wise wrist rotation (ccw) were obtained from the NINAPRO DATABASE, a resource for bio robotics community of hand movements. The introduction of Variational Mode Decomposition (VMD) as a new signal pre-processing technique along with the different decision trees have provided good classification performance. VMD allows decomposition of the signal into various modes by identifying a compact frequency support around its central frequency, such that adding all the modes reconstructs the original signal. The statistical features were extracted .Out of these the useful features were identified using the J48 decision tree algorithm and selected features were classified using Naïve Bayes and Part rule algorithms. The classification accuracies of both classifiers have been compared for the EEG signals.

Keywords - Prosthetics, EEG signal classification, VMD, Decision Tree, Signal Processing, J48 algorithm, Naïve Bayes and Part rule algorithms

1. Introduction

Prosthesis is an artificial device that replaces a missing body part. The loss of the human forearm is a major disability that profoundly limits the everyday capabilities and interactions of individuals with upper-limb amputation (Kuiken et al., 2009). The interaction capability with the real-world can be restored using myoelectric control (Englehart & Hudgins, 2003; Hudgins, Parker, & Scott, 1993), where the electroencephalogram (EEG) signals generated by the human muscles are used to derive control commands for powered upper-limb prostheses. A person's prosthesis should be designed and assembled according to the patient's appearance and functional needs. It could be mechanical, electrical or myoelectric.

Electroencephalogram (EEG) or myoelectric signals are an electrical potential generated by the muscles. Normally, EEG signals can be measured by either an invasive method using a needle electrode sensor or a non-invasive method using a surface electrode sensor. Among the non-invasive techniques for probing human brain dynamics, electroencephalography (EEG) provides a direct measure of cortical activity with millisecond temporal resolution. EEG is a record of the electrical potentials generated by the cerebral cortex nerve cells. . The EEG signal is highly complex; it is one of the most common sources of information used to study brain function and neurological disorders (Agarwal, Gotman, Flanagan, & Rosenblatt, 1998; Adeli, Zhou, & Dadmehr, 2003; Hazarika, Chen, Tsoi, & Sergejew, 1997).

EEG signals are complex due to the non-stationary characteristics and subject dependency of the signals (Aschero & Gizdulich, 2009). There are some difficulties in extracting sufficient information from the EEG for prosthetic control like electrode placement, electrode type, skin and the muscle. The Autoregressive model will overcome the electrode placement noise. The classification of actions associated with EEG signals for multifunction Myoelectric Control Systems (MCSs) is not simple when there are a number of simultaneously active muscles and when the muscle activity is weak (Arjunan, 2008; Arjunan & Kumar, 2010; Maitrot, Lucas, Doncarli, & Farina, 2005; Naik, Kumar, & Arjunan, 2009, 2010; Singh & Kumar, 2008).

The present study makes use of a new pre-processing technique to decompose the signal into various modes or IMFs using calculus variations. The modes have compact frequency support around the central frequency. Alternating Direction Multiplier Method (ADMM) was used as optimization tool to find such central frequencies concurrently. The main purpose of decomposing a signal is to identify various components of the signal. This work focuses on a new algorithm - variational mode decomposition (VMD), which extracts different modes present in the signal. In the present study, an attempt is made to compare the accuracy of the EEG Signal using Naïve Bayes and Part Rule algorithms. To extract best possible features, the signals were preliminarily pre-processed for finding the modes and IMFs. Then, descriptive statistical features like mean, median, kurtosis etc. were extracted. With the extracted statistical features, feature selection is done using J48 decision tree algorithm, further classification was carried out using above mentioned decision tree algorithms.

2. SYSTEM ARCHITECTURE AND DATA ACQUISITION

The EEG signal is acquired after proper skin preparations and are amplified before being filtered and sampled. The pre-processed signals are then used to extract features and subsequently the extracted features are given to a classifier.

2.1 DATA ACQUISITION

NINAPRO database consists of kinematic and SEEG data from the upper limbs of 27 intact subjects while performing 52 finger, hand and wrist movements. The database is publicly available to download in standard ASCII format [5]. Surface EEG was collected from a subject's forearm skin while performing a number of movements of interest, or producing force patterns of interest. While intact subjects were examined by recording SEEG from the same arm, in the case of amputees recording of SEEG was from a stump while eliciting movements of interest either by imitation or bilateral coordinated motion. Surface EEG activity was gathered using ten active double-differential OttoBock MyoBock 13E200 surface EEG electrodes which had an amplification factor of 14000.

The Electroencephalogram (EEG) experimental setup performs four different classes viz., fopen, fclose, cw and ccw, principally focusing on data from 27 healthy subjects. The EEG signals were collected from the subject's four different hand movements. The data in the EEG database were obtained by the following procedure: The subject was made to sit on an adjustable chair and instructed to have electrodes (C3, C4, CZ, FZ and PZ) with conductive gel medium on scalp surface. Initial signal artefacts due to head motion will be generally ignored in the analysis. Experiment will be scheduled based on specific time series with respect to the classes. Signals from neurons are acquired with the help of these five electrodes which in turn connected with Electroencephalogram device with the frequency ranges from 8 to 3 Hz.

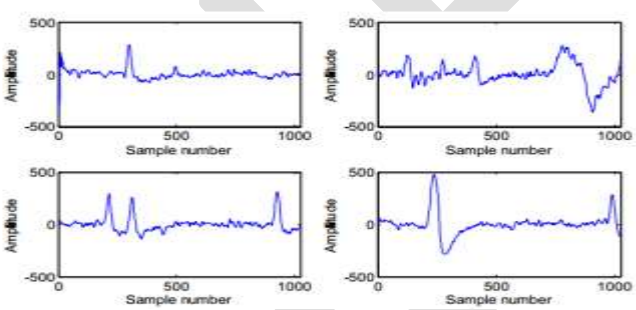


Fig.1 Time Domain EEG Signal

2.2 FILTERING AND SAMPLING

The EEG signals for various classes of hand movements have to be filtered to extract the region of activity. In the spectrum of signals most of information is contained in frequencies up to 500 HZ. Second order Butterworth band pass filter with cut off frequencies 20 Hz and 500 Hz is used. Butterworth filter exhibits a maximally flat response without any ripples in the pass band region. With amplitude distinction being very critical in EEG analysis, low distortion Butterworth filter is preferred. Sampling is done in accordance with the nyquist criterion the signal is then sampled at 2 KHZ.

3. Pre-Processing using Variational Mode Decomposition

Variational Mode decomposition decomposes the signal into various modes or intrinsic mode functions using calculus of variation. Each mode of the signal is assumed to have compact frequency support around a central frequency. VMD tries to find out these central frequencies and intrinsic mode functions centred on those frequencies concurrently using an optimization methodology called ADMM. The original formulation of the optimization problem is continuous in time domain.

VMD is formulated as; Minimize the sum of the bandwidths of *k* modes subject to the condition that sum of the *k* modes is equal to the original signal. The unknowns are *k* central frequencies and *k* functions centred at those frequencies. Since part of the unknowns is function, calculus of variation is applied to derive the optimal functions.

Bandwidth of an AM-FM signal primarily depends on both, with the maximum deviation of the instantaneous frequency $\Delta f \sim \max\left(\left|\omega_k(t)-\omega_k\right|\right)$ and the rate of change of instantaneous frequency. Dragomiretskiy and Zosso proposed a function that can measure the bandwidth of a intrinsic mode function $u_k(t)$. At first they computed Hilbert transform of $u_k(t)$. Let it be $u_k^H(t)$. Then formed an analytic function $\left(u_k(t)+ju_k^H(t)\right)$. The frequency spectrum of this function is one sided (exist only for positive frequency) and assumed to be centered on ω_k. By multiplying this analytical signal with $e^{-j\omega_k t}$, the signal is frequency translated to be centered at origin. The integral of the square of the time derivative of this frequency translated signal is a measure of bandwidth of the intrinsic mode function $u_k(t)$.

Let $u_k^M(t)=\left(u_k(t)+ju_k^H(t)\right)e^{-j\omega_k t}$

It is a function whose spectrum is around origin (baseband). Magnitude of time derivative of this function when integrated over time is a measure of bandwidth. Hence,

$$\Delta\omega_k=\int\left(\partial_t\left(u_k^M(t)\right)\right)\overline{\left(\partial_t\left(u_k^M(t)\right)\right)}dt$$

where, $\partial_t\left(u_k^M(t)\right)=\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right].$

By the absorbing the last inner product which is basically $\int\lambda(t)\left(f(t)-\sum_i u_i(t)\right)dt$ in to the term $\left\|f-\sum_i u_i\right\|_2^2=\int\left(f(t)-\sum_i u_i(t)\right)^2 dt$, then

$$\left\|f-\sum_i u_i\right\|_2^2+\left\langle\lambda, f-\sum_i u_i\right\rangle=\left\|f-\sum_i u_i+\frac{\lambda}{2}\right\|_2^2$$

Therefore

$$u_k^{n+1}=\underset{u_k(t)}{\arg\min}\ \alpha\sum_k\left\|\partial_t\left[\left(\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right)e^{-j\omega_k t}\right]\right\|_2^2+\left\|f-\sum_i u_i+\frac{\lambda}{2}\right\|_2^2$$

This problem can be solved in spectral domain by noting the fact that norm in time domain is same as norm in frequency domain.

The following results are used in Fourier transform

$$u_k(t) \Leftrightarrow \hat{u}_k(\omega) \Rightarrow \partial_t\left(u_k(t)\right) \Leftrightarrow (j\omega)\hat{u}_k(\omega)$$

$$u_k(t) \Leftrightarrow \hat{u}_k(\omega) \Rightarrow \left(\delta(t)+\frac{j}{\pi t}\right) * u_k(t) = u_k(t)+\frac{j}{\pi t} * u_k(t) \Leftrightarrow \left(1+\operatorname{sgn}(\omega)\right)\hat{u}_k(\omega)$$

Note that,

for negative ω , $\left(1+\operatorname{sgn}(\omega)\right)\hat{u}_k(\omega)=0$

and for positive ω , $\left(1+\operatorname{sgn}(\omega)\right)\hat{u}_k(\omega)=2\hat{u}_k(\omega)$

$$u_k(t)+\frac{j}{\pi t} * u_k(t) \Leftrightarrow \left(1+\operatorname{sgn}(\omega)\right)\hat{u}_k(\omega) \Rightarrow \left(u_k(t)+\frac{j}{\pi t} * u_k(t)\right)e^{-j\omega_k t} \Leftrightarrow \left(1+\operatorname{sgn}(\omega+\omega_k)\right)\hat{u}_k(\omega+\omega_k)$$

Therefore

$$u_k^{n+1} = \underset{\hat{u}_k(\omega)}{\arg\min}\ \alpha\left\| j\omega\left(1+\operatorname{sgn}(\omega+\omega_k)\right)\hat{u}_k(\omega+\omega_k)\right\|_2^2 + \left\|\hat{f} - \sum_i \hat{u}_i + \frac{\hat{\lambda}}{2}\right\|_2^2$$

Replacing $\omega \rightarrow \omega + \omega_k$

$$u_k^{n+1} = \underset{\hat{u}_k(\omega)}{\arg\min}\ \alpha\left\| j(\omega-\omega_k)\left(1+\operatorname{sgn}(\omega)\right)\hat{u}_k(\omega)\right\|_2^2 + \left\|\hat{f} - \sum_i \hat{u}_i + \frac{\hat{\lambda}}{2}\right\|_2^2$$

In the above expression, the first term vanishes for negative frequencies

$$\left\|\left(1+\operatorname{sgn}(\omega+\omega_k)\right)\hat{u}_k(\omega+\omega_k)\right\|_2^2 = \int_w \left(j(\omega-\omega_k)\left(1+\operatorname{sgn}(\omega)\right)\hat{u}_k(\omega)\right)\overline{\left(j(\omega-\omega_k)\left(1+\operatorname{sgn}(\omega)\right)\hat{u}_k(\omega)\right)} d\omega$$

$$= \int_0^\infty 4(\omega-\omega_k)^2 \left|\hat{u}_k(\omega)\right|^2 d\omega$$

Second term is symmetric around origin, therefore

$$\left\|\hat{f}(\omega) - \sum_i \hat{u}_i + \frac{\hat{\lambda}}{2}\right\|_2^2 = \int_{-\infty}^{\infty}\left(\hat{f} - \sum_i \hat{u}_i + \frac{\hat{\lambda}}{2}\right)\overline{\left(\hat{f} - \sum_i \hat{u}_i + \frac{\hat{\lambda}}{2}\right)} d\omega = 2\int_0^\infty \left(\hat{f}(\omega) - \sum_i \hat{u}_i + \frac{\hat{\lambda}}{2}\right)\overline{\left(\hat{f} - \sum_i \hat{u}_i + \frac{\hat{\lambda}}{2}\right)} d\omega$$

Also $\left(\hat{f}(\omega) - \sum_i \hat{u}_i + \frac{\hat{\lambda}}{2}\right)$ being a complex number

$$\left(\hat{f}(\omega)-\sum_i \hat{u}_i+\frac{\hat{\lambda}}{2}\right)\left(\overline{\hat{f}-\sum_i \hat{u}_i+\frac{\hat{\lambda}}{2}}\right)=\left|\hat{f}-\sum_i \hat{u}_i+\frac{\hat{\lambda}}{2}\right|^2$$

, where $|\;|$ represent magnitude of the complex number.

Therefore,

$$\hat{u}_k^{n+1}=\underset{\hat{u}_k(\omega),\omega>0}{\arg\min}\int_0^{\infty}\left(4\alpha(\omega-\omega_k)^2\left|\hat{u}_k(\omega)\right|^2+2\left|\hat{f}-\sum_i \hat{u}_i+\frac{\hat{\lambda}}{2}\right|^2\right)d\omega$$

Here unknown is a function. Hence, apply Euler Lagrangian condition to obtain the solution.

$$Let\ F=4(\omega-\omega_k)^2\left|\hat{u}_k(\omega)\right|^2+2\left|\hat{f}-\sum_i \hat{u}_i+\frac{\hat{\lambda}}{2}\right|^2$$

$$\frac{dF}{d\hat{u}_k}=0\Rightarrow 8\alpha(\omega-\omega_k)^2\hat{u}_k+4\left(\hat{f}-\sum_i \hat{u}_i+\frac{\hat{\lambda}}{2}\right)(-1)=0$$

$$\Rightarrow 2\alpha(\omega-\omega_k)^2\hat{u}_k+\hat{u}_k=\left(\hat{f}-\sum_{i\neq k}\hat{u}_i+\frac{\hat{\lambda}}{2}\right)\Rightarrow \hat{u}_k\left(1+2\alpha(\omega-\omega_k)^2\right)=\left(\hat{f}-\sum_{i\neq k}\hat{u}_i+\frac{\hat{\lambda}}{2}\right)$$

$$\hat{u}_k^{n+1}=\left(\hat{f}-\sum_{i\neq k}\hat{u}_i+\frac{\hat{\lambda}}{2}\right)\frac{1}{\left(1+2(\omega-\omega_k)^2\right)}\ ,\ \ \omega\geq 0$$

Update for ω_k s

$$\omega_k^{n+1}=\underset{\omega_k}{\arg\min}\left\|\partial_t\left[\left(\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right)e^{-j\omega_k t}\right]\right\|_2^2$$

$$\omega_k^{n+1}=\underset{\omega_k}{\arg\min}\left\|j\omega\left(1+\operatorname{sgn}\left(\omega+\omega_k\right)\right)\hat{u}_k(\omega+\omega_k)\right\|_2^2$$

$$\omega_k^{n+1}=\underset{\omega_k}{\arg\min}\left\|j\left(\omega-\omega_k\right)\left(1+\operatorname{sgn}\left(\omega\right)\right)\hat{u}_k(\omega)\right\|_2^2$$

$$\omega_k^{n+1}=\underset{\omega_k}{\arg\min}\int_0^{\infty}\left(\omega-\omega_k\right)^2\left|\hat{u}_k(\omega)\right|^2 d\omega$$

Here

ω_k^{n+1} is given by the solution of $\int_0^{\infty}\frac{d}{d\omega_k}\left(\left(\omega-\omega_k\right)^2\left|\hat{u}_k(\omega)\right|^2\right)d\omega=0$

$$\int_0^\infty -2\left(\omega-\omega_k\right)\left|\hat{u}_k(\omega)\right|^2 d\omega = 0$$

$$\Rightarrow \omega_k^{n+1} = \frac{\int_0^\infty \omega \left|\hat{u}_k(\omega)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_k(\omega)\right|^2 d\omega}$$

Update for λ (Lamda)

$$\lambda^{n+1} \leftarrow \lambda^n + \tau\left(f - u_k^{n+1}(t)\right)$$

Final algorithm for VMD:

initialize $\hat{u}_k^1,\ \hat{\omega}_k^1,\ \hat{\lambda}^1,\ \mathrm{n} \leftarrow 0$

repeat

$n \leftarrow n+1$

for $k = 1:K$ do

Update $\hat{u}_k$ for all $\omega \geq 0$

$$\hat{u}_k^{n+1} \leftarrow \frac{\hat{f} - \sum_{i<k} \hat{u}_i^{n+1} - \sum_{i>k} \hat{u}_i^n + \frac{\hat{\lambda}^n}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2} \qquad (2)$$

Update ω_k:

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega \left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega} \qquad (3)$$

end for

Dual ascent for all $\omega \geq 0$:

$$\hat{\lambda}^{n+1} \leftarrow \hat{\lambda}^n + \tau(\hat{f} - \sum_k \hat{u}_k^{n+1}) \qquad (4)$$

until convergence: $\sum_k \left\|\hat{u}_k^{n+1} - \hat{u}_k^n\right\|_2^2 \Big/ \left\|\hat{u}_k^n\right\|_2^2 < \varepsilon$

3.1 Discretization of Frequency

It is first assumed that length of the mirrored signal in the time domain is 1. If total length of the mirrored signal in terms of number of discrete values is T, then sampling interval is 1/T.

The discrete frequency is assumed to vary from -0.5 to +0.5 so that it represents normalized discrete frequency. It must be noted that algorithm construct Fourier transform of different mode function values for positive frequencies only. The other half can be easily created by conjugating and reflecting on the left side.

Once all the mode functions in the frequency domain are obtained, then obtain the time domain mode functions by taking inverse Fourier transform. These mode functions correspond to mirrored signal. Then cut off the appended (reflected portions) part of the signal to obtain the desired intrinsic mode functions.

4. Feature Extraction

Descriptive statistical parameters such as kurtosis, mean, variance and standard deviation extracted from the vibrational signals are computed to serve as features. They are named as 'statistical features' here. Brief descriptions about the extracted features are given below.

(a) **Standard deviation**: This is a measure of the effective energy or power content of the vibration signal. The following formula was used for computation of standard deviation.

$$\text{Standard Deviation} = \sqrt{\frac{\sum x^2 - \left(\sum x\right)^2}{n(n-1)}}$$

(a) **Standard error**: Standard error is a measure of the amount of error in the prediction of y for an individual x in the regression, where x and y are the sample means and 'n' is the sample size.

$$Y = \sqrt{\frac{1}{n-2}\left[\sum (y-\bar{y})^2 - \frac{\left[\sum (x-\bar{x})(y-\bar{y})\right]^2}{(x-\bar{x})^2}\right]}$$

(b) **Sample variance**: It is variance of the signal points and the following formula was used for computation of sample variance.

$$\text{Sample Variance} = \frac{\sum x^2 - \left(\sum x\right)^2}{n(n-1)}$$

(c) **Kurtosis**: Kurtosis indicates the flatness or the spikiness of the signal. Its value is very low at normal condition.

$$\text{Kurtosis} = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_i - \bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

where 's' is the sample standard deviation

(d) **Mean**: Mean is computed as arithmetic average of all points in the signal.

$$\text{Mean} = \sum_{i=1}^{n} x_i$$

5 Feature Selection using J48 Decision tree

It is essential to make use of only those statistical features which actually contribute to the classification accuracy. Some of the features are purely irrelevant and adds to the computational load of the system. The process of selecting only the relevant statistical features for the classification process so as to reduce the computational effort and improve classification accuracy is known as feature selection. In the present study, the dataset is used with J48 algorithm to generate the decision tree which facilitates the feature selection process, here we have achieved an accuracy of **91.67%.** The decision tree generated for EEG signals is shown in Fig.2

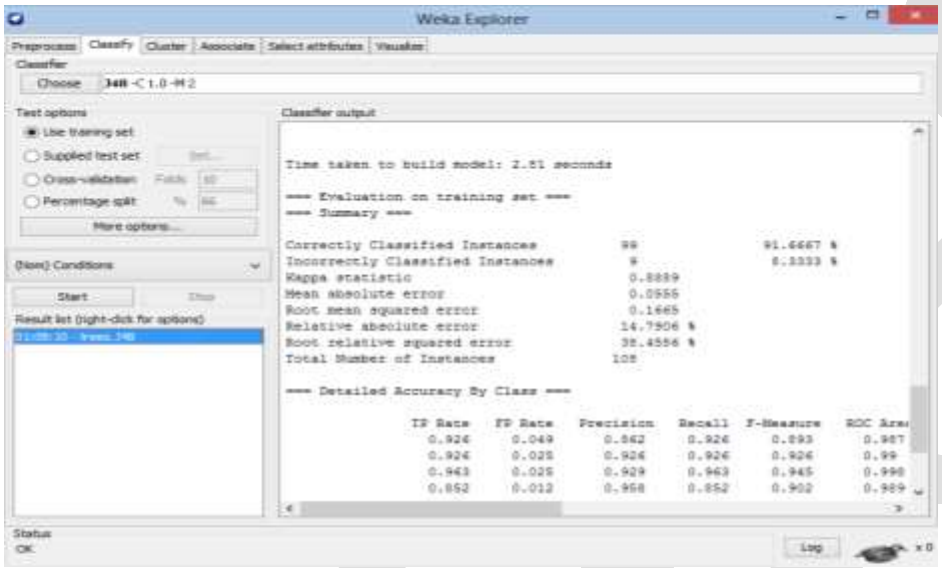


Fig.2a Result of EEG signals for J48

```
=== Confusion Matrix ===

  a  b  c  d   <-- classified as
 25  1  0  1 |  a = Fclose
  2 25  0  0 |  b = Fopen
  1  0 25  1 |  c = wccw
  1  1  2 23 |  d = wcw
```

Confusion Matrix using J48

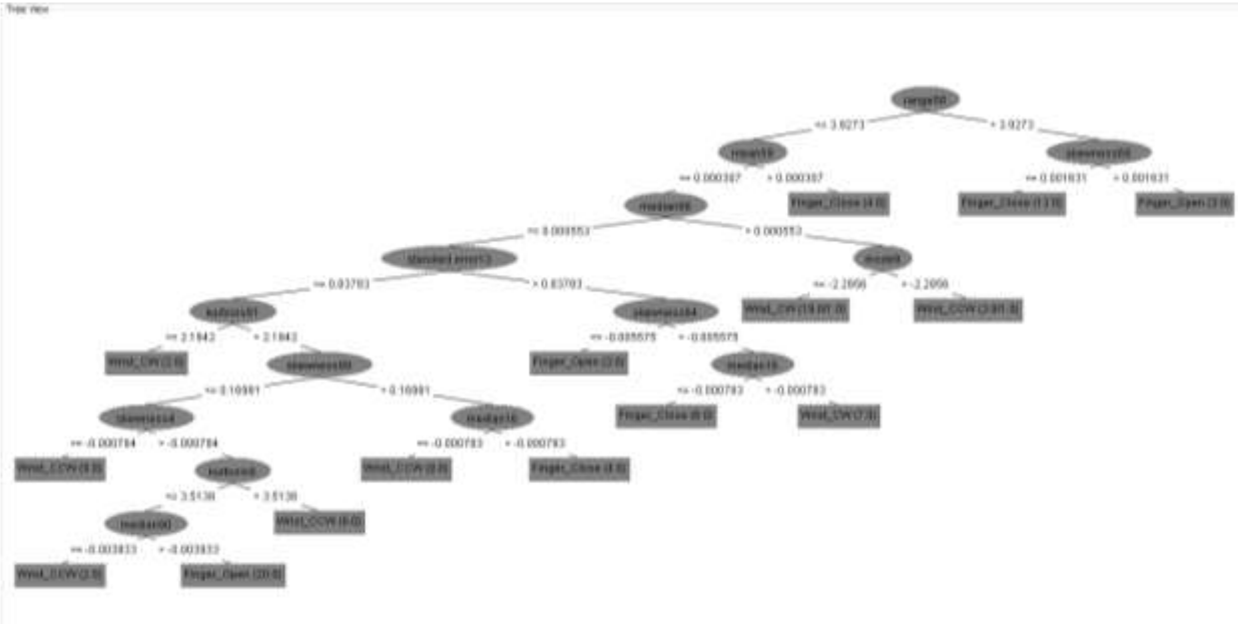


Fig.3 Decision tree of EEG signal

The features that are appearing on top of the decision tree are good for classification. The ones that do not appear are not useful for classification. The features appearing in the bottom of the tree are relatively less important ones. Hence, one can consciously choose or omit depending on the classification accuracy requirement and computational resources available.

6 Classifier

In machine learning, classification is considered an instance of supervised learning, i.e. learning where a training set of correctly identified observations is available. A path from the root to a leaf represents the rules for classification (Mohamed et al. 2012, Breiman et al. 1984). An algorithm that implements classification, especially in a concrete implementation, is known as a classifier. In the present study, classifier used is, Naïve Bayes and Part rule algorithm. A brief description is given below

6.1 Naïve Bayes

Naïve Bayes Classifier uses estimator classes to classify. Numeric estimator precision values are chosen based on analysis of the training data. For this reason, the classifier is not an Updateable Classifier (which in typical usage are initialized with zero training instances)

6.2 Part Algorithm

Part Algorithm is a Class for generating a PART decision list. Uses separate-and-conquer. Builds a partial C4.5 decision tree in each iteration and makes the "best" leaf into a rule. It has the Following parameters, that can be varied to improve the classification efficiency

Confidence Factor -The confidence factor used for pruning (smaller values incur more pruning).

debug - If set to true, classifier may output additional info to the console.

minNumObj - The minimum number of instances per rule.

numFolds - Determines the amount of data used for reduced-error pruning. One fold is used for pruning, the rest for growing the rules.

reducedError Pruning - Whether reduced-error pruning is used instead of C.4.5 pruning.

seed - The seed used for randomizing the data when reduced-error pruning is used.

7 Results and Discussion

Data from 27 healthy subjects while performing four different classes viz., fopen, fclose, cw and ccw were taken and necessary statistical features like mean, median, standard deviation, kurtosis were computed for each signal for EEG signals. J48 algorithm was used to select the features necessary for classification purpose. With these features, the classification accuracy was computed using Naïve Bayes and Part Rule algorithm

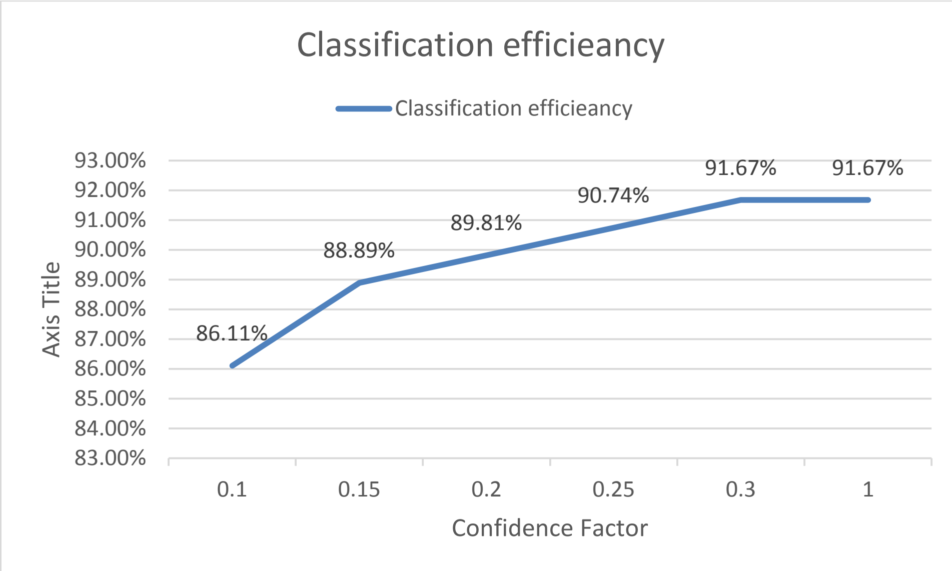
7.1 Statistical Features with Decision Tree

Ramalingam et al, 2013 recorded signal samples and used it for generating decision tree for the purpose of feature selection. The class wise accuracy generated by this study is illustrated in Table 1. The results indicate that it generates a classification accuracy of **38.88%** for EEG signals.

Table 1: Class wise accuracy of EEG signals

	fopen	fclose	cw	ccw
fopen	9	9	7	2
fclose	12	6	2	7
cw	3	6	16	2
ccw	5	6	5	11

Graph 1: Variation of Classification Efficiency with respect to Confidence Factor



As it can be seen from the graph, the maximum classification efficiency is 91.67% and is found at confidence factor 0.3 and remains the same till confidence factor of 1.

7.2 Variational Mode Decomposition with Naïve Bayes algorithm

This section discusses the results obtained from Naïve Bayes Algorithm. Confusion matrix obtained by optimizing the parameters for EEG signals is shown in the Fig. 4. The diagonal elements of the confusion matrix represent the correctly classified instances indicating an overall accuracy of **84.2593 %** for the EEG signals.

```
=== Confusion Matrix ===

  a  b  c  d   <-- classified as
 24  0  3  0 |  a = Fclose
  5 20  2  0 |  b = Fopen
  1  1 25  0 |  c = wccw
  2  0  3 22 |  d = wcw
```

Fig.4 Confusion matrix of Naïve Bayes:

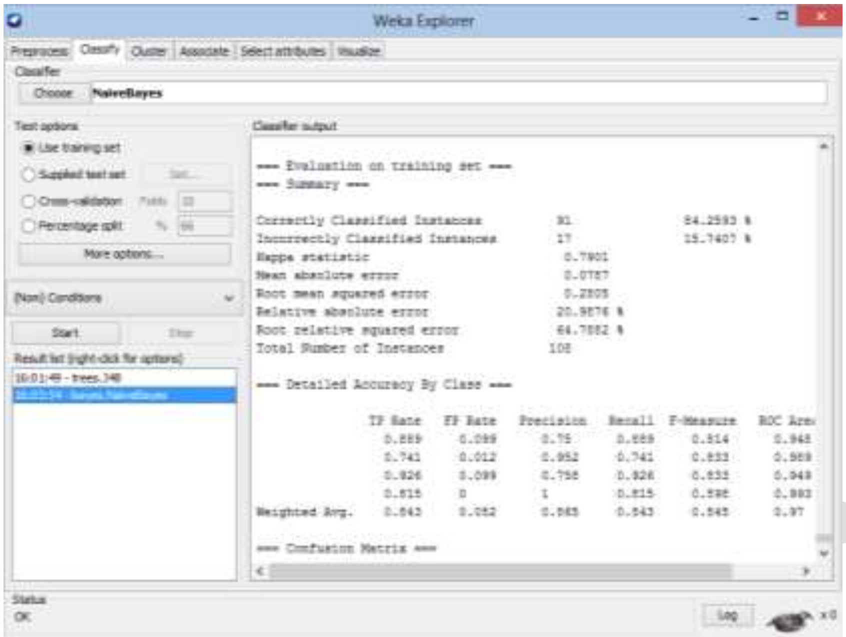


Fig.5 Results of Naïve Bayes:

7.3 Variational Mode Decomposition with Part rule algorithm:

Part is a Class for generating a PART decision list. Uses separate-and-conquer. Builds a partial C4.5 decision tree in each iteration and makes the "best" leaf into a rule. This section discusses the results obtained from Part rule Algorithm. Result obtained by optimizing the parameters for EEG signals is shown in the Fig. 6. The diagonal elements of the confusion matrix represent the correctly classified instances indicating an overall accuracy of **97.22 %** for the EEG signals

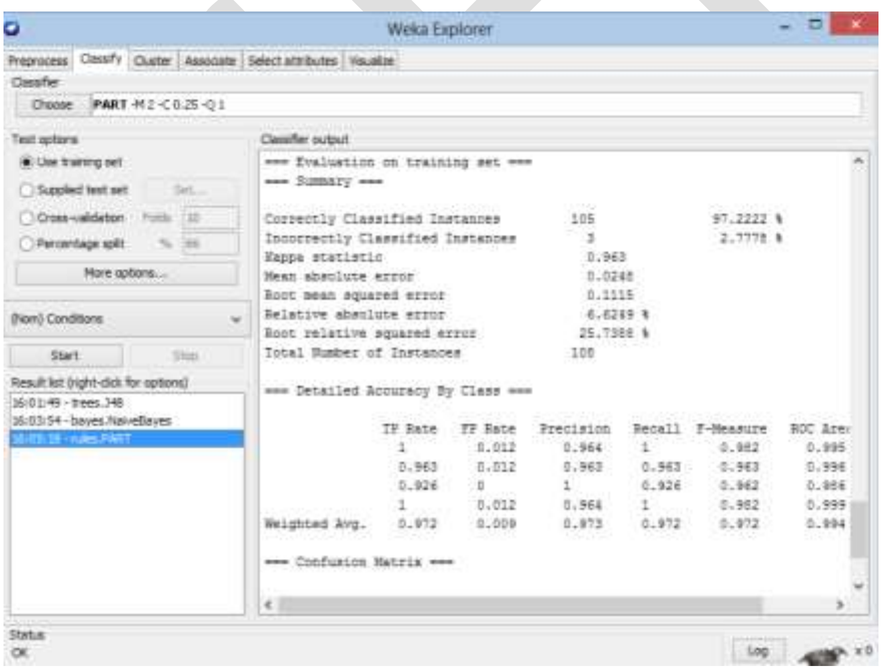


Fig.6 Results of Part:

```
=== Confusion Matrix ===

  a  b  c  d   <-- classified as
 27  0  0  0 |  a = Fclose
  0 26  0  1 |  b = Fopen
  1  1 25  0 |  c = wccw
  0  0  0 27 |  d = wcw
```

Fig.7 Confusion Matrix of Part rule Algorithm

8 Conclusion

The results and observations from the present study suggest that prosthetic arm using decision tree based approach is a viable option. An attempt is made to compare the performances of EEG signals using different classifiers. The introduction of Variational Mode Decomposition (VMD) as a new signal pre-processing technique along with the **Part rule algorithm** have provided outstanding performance characteristics with a classification accuracy reaching **97.22 %** and **84.2593%** using **Naïve Bayes for EEG Signals**. Statistical features extracted from raw signal (without VMD pre-processing) and various decision tree algorithms have been studied for bench marking the new features and classier. The accuracy achieved by VMD pre-processed signals (**91.67%**) is far superior to that generated using the signals which were not VMD pre-processed (**38.88%**). From the results and discussions, one can conclude that Part Rule Algorithm is better suited for classifying EEG signals (**with an accuracy of 97.22%**) for the application in prosthetic arm.

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