



IMAGE BASED APPROACH FOR COGNITIVE CLASSIFICATION USING EEG SIGNALS

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ABSTRACT

The EEG state classifier distinguishes different states and these information are used to understand the normal and abnormal states of users and to adapt their interfaces and add new functionalities. EEG classification is performed conventionally by extracting statistical parameters. But, this classification is affected more by artifacts and hence a better approach using image based is proposed. Typically, EEG signals are captured using multiple electrodes and subsequently used to map the cognitive states. It is useful for control applications, human machine interface, virtual reality concepts, etc suited to critically ill persons.] This paper deals with the classification of state based on standalone EEG signals using Hamming distance measure and assist the critically ill person to perform tasks. The cognitive states the brain can be studied at state space level and it is possible to discriminate between different tasks (though complex).

Keywords: EEG signals, hamming distance technique, state classifier.

INTRODUCTION

EEG (Electroencephalography) is the study of electrical activity of brain signals and provides the information or signal flow occurring between a person's sensory organs such as ears, eyes, tongue etc. For Example, if a person is unable to understand the language, the reason could be either abnormality in ears or the input could be chaotic, and this can be inference requires EEG measurement. Similar inference can be done for Tongue/ Eye or any other sensory organ. Coma patients in particular shall understand the events happening around, but are unable to respond. For such patients EEG signals can be collected and their mental states can be classified and Human Machine Interface applications can be developed. Typical interfaces such as voice based control to interpret speech inputs from patients have been reported. The focus is to extend the range over which critically ill persons can continue their routine activities without dependency on other humans. In this work, from the EEG signal, the states (with artifacts during measurement) are classified using and hybrid Hamming Distance and Position Matching Algorithm. This approach outperforms conventional classifiers with respect to classification accuracy. With proper location of electrodes the different brain wave activities (Delta, Theta, Alpha, and Beta) relate the specific states such as sleep, awake, abnormal functioning, hyperactivity, arithmetic, logical states, emotional state etc.

Delta waves are generally located at frontally in adult's posteriorly in Childs. These are high amplitude waves and frequency is less than 4Hz and has been found during some continuous-attention tasks

Theta waves are Associated with inhibition of elicited responses i.e. has been found to spike in situations

where a person is actively trying to repress a response or action. The frequency is (4-7) Hz. Theta rhythm occurs as a normal rhythm during drowsiness. In young children , this occur with a predominance over the fronto-central regions during drowsiness between the age of 4months to 8 years of age. In adult, theta slowing can occur diffusely or over the posterior head regions during drowsiness.

Alpha waves are also associated with inhibition control, seemingly with the purpose of giving timing information inhibitory activity in different locations across the brain. These are found at posterior regions of head, both sides, higher in amplitude on dominant side. Thus, this wave provides timeline information and is analogous to entropy. The Alpha variant pattern consists of activity over the posterior head regions which has a harmonic relationship to the Alpha rhythm and shows a similar reactivity and distribution as the Alpha rhythm. The slow alpha variant is a subharmonic pattern consisting of dicrotic or notched waveforms having a frequency of one-half the resting Alpha rhythm, usual range is (4-5)Hz, and alternating or admixed with the Alpha activity. There is also a fast alpha variant in which the frequency is twice the resting Alpha and which looks like Beta frequency activity, but it occurs over the posterior head regions and reacts to eye opening.

Beta activity having a frequency of over 13Hz. The average voltage of (10-20) μ v. there are two main Beta activities in adults. First one , the frontal type which occurs predominantly over the anterior and central regions and which appears to be related to the functions of the sensorimotor cortex and reacts to movement or touch. The second type consisting of generalized beta activity which is induced or enhanced by drugs and in which the Beta activity may an amplitude of over 25 μ v.



OBJECTIVES OF THIS WORK

The focus of this work is

- The signal processing algorithms are best tested when applied to a nonlinear, highly correlated, low frequency signal with high order statistics. This work, propose a model to correctly correlate the different types of abnormality (hidden as information) in the low frequency EEG signal waves.
- To remove the contour effects in due to the difference between the perception of the sensory organs and the signals captured by the electrodes. For example the noise perceived by the human ear is pink, but the noise produced in a factory environment is different. Hence, to correctly understand the noise by human ear contour filters are required and it is appropriate to measure noise in dBA.
- To eliminate the truncation effects due to the use of transforms.

LITERATURE SURVEY

Apostolicoet *al* (2014) contributed a method where measures of sequence similarity are introduced and studied in which patterns in a pair are considered similar if they coincide up to a preset number of mismatches that is, within a bounded Hamming distance. It is shown here that for some such measures bounds are achievable [1].

Zouet *al* (2014) proposed an automatic algorithm for the identification of general artifacts. The proposed algorithm consists of two parts namely an event-related feature based clustering algorithm used to identify artifacts which have physiological origins and the electrode-scalp impedance information employed for identifying non-biological artifacts. The results on subject show that his algorithm can effectively detect, separate, and remove both physiological and non-biological artifacts [2].

Hua-Chin Lee (2014) incorporated optimized feature selection using an inheritable bi-objective combinatorial genetic algorithm (IBCGA) and mathematic modeling for classification and analysis of EEG based attention network. 1) He first designs the attention network experiments, record the EEG signals of subjects from NeuronScan instrument, and filter noise from the EEG data. 2) Based on an intelligent evolutionary algorithm as the core technique, we analyze the large-scale EEG data [3].

ChunchuRambabuet *al* (2014) proposed a method where the EEG signals are analysed and the features are extracted using SVM and ICA classifier techniques. The EEG signals are taken and then SVM and ICA classifiers are applied and features are extracted and classified [4].

Hariet *al* (2013) contributed a Hamming-distance classifier for ECG biometrics based on SPEC-Hashing. The proposed system was evaluated over a database of ECG signals from 52 different subjects that were collected at the Biometrics Security Laboratory of the University of Toronto. The EER of the Hamming-distance classifier was found to be 5.5% for closed-set matching and 14.82% for open set matching [5].

Junyatomaet *al* (2013) proposed a simple character identification method demonstrated by using EEG with a stimulus presentation technique. The method assigns a code maximizing the minimum Hamming distance between character codes. Character identification is achieved by increasing the difference between target and non-target responses without sophisticated classifiers such as neural network or support vector machine. They then applied this method to character identification using a 3×3 matrix and compared the results to that of a conventional P300 speller [6].

Fukamiet *al* (2012) proposed a study where they have improved upon the P300 speller Brain-Computer Interface paradigm by introducing a new character encoding method. It is based on an identification of the character which maximizes the difference between P300 amplitudes in target and nontarget stimuli. The codes were constructed in order to maximize the minimum hamming distance between the characters and the results were compared with that of a conventional P300 speller of the same size [7].

Kostileket *al.*, (2012) described the use of EEG signal as biometric characteristic for person identification. He used Frequency-Zooming Auto-Regression modelling and Mahalanobis distance-based classifier for classification of EEG segments, which lead to subject identification with success rate for single session identification up to 98%. Experiments show that use of the movement-related EEG leads to better identification results [8].

Xiao-Dong ZHANG *et al* (2011) analyzed the EEG signal based on multi-complicated hand activities. And then, two methods of EEG pattern recognition are investigated, a neural prosthesis hand system driven by BCI is set up, which can complete four kinds of actions (arm's free state, arm movement, hand crawl, hand open). Through several times of off-line and on-line experiments, the result showed that the neural prosthesis hand system driven by BCI is reasonable and feasible, the C-support vector classifiers based method is better than BP neural network on the EEG pattern recognition for multi-complicated hand activities [9].

Prochazkaet *al* (2010) invented a method for EEG signal processing including signal de-noising; evaluation of its principal components and segmentation based upon feature detection both by the discrete wavelet transform (DWT) and discrete Fourier transform (DFT). The self-organizing neural networks are then used for pattern vectors classification using a specific statistical criterion proposed to evaluate distances of individual feature vector values from corresponding cluster centres [10].

Zaidi Raziket *al* (2009) contributed a method with focus on off-line character recognition. The algorithm of pre-processing such as line and character segmentation is studied and a transformation towards characters is done using discrete wavelet transform. A process to generate a sequence of binary using a threshold value is done which will be classified using Hamming distance [11].



Yi Li *et al* (2009) contributed an automatic sleep stage classification technique of EEG using Hilbert-Huang transform. The energy-frequency distribution of EEG was used as features for each sleep stage; the nearest neighbor method for pattern classification was used to classify sleep stage [12].

Nakagawa *et al* (2008) contributed a method to classify electroencephalogram (EEG) signal recorded from left- and right-hand movement imaginations. He used a technique of complexity measure based on fractal analysis to reveal feature patterns in the EEG signal using detrended fluctuation analysis (DFA) algorithm. Finally, featured data are classified by a three-layer feed-forward neural network based on a simple back propagation algorithm [13].

STATE CLASSIFICATION USING HAMMING DISTANCE APPROACH

The Motif Finding problem is a maximization problem, given a set of EEG sequences, finds a set of l -mers, one from each sequence that maximizes the consensus score.

Input: A $t \times n$ matrix of EEG, and l , the length of the pattern to find.

Output: An array of t starting positions $s = (s_1, s_2, \dots, s_t)$ maximizing $\text{Score}(s, \text{EEG})$.

Another view onto this is to reframe the Motif Finding problem as the problem of finding a median string. Given two l -mers v and w , we can compute the Hamming distance between them, $dH(v, w)$, as the number of positions that differ in the two strings. For example, $dH(\text{ATTGTC}, \text{ACTCTC}) = 2$:

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A T T G T C
: X : X : :
A C T C T C

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The Median String problem is a minimization problem, given a set of EEG sequences, finds a median string.

Input: A $t \times n$ matrix EEG, and l , the length of the pattern to find.

Output: A string p of l nucleotides that minimizes

Total Distance (p, EEG) over all strings of that length.

Notice that this is a double minimization: we are finding a string v that minimizes Total Distance (p, EEG), which is in turn the smallest distance among all choices of starting points s in the EEG sequences.

The above two problems is computationally equivalent. Let s be a set of starting positions with consensus score $\text{Score}(s, \text{EEG})$, and let w be the consensus string of the corresponding profile. Then $dH(w, s) = lt - \text{Score}(s, \text{EEG})$

The consensus string for the solution of the Motif Finding problem is the median string for the input EEG sample. The median string for EEG can be used to generate a profile that solves the Motif Finding

Given two n -mers p and q , the Hamming distance $dH(p, q)$ between them, is the number of positions that differ in the two strings. Now suppose that $s = (s_1, s_2, \dots, s_t)$ is an array of starting positions, and that p is some n -mer. Then $dH(p, s)$ denotes the total Hamming distance between p and n -mers starting at positions s : $dH(p, s) = \sum_{i=1}^t dH(p, s_i)$, where $dH(p, s_i)$ is the Hamming distance between p and the n -mer that starts at " s_i " in the i -th sequence of EEG wave represented as image. The Total Distance ($p, \text{EEG Signal}$) = $\min_s (dH(p, s))$ denotes the minimum total Hamming distance between a given string v and any set of starting positions in the EEG Signal. The steps involved in finding Total Distance ($p, \text{EEG Signal}$) are first one has to find the best match for v in the first EEG sequence (i.e., a position minimizing $dH(p, s_1)$ for $1 \leq s_1 \leq n-l+1$), then the best match in the second one, and so on. That is, the minimum is taken over all possible starting positions s . Finally, we define the median string for EEG as the string p that minimizes Total Distance (p, EEG); this minimization is performed over all $4l$ strings p of length l . We can formulate the problem of finding a median string in EEG sequences as follows.

STEP 1

Find the best match for p in the first EEG Signal frame (i.e., a position minimizing $dH(p, s_1)$ for $1 \leq s_1 \leq n-l+1$), subsequently the best match in the second one, and so on. This represents the minimum value over all possible starting positions. Different snapshots of the EEG wave represents the level of disorder in the i^{th} to $(i+1)^{\text{th}}$ image and this measures the entropy i.e. time line. Thus, the image data representing the EEG wave is analyzed using Hamming distance approach and corresponding to maximum entropy (a measure of the disorder with respect to time line) the decision is taken by the state classifier.

STEP 2

Define the median string for EEG signal as the string p that minimizes Total Distance ($p, \text{EEG Signal}$); this minimization is performed over all the strings p of length l . Similarly, edit distance measures the minimum number of substitutions required to change one string into the other, and identify the minimum number of errors that could have transformed one string into the other.

STATE CLASSIFIER IMPLEMENTATION

In this paper, three classifier regions are selected, (but more regions can be included) namely, first 625 pixel values, mid 625 pixel values and the end 625 pixel values. The acquired EEG signal has a feature vector of length 25, and this feature vector is compared with the database EEG waveforms frame by frame with or without overlapping



manner and the Hamming distance is obtained. Conventionally, the primary waves Delta, Theta, Alpha, and Beta are evaluated for each snapshot of the image and the entropy is calculated. Based on maximum entropy, the state is classified. In this work these snapshots of Delta, Theta, Alpha, and Beta are provided as image input. The model is shown in Figure-1b.

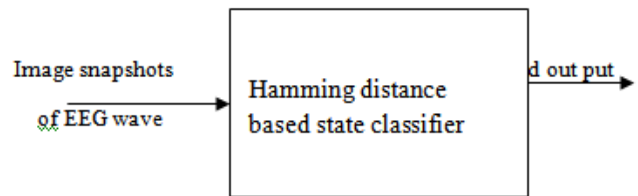


Figure-1(b).Proposed approach.

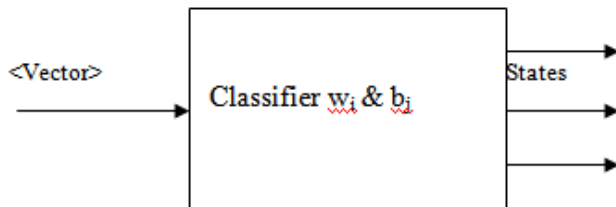


Figure-1(a).Conventionally classifier network architecture.

Notes: The vector contains statistical parameters extracted from Delta, Theta, Alpha, and Beta waves.

RESULTS AND DISCUSSIONS

The acquired signal with artefacts removed is compared with the data base reference in the context of minimum Hamming distance i.e. the Hamming distance between the test image and the reference frames (of same size) is computed as discussed in section3 of this paper. The reference signal that has the lowest Hamming distance or maximum entropy is selected. This is shown in table 1 for first 25 blocks. Similar values for middle & end blocks are also used, but not shown for brevity.

Table-1. Details of 1st 25 blocks.

Reference vector1.txt	253 253 253 255 245 254 225 251 253 253 253 253 255 245 254 225 251 248 248 254 180 25 0 0 219 253 253 253 255 245 254 225 251 253 253 253 253 255 245 254 225 251 248 248 254 180 25 0 0 219 253 253 253 255 245 254 225 251 253 253 253 253 255 245 254 225 251 248 248 254 180 25 0 0 219 253 253 253 255 245 254 225 251 253 253 253 253 255 245 254 225 251 248 248 254 180 25 0 0 219 253 253 253 255 245 254 225 251 253 253 253 253 255 245 254 225 251 248 248 254 180 25 0 0 219 253 253 253 255 245 254 225 251 253 253 253 253 255 245 254 225 251 248 248 254 180 25 0 0 219
Reference vector2.txt	222 213 223 243 295 213 213 203 215 254 254 298 299 231 275 266 248 248 254 227 25 0 0 219 231 223 221 220 221 222 234 256 222 213 223 243 295 213 213 203 215 254 254 298 299 231 275 266 248 248 254 227 25 0 0 219 231 223 221 220 221 222 234 256 222 213 223 243 295 213 213 203 215 254 254 298 299 231 275 266 248 248 254 227 25 0 0 219 231 223 221 220 221 222 234 256 222 213 223 243 295 213 213 203 215 254 254 298 299 231 275 266 248 248 254 227 25 0 0 219 231 223 221 220 221 222 234 256 222 213 223 243 295 213 213 203 215 254 254 298 299 231 275 266 248 248 254 227 25 0 0 219 231 223 221 220 221 222 234 256 222 213 223 243 295 213 213 203 215 254 254 298 299
Reference vector3.txt	153 153 145 155 148 153 153 155 145 155 154 125 151 155 141 148 148 154 127 125 0 0 119 131 137 138 124 126 152 165 147 149 153 153 145 155 148 153 153 155 145 155 154 125 151 155 141 148 148 154 127 125 0 0 119 131 137 138 124 126 152 165 147 149 153 153 145 155 148 153 153 155 145 155 154 125 151 155 141 148 148 154 127 125 0 0 119 131 137 138 124 126 152 165 147 149 153 153 145 155 148 153 153 155 145 155 154 125 151 155 141 148 148 154 127 125 0 0 119 131 137 138 124 126 152 165 147 149 153 153 145 155 148 153 153 155 145 155 154 125 151 155 141 148 148 154 127 125 0 0 119 131 137 138 124 126 152 165 147 149 153 153 145 155 148 153 153 155 145 155 154 125 151
Reference vector4.txt	103 203 205 205 208 153 153 155 145 155 204 205 201 205 201 208 148 154 207 205 5 2 119 131 137 156 214 206 202 206 203 209 103 203 205 205 208 153 153 155 145 155 204 205 201 205 201 208 148 154 207 205 5 2 119 131 137 156 214 206 202 206 203 209 103 203 205 205 208 153 153 155 145 155 204 205 201 205 201 208 148 154 207 205 5 2 119 131 137 156 214 206 202 206 203 209 103 203 205 205 208 153 153 155 145 155 204 205 201 205 201 208 148 154 207 205 5 2 119 131 137 156 214 206 202 206 203 209 103 203 205 205 208 153 153 155 145 155 204 205 201 205 201 208 148 154 207 205 5
Acquired vector	253 253 253 255 245 254 225 251 253 253 253 253 255 245 254 225 251 248 248 254 180 25 0 0 219



The obtained results for two sample cases is illustrated in. Figures 12(a) to 12(d) and Figures 13(a) to 13(d). The EEG signals are examined from real-time subjects (Table-2) and the different features are extracted for further classification.

The implementation result (using python program in Linux kernel) corresponding to EEG state 4 and state 5 is captured online and shown in Figure-2 and Figure-3. The trained neural output for the five different states is listed in Appendix - I. The value of '€' (classification error) is listed in Table-3. The error plot with ϵ_{min} is drawn in Figure-13.

Table-2. Analysis of patients in various modes.

S. No.	Age (years)	Normal / Abnormal	Condition	Wave type	category
Patient 1	17	Normal	Awake	Alpha	Adolescent
Patient 2	2	Abnormal	Sleep	Beta and Delta wavamixed	Infant
Patient 3	0.5	Normal	Sleep	Theta	Natal

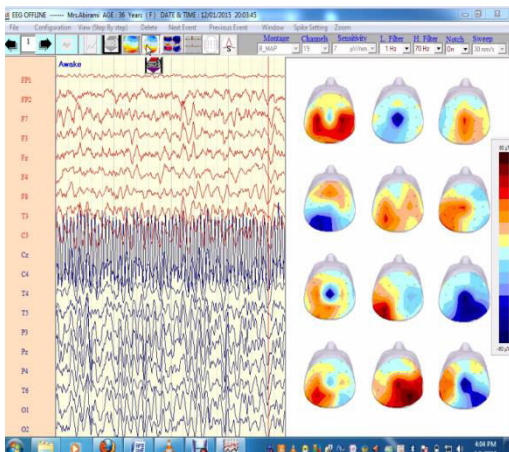


Figure-2. Progressive map of the patient1.

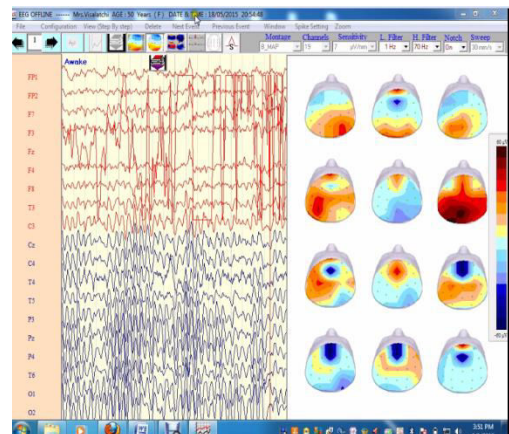


Figure-4. Progressive map of the patient3.

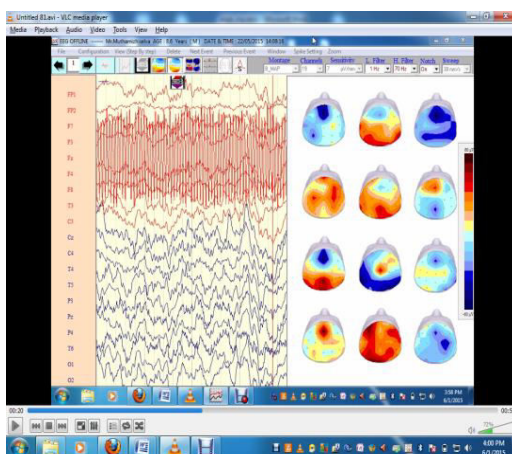


Figure-3. Progressive map of the patient2.

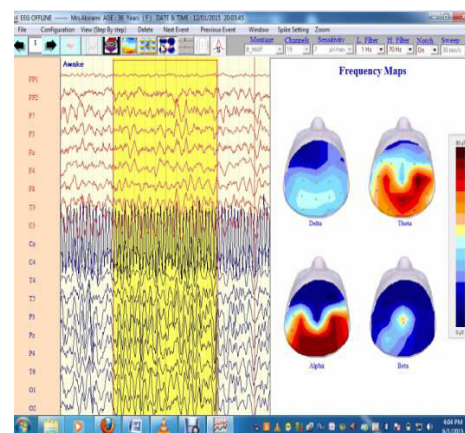


Figure-5. Frequency map of patient1.

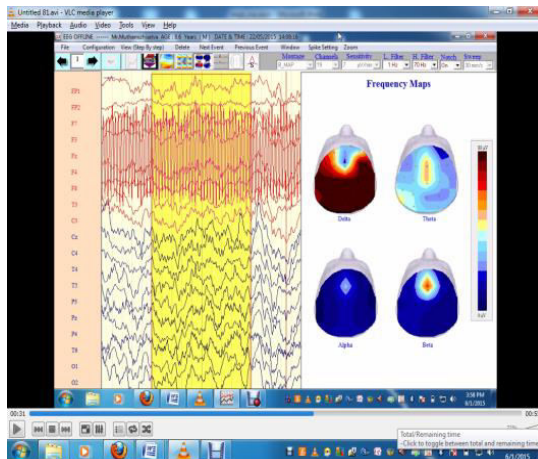


Figure-6. Frequency map of patient2.

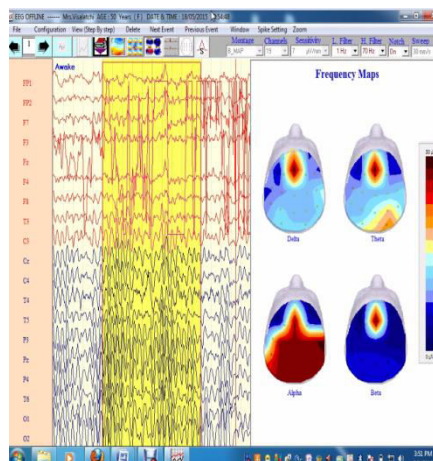


Figure-7. Frequency map of patient3.

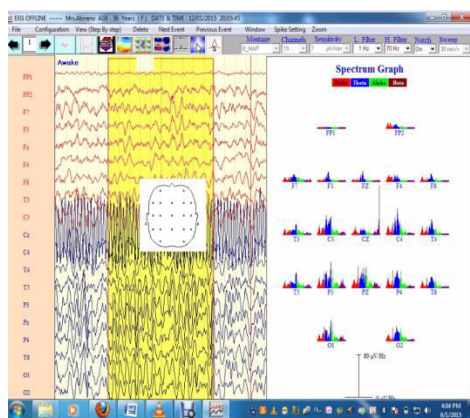


Figure-8. Spectrum graph of patient1.

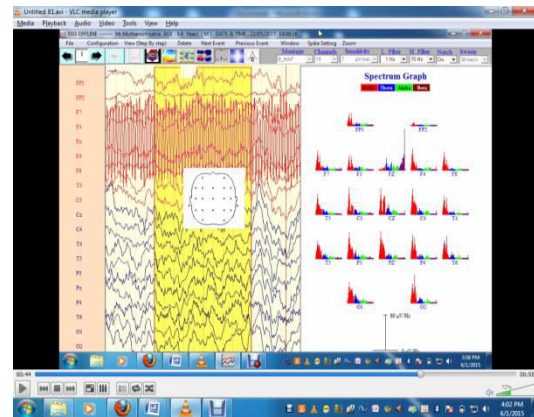


Figure-9. Spectrum graph of patient2.

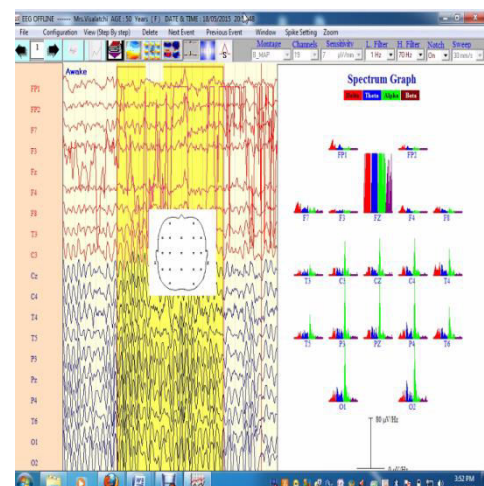


Figure-10. Spectrum graph of patient3.

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minimum of non-match value for input1:0
number of time non-match value in input1:23
minimum of non-match value for input2:18
number of time non-match value in input2:19
minimum of non-match value for input3:23
number of time non-match value in input3:19
minimum of non-match value for input4:25
number of time non-match value in input4:613
matched with input1

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Figure-11. Matched category output.

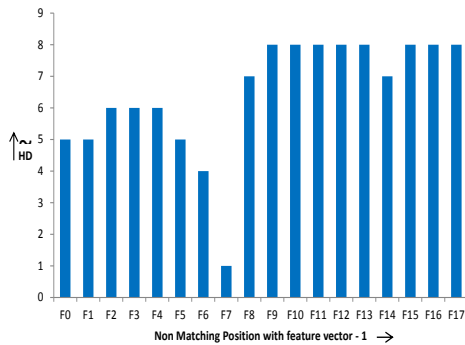


Figure-12(a). Hamming distance vs graph [Feature Vector1].

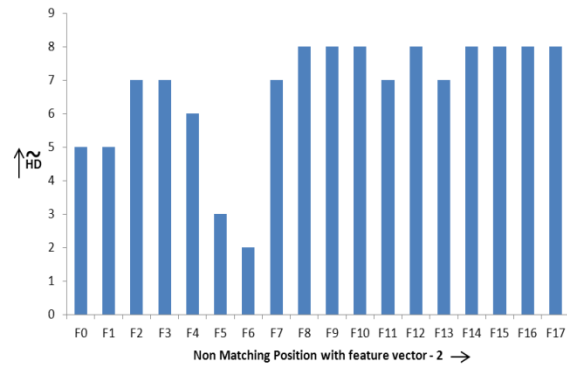


Figure-12(b). Hamming distance vs matching matching position position graph [Feature Vector2].

Table-3. Error value for the classified states (diagonal elements).

EEG state	Value of $ \epsilon $				
	ϵ_1	ϵ_2	ϵ_3	ϵ_4	ϵ_5
1	0.1445	45.485	43.993	46.659	23.127
2	+4.8754	0.5018	1.72198	2.94572	6.595
3	64.47	53.35	0.1648	56.309	99.592
4	15.0989	61.0564	9.022	3.555	69.054
5	41.183	131.605	27.263	42.844	1.619

The error plot is given in Figure-13

Legend: Blue, Red, Green, Purple, Cyan

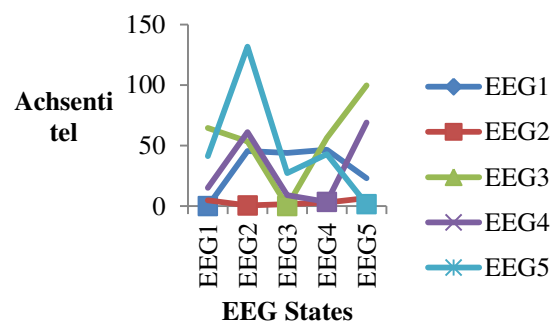


Figure-13. Error plot from table 3 for the different EEG states misclassification rate.

Table-4. Five states.

	State1	State2	State3	State4	State5	PPV
State1	100	0	0	0	0	100%
State2	0	100	0	0	0	100%
State3	4	0	96	0	0	96/100%
State4	0	3	0	97	0	97/100%
State5	0	0	0	2	98	98/100%

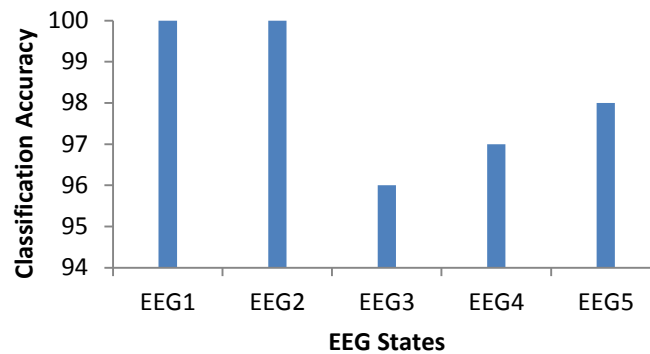


Figure-14. EEG states vs classification accuracy.

Appendix-1

EEG state	Trained output					Classified output				
	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5
State1	50.142	4.8	6.2924	3.627	27.158	50.286	4.8	6.29	3.627	27.15
State2	7.9861	2.608	4.832	0.1649	9.706	7.9861	3.11	4.832	0.1649	9.706
State3	-10.169	-21.289	-74.8	-18.3	24.95	-10.169	-21.289	-74.6	-18.3	24.95
State4	-66.25	9.629	-42.4	-47.87	17.627	-66.52	9.629	-42.4	-51.4	17.62
State5	6.641	97.06	-7.279	8.3	-32.92	6.641	97.06	-7.27	8.3	-34.5

CONCLUSIONS

In this work, low frequency signals that exhibit high degree of variability and highly non-stationary is studied. The state classifier reported in this research work is applied to EEG signals. Also, in EEG research, there are pathological as well as non-pathological conditions (commonly observed in children but of less impact). With the help of Hamming distance measurement of input EEG signal to the sample EEG signal and applying state classification the best EEG signal with low frequency noise is obtained which helps in accuracy of diagnosing the patient. The current research work can easily be extended to study the non-pathological EEG signals with high classification accuracy.

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