Channel selection using visual data mining and pattern matching techniques on electroencephalograph (EEG) sensor data.

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Abstract

The amount of data collected from different biomedical devices is increasing rapidly due to various disease and disorder detection. The use of visual data mining techniques on biomedical device is an interactive tool for bio-medical data analysis. This paper introduces concepts and algorithm for channel selectionthrough channel ranking using visual data mining technique. The aim is to propose a novel algorithm for channel ranking and ranked channels performance is evaluated using classification. Channel ranking toward classification is a task to find relevant channels that are minimal subset of channels, which are essential to group the data in a meaningful way. To extract useful information for classification on biomedical devices; visual data mining technique combines traditional data mining with information visualization. Information visualization on biomedical device uses statistical and artificial intelligence technique for data exploration and analysis. There are various types of biomedical devices like EEG, ECG, EMG, EOG etc. Multichannel EEG device is used to show the useful of proposed work. EEG device is normally used in brain computer interface and many other applications. The proposed algorithm gives optimal channel ranking to rank the channel as per their importance in increasing order of their relevancy for EEG eye state recognition. To rank the channels proposed methodology combines Quad Tree data structure and SIFT (Image Matching) algorithm. Performance of proposed method is evaluated and compared with different channel ranking algorithms. The proposed algorithm is remarkable and comparable with conventional algorithms for channel ranking. The maximum accuracy on EEG eye state classification founds using proposed algorithm is 89.05 %.

Keywords: Visual data mining, Channel selection, Electroencephalograph (EEG), Visual data mining, Quad tree, Sift.

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Introduction

In recent years, biomedical medicals devices have been developing in a high speed. These device utilities in many areas. These Devices are required todetect the state of human body parts like eye state detection, feet movement detection, hand detection etc. EEG is one of the wider used medical devices [1,2]. Visual exploration of massive and complex biomedical device dat a sets had been used as an interactive technique to extract additional information about the data set. Discovering patterns from the information and its extracted knowledge is used in decision making. Pattern recognition techniques are used to collect, store and process this complex and massive data and one observable point about pattern recognition is that how statistics and graphical methods involved recognizing the pattern. Star coordinates is a simple, and efficient technique used in many areas [3-5] to visualize multivariate and multidimensional data. Generally the bio medical device data are multidimensional and multivariate. The star coordinate method used in outlier detection [6], trend analysis [7], cluster analysis [8] etc. Many researchers also focused on automatically finding, configuration of star coordinate axis vectors to optimize data analysis [9-11]. In the proposed method star coordinate is applied on EEG device. EEG device is a brain activities measuring device and it is useful in many areas [12-14]. To analyze brain activities graphical analysis is done using visual data techniques. All the channels present on EEG are collectively identifying the state of eye, motor neuron, body movement etc. Method considers eye state recognition using visual techniques. To identifying the state of eye channels are selected. Channel selection is a process to select minimal channel that are sufficient for recognition. Proposed technique used machine learning and visual data analysis technique for optimal channel finding.

Origin of the problem

Selecting appropriate channels in EEG applications helps to increase the usability and performance of the EEG. The use of EEG as the basic of assessment in brain-computer interface [15] and others. Brain Computer system capturing brain signals and then translates in to executable form for direct communication between brain and computer [16]. Due to low casting and high time resolution properties EEG is most popular among other brain signals used in BCI [17]. Present work is taking eye state recognition using EEG. In EEG an important aspect is to find optimal number of channels that are sufficient to obtain optimal performance to classifying eye state. Each Channels of EEG data contributes a number of time-samples (features) for classification decisions [18], Channel selection can be viewed as a feature selection problem.

Related work

Channel selection is a task to find uncorrelated and relevant channel in order to increase performance of the EEG used in BCI and other systems.

Fisher criteria (FC): This method determines how strongly channels are correlated with class label [19-21]. Channels have to be arranged based on correlation factor. The advantage of this method is its simplicity but it is not finding channel to channel correlation. Some time it is giving redundant information containing channels because channel to channel correlation is missing.

Mutual information (MI): Mutual information of two channels is a measure of mutual dependence between them. This method firstly initializes a set of channels C= {C_1, C_2, C_3…, C_n} and then it computes mutual information of channels with the class label [22-24]. Scoring of channels is done that maximize mutual information of class label.

Support vector machine (SVM): In Support vector machine based channel selection, the channels are selected using Recursive Feature Elimination [24-26].

Common spatial pattern (CSP): The CSP algorithm [27] applied in binary EEG classification problems. CSP works on covariance matrices of both classes. Method maximize variance of one class while minimize the variance of the other class [28].

Association rule (AR): Channel selection using association rule mining is described in [29]. In this method rank list generated from various scoring techniques has considered as transactions and presented channels on scalp is treated as item set, method found redundant channels using a priori algorithm. The advantage of this method is that it considers occurrence of one channel in respect of other channel indirectly it finds correlation among channel properties.

Incremental feature reordering: Channel selection using incremental feature reordering [30], explaining how ranks are evaluated with different criteria like info gain, entropy, etc. Every method orders the channel list and placed un-important channels to last position. Last position channels are stored in doubly linked list for iterative channel elimination, channel which removal not affects the classifier performance declare unimportant channel among channel set. Advantage of method is that it has taken many scoring criteria and finds redundant information containing channel.

Decision tree based: Decision tree is a well-known method for classification. Channels selection is also done using decision tree [31], method creates tree for channel reduction and tree pruning for channel ranking. This work has used gini index criteria to build the tree [32].

Independent component analysis (ICA): This channel selection technique is proposed in 90s. Multivariate data is decomposed using statistical component [33]. The selection of ICA components using visual inspection in time domain analysis can also be done, this method is analysed in [34].

Recursive feature elimination (RFE): This method is proposed by Guyon et al. [35]. This method is based on margin of a trained SVM [36]. Good feature ranking criteria is not necessarily a good feature subset ranking criterion; this problem is overcome by using RFE algorithm [37,38].

Relief and relief: In binary classification Relief is widely used [39]. Relief is an extension of Relief; this is designed for multiclass problems [40]. Relief is to estimating quality of channels based on nearest K sample drawn from training set.

Contribution and outline of the paper: In this study EEG eye state data is taken for showing the usefulness of research. Research contributed for finding optimal number of channels from multichannel EEG using visual data mining. The motivation for this investigation is to enhance human interpretation for EEG optimal channel selection. This is the first study that combines visual data mining and image processing techniques.

Block diagram of proposed technique: The block diagram of proposed is shown in Figure 1, input for method is EEG electrode sensor data and this sensor data is stores in 2-Dimensional array, Data get segmented for further analysis. Few segments are selected using random function. In next step visual data mining approach (Star Plot) is applied and getting various intersecting outcomes from them. After completing these steps frequent pattern recognition from visual data mining approach is performed. The Star plot outcomes are stored in Quad tree data structure for efficient storage for analysing and for pattern matching purposes. Filter model is applied for channel selection and classification is done after channel selection. Performance of selected classifier is evaluated.

Methods and Materials

Quad tree decomposition

The Quad tree structure for image was first introduced by Hanan Samet [41]. Quad Tree is image segmentation technique [42]. This technique recursively divides the image in to homogeneous segment by merging adjacent regions(R) using border. It detects the large object and this method provides any time segmentation. Our method convert color image data (Star Plot) into grey color then detects its edges. After edge detection it segmented using quad tree data structure. The functional diagram of Quad Tree data structure is shown in (Figure 2).

SIFT image matching algorithm

Scale Invariant Feature Transform (SIFT) is an image matching algorithm. The basic idea behind SIFT method is that its Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters [43]. In proposed method stable pattern from star plot is identified using SIFT method. After segmentation each segmented pattern is stored and iterate for maximum matched score. Maximum matched pattern is extracted and finds its importance toward classification.

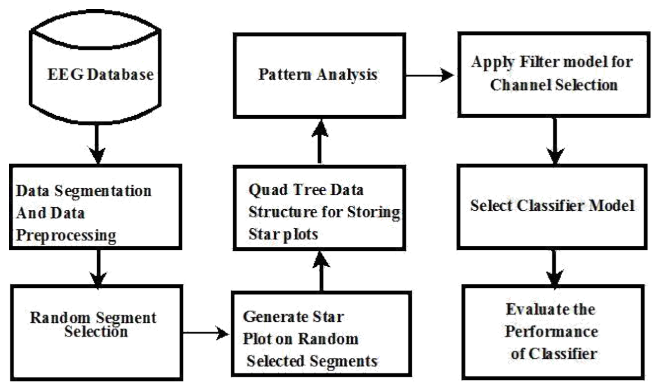


Figure 1. *Block diagram of proposed work.*

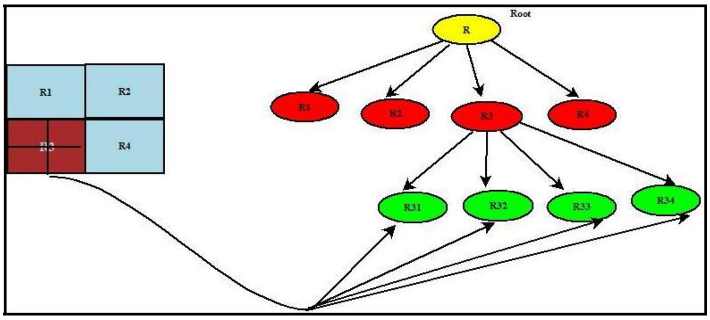


Figure 2. *Functional diagram of image segmentation using Quad tree data structure.*

EEG data set description

Electroencephalogram (EEG) is useful for measuring brain activity. During the test very little electricity is passed between the electrodes and skin. EEG usually takes 30-60 minutes. The technician will put a sticky gel adhesive on 16 to 25 electrodes at various spots on our scalp [5-6]. There are various spatial resolution of EEG systems like 10/20, 10/10, 10/5 systems as relative had surface based positioning system. The international 10/20 system a standard system for electrode positioning with 21 electrodes extended to higher density electrode such as 10/10 and 10/5 systems allowing more than 300 electrodes. Placement of electrode is shown (Figure 2). Numbering system for electrode placement is either even or odd, even number shows electrode placed in right hemisphere and odd number shows electrode placed in left semi sphere different alphabet along with numbering is used for electrode naming description about this is shown in (Table 1).

EEG data classification

EEG data is a time series data. The problem of classification determines predefined groups of entities that are most similar to a time series entity [44]. The determination of the class it belong to be extremely challenging because similarities and dissimilarities across different time series. Proposed method classifying EEG eye state data. EEG data is a high dimensional data and high dimensionality has presented serious challenges to existing learning method [45]. Dimensionality reduction techniques are broadly classified in to two categories first is feature extraction and feature selection. In feature extraction extracted features are projected into new feature space [46]. On other hand feature selection selects subset of features from existing feature set. Presented paper reduces EEG data dimensionality using feature selection. The feature selection method is applied on EEG data for relevant channel finding. Relevant channels are identified using visual data (Star Plot) technique. Star coordinates represent each channel as an axis radiating from the centre of a circle to the circumference of the circle [47]. After channel selection classification task is done using K* (Instance Based classifier).

K * (Instance based classifier): K* is an instance based algorithm nearest neighbour pattern classification is a synonymous of instance base classifier [48,49]. The idea behind K* algorithm is that similar instances have similar classification [50]. There are various types of classifiers method uses instance based only because it is already proved in literature that it is a well suited classifier for EEG eye state data set.

Table 1: *Terms used in EEG.*

Alphabet	Position
F	Frontal
T	Temporal
C	Central
P	Parietal
O	Occipital

Performance evaluation: Performance comparison of the proposed approach with some recently studies. Classification performance measures are listed below.

Area under the curve (AUC): AUC is based on notation of decision variable. The AUC is an effective and combined measure of sensitivity and specificity that describes the inherent. Sensitivity is a true positive rate and it is a proposition of positives that are correctly classified and specificity is also known as true negative rate and it is a proportion of negatives that are correctly classified.

Recall or true positive (TP) or sensitivity: Where P = True Positive, Q = False Negative

Precision (PR): Precision is the proportion of the predicted true cases that were correct, as calculated using the equation.

Where P=True Positive, R=False Positive

Accuracy (AUC): Accuracy is the proposition of the total number of instances that are correctly classified. This value is calculated by give formula.

Where P = True Positive, Q = False Negative, R= False Positive and S = True Negative.

F-measure: F-measure is defined as a balance mean between specificity and sensitivity. This value is computed using harmonic mean. This value indicates a higher classification quality.

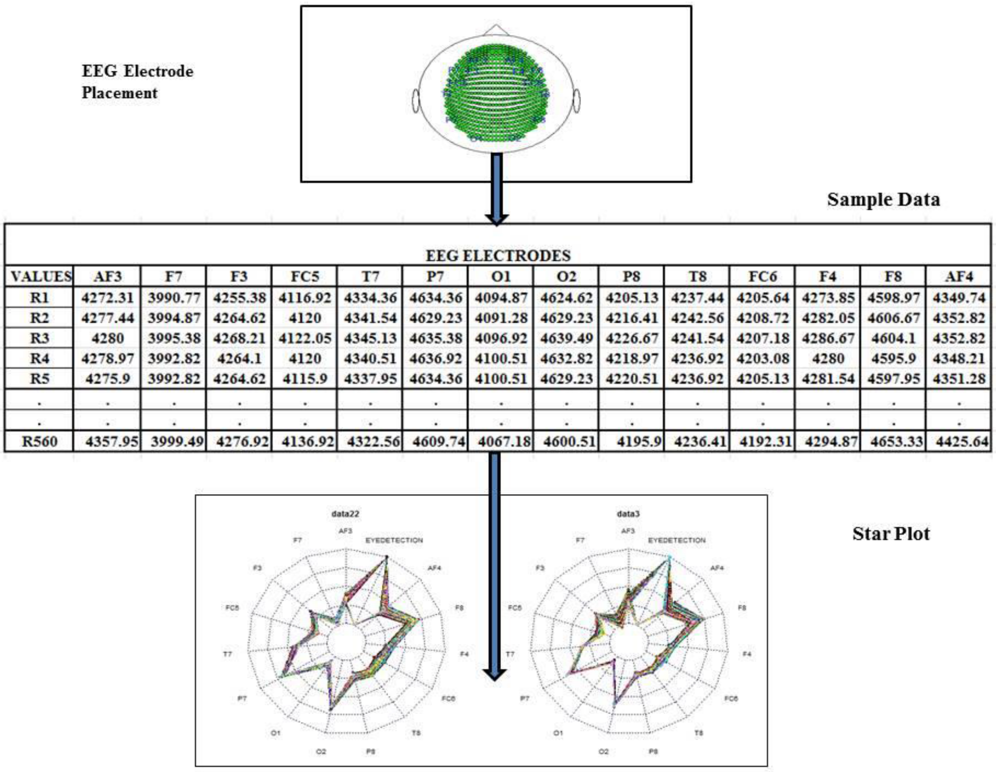
Star Stable Patterns (SSP) based channel selection

To select channels using proposed method, first EEG data present in two dimension array (Matrix) is pre-processed for data cleaning. An only clean data sample istaken for further analysis. The size of data is big so segmentation work is performed. There are N samples are created from clean data. And method selects n(n<<N) for random segment selection because randomly selected n samples are unbiased and a representative samples is important in drawing conclusion from the overall EEG data distribution. Functional diagram of proposed work is shown in (Figure 2). Describes about EEG placement and how data is represented in memory. Visual analysis on segmented data plotted using *Star Plot* technique. Outcomes of visual analysis are images so image processing techniques are applied

to identifying the presented patterns on image. Image data is segmented further using Quad tree. Quad Tree is a hierarchical structure applying divisive process for image segmentation. After Segmentation SIFT method is used for finding maximum matched score to find stable pattern among various patterns presented on Star Plot. Process flow for stable pattern finding is shown in (Figures 3 and 4).

Algorithm

This section describes algorithm for proposed work. Input for



EEG ELECTRODES														
VALUES	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
R1	4272.31	3990.77	4255.38	4116.92	4334.36	4634.36	4094.87	4624.62	4205.13	4237.44	4205.64	4273.85	4598.97	4349.74
R2	4277.44	3994.87	4264.62	4120	4341.54	4629.23	4091.28	4629.23	4216.41	4242.56	4208.72	4282.05	4606.67	4352.82
R3	4280	3995.38	4268.21	4122.05	4345.13	4635.38	4096.92	4639.49	4226.67	4241.54	4207.18	4286.67	4604.1	4352.82
R4	4278.97	3992.82	4264.1	4120	4340.51	4636.92	4100.51	4632.82	4218.97	4236.92	4203.08	4280	4595.9	4348.21
R5	4275.9	3992.82	4264.62	4115.9	4337.95	4634.36	4100.51	4629.23	4220.51	4236.92	4205.13	4281.54	4597.95	4351.28
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
R560	4357.95	3999.49	4276.92	4136.92	4322.56	4609.74	4067.18	4600.51	4195.9	4236.41	4192.31	4294.87	4653.33	4425.64

Figure 3. *EEG data acquisition, memory representation and star plot creation.*

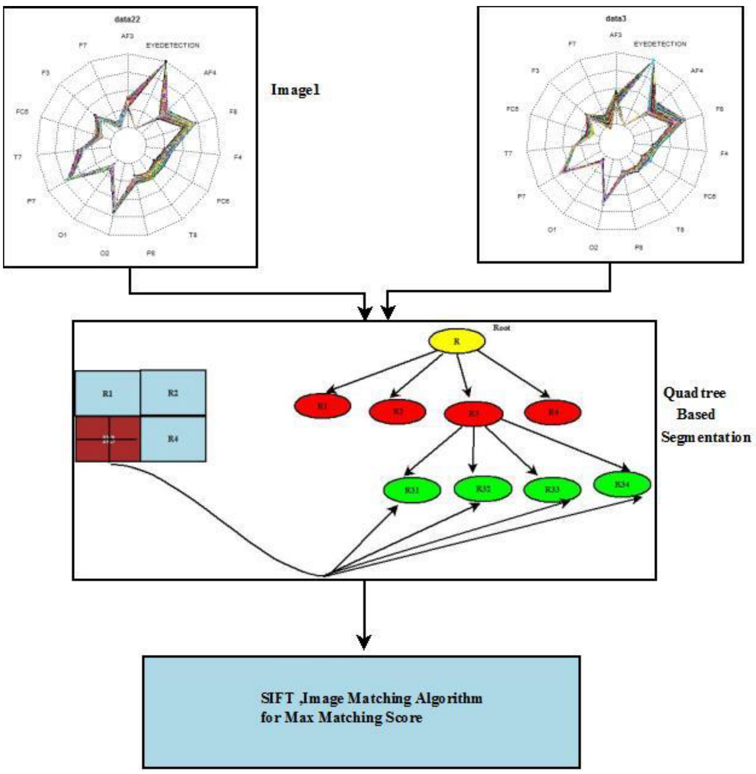


Figure 4. *Star plot image data store in quad tree data structure and stable pattern matching using SIFT algorithm.*

algorithm is EEG eye state data set and output is redundant channels set that not contributing more to classify the EEG data.

An algorithm describes steps required for RIC (Redundant Information Channel) set generation, input for algorithm in EEG eye state dataset. For improving the performance of classification model data is equally (N) segmented in first step. After this random selection is applied on N Segments and selects n (n<<N) segments only because distribution of data in overall data base can be analysed efficiently using few numbers of random segments. Then n segments for creating star plots to visualize the distribution of data. Outcome from Star Plot is an image, for further analysis it is stored in quad tree data structure because using this storage region base segmentation and pattern analysis to be easy. After region based segmentation pattern finding and matching is done using SIFT algorithm, first finds stable pattern then finds minimum circle convergence pattern. After getting stable and minimum convergence, method extracts channels from this patterns then it finds their importance toward classification. In next step information gain of channels present in patterns is evaluated and sorted. Filter feature selection technique is applied further for RIC generation.

Result and Discussion

SSP patterns channel extraction

Channels presented on SSP are extracted using image processing techniques and even this pattern is also clearly interpreted using human perception. According to data set there are 21 equal size segments are created and randomly selected samples on first and second run is shown in **(**Figures 5 and 6). There are 4 randomly samples are drawn out of 21 samples in first run. These star plots are stored as image on image database for stable pattern finding. Extracted channels from image database are {T7, P7, O1, O2, and P8}.

SSP channels and channel ranking: Extracted channels using SSP method finds these channels can be the part of redundant and irrelevant channels. Classification based on channel ranking is done using different methods like correlation, info gain, gain ratio etc. and after removing last five channels from different scoring mechanism because patterns also extracted five channels from image data base. After comparing this ranking method it is observed that it is giving equal or higher classification accuracy as compare to other ranking methods. The rank list generated from different ranking methods is shown in (Table 1). Once channels are selected, the classifier built its model on the training data and classifies the test instance based on learning model. Afterwards, evaluation measures are needed to describe how similar the predicted classes of the test instances are to the real classes. Evaluation measures like F-Score, AUC curve are calculated and it is presented in (Figure 6).

SSP redundant channel removal based on information gain (IG): Information gain is an evaluated of every EEG channels. And Channels are sorted as per IG values. Stable Patterns extracted from star plot are iteratively removed as per sorting. Performance of classifier is evaluated after each removal of channels from pattern if classification accuracy is greater than threshold classifier performance; it is removed from channel

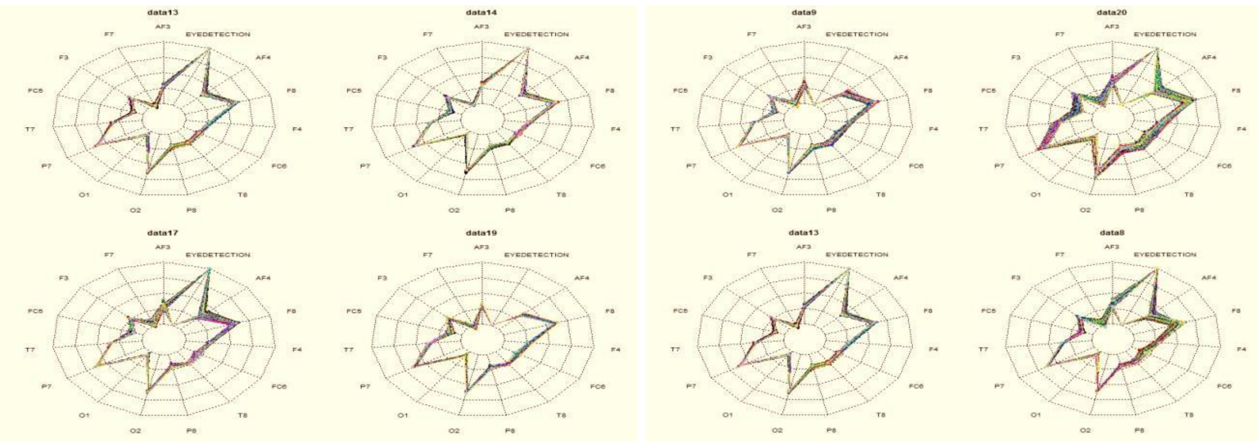


Figure.5. *Star plot on randomly selected (13, 14, 17 & 19) samples and star plot on randomly selected (9,20, 13 & 8) samples.*

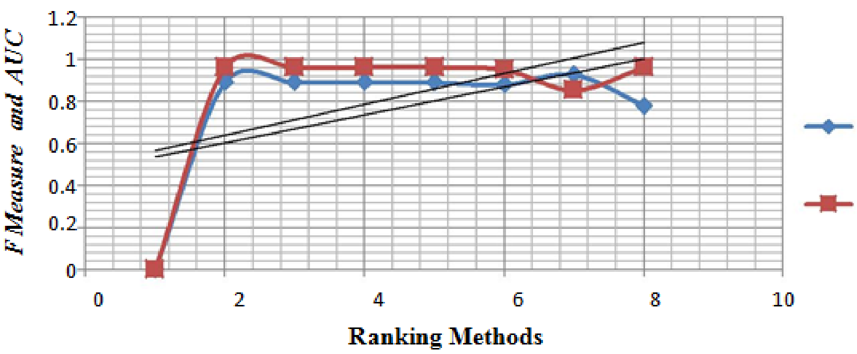


Figure 6. *F-measure and ROC values of proposed method with other conventional ranking methods.*

set and inserted this on redundant channel set. Individual channel removal from stable pattern and its computed classifier accuracy and its information gain value is shown in Table 2. It is observed that after redundant information removal classification accuracy is increased. In Table 3, it is clearly showing that P8 channel having minimum IG value after removal of this channel classification accuracy is raised. P8 channel is the first channel inserted in RC after this next minimum IG value is shown by T7 individual channel removal from channel set its accuracy is 94.19 and after P7 removal the combination of T7 and P7 accuracy is raised and it is calculated 95.164 and it is shown in Table 3. The space requirement to build the model is sufficiently reduced and threshold for this model is 93% if the removal channel giving equal or higher threshold value then this channel is become the part of RC else it is not removed. According to present work four channels are inserted in RC set. Removal of this channel will sufficiently reduce the space requirement and increasing the classification

Table 2. *Channel ranking and classifier (K*) accuracy after removal of redundant channels obtained from different ranking algorithms.*

S.NO	Feature Ranking Algoritm	Selected Attributes for Filter Model (After Last Five Removal)	Accuracy
1	SSP	Pattern Attributes (P7, T7, O1, O2, P8)	89.0581
2	Correlation	AF4, F7, F8, F4, T8, AF3, FC6, P7, P8, FC5, F3, O2, O1, T7	89.0581
3	Gain Ratio	P8, AF3, O1, FC6, P7, AF4, F8, T8, T7, F4, FC5, O2, F3, F7	89.0079
4	Info Gain	O1, P7, AF3, AF4, F8, F4, P8, FC6, T8, O2, T7, FC5, F7, F3	89.0070
5	One R Attribute	O1, P7, AF3, AF4, F8, P8, F3, T7, T8, FC5, O2, F4, FC6, F7	87.9036
6	Symmetrical Uncertain	AF3, O1, P7, AF4, P8, F8, FC6, F4, T8, T7, FC5, O2, F7, F3	89.0079

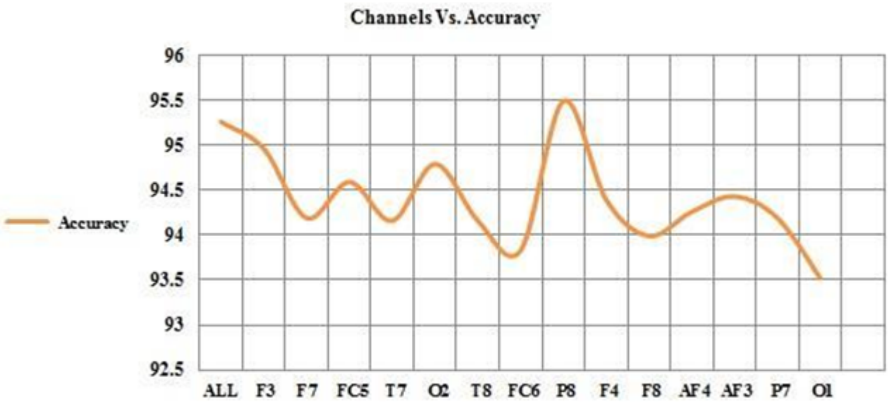


Figure 7: *Classification accuracy after single channel removal.*

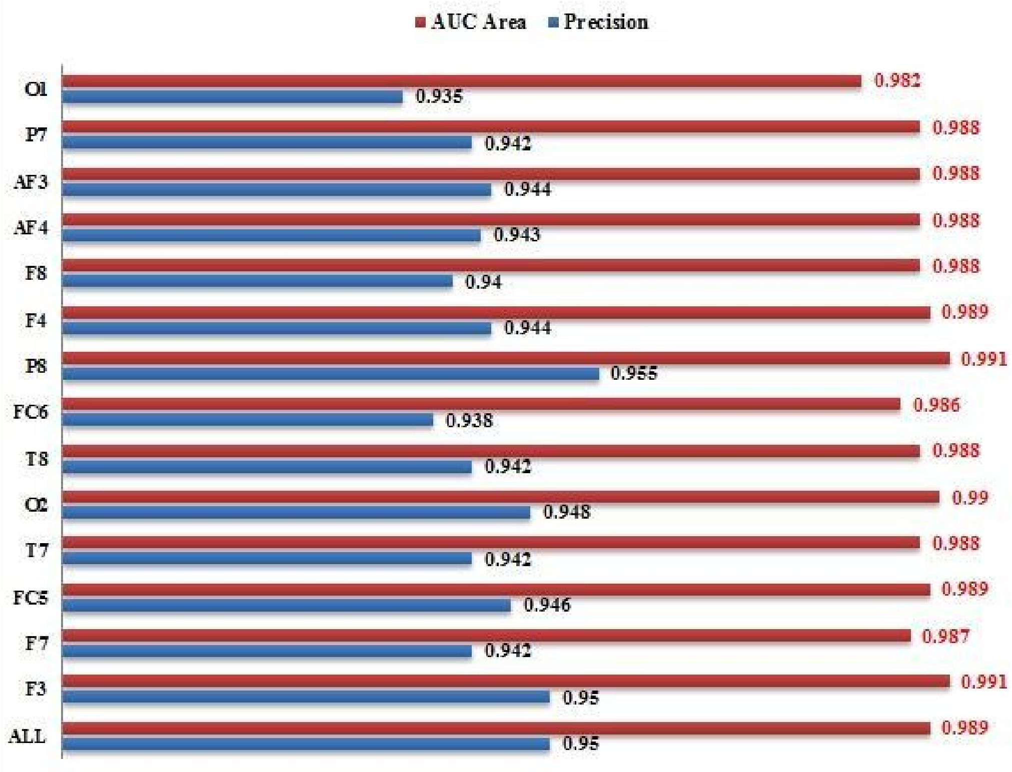


Figure 8. *Classification accuracy after single channel removal.*

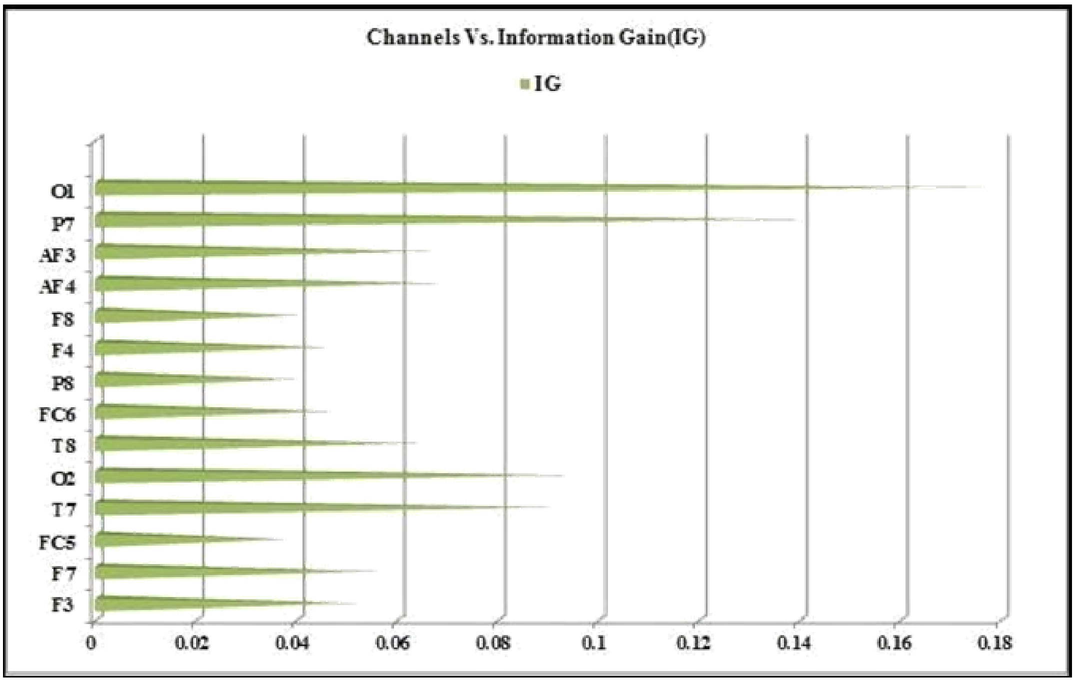


Figure 9. *Information gain values of EEG channels.*

Table 3. *Information gain and classification accuracy after one channel removal from channel set.*

Channels	Precision	ROC Area	Accuracy	IG
ALL	0.95	0.989	95.26	....
F3	0.95	0.991	94.96	0.05253929
F7	0.942	0.987	94.19	0.05625747
FC5	0.946	0.989	94.59	0.03829347
T7	0.942	0.988	94.16	0.09153695
O2	0.948	0.99	94.79	0.09534856
T8	0.942	0.988	94.16	0.06544651
FC6	0.938	0.986	93.83	0.04744382
P8	0.955	0.991	95.49	0.04042552
F4	0.944	0.989	94.39	0.0465493
F8	0.94	0.988	93.99	0.04102799
AF4	0.943	0.988	94.26	0.06929533
AF3	0.944	0.988	94.43	0.06739485
P7	0.942	0.988	94.19	0.14362883
O1	0.935	0.982	93.52	0.17979839

Table 4. *Redundant channel set generation.*

Pattern Channels	Accuracy(K*)	Pattern Channels	Accuracy(K*)
P8	95.49	P8	95.49
T7	*94.16*	*P8, T7*	*95.164*
O2	94.79	P8, T7, O2	94.6294
P7	94.19	P8, T7, O2, P7	93.4248
O1	93.52	P8, T7, O2, P7, O1	89.4261

accuracy. Single channel removal and its effect on accuracy are shown in (Figures 7 and 8). Channel and its information gain is shown in Figure 9.

Conclusion and Future Scope

Present work analysed related work in the field of feature selection in bio medical area. The article proposed feature selection using visual data mining approaches to find irrelevant features. This is first study to find irrelevant using radar plot with image matching technique, in the area of subset feature selection. Image matching using quad tree decomposition combines with SIFT technique plays vital role for irrelevant attribute finding. Recently many researchers have given solution for feature subset selection and considering many heuristics for searching important features in this domain. It was observed that the goodness of a selected features is evaluated by different criteria, optimal subset is based on one criteria may or may not be optimal for another criteria. The article is finding best subset of feature for bio medical device data towards on application of eye state recognition. The performance of proposed article compare with different feature ranking algorithm and it founds that visual analysis is another method for subset declaration from attribute set.

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