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An InvoluntarySingle Channel EEG Signals Sleep Stage Detection, Classification and Analysis

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Abstract - **Sleep stage detection and further accurate classification is an important step for diagnosing the different sleep related diseases. In this research paper an effective method for automatic sleep stages detection from single channel EEG signal is presented. In this present work the various stages as Awake, first, second, third and fourth sleep stages and rapid eye movement are classified by using Empirical Mode Decomposition (EMD), Chi-square and Adaboost algorithm. This classification is based on some selected attributes. The accuracy of classifier for five stage and 6 stage is obtained as 92.14% and 90.77% respectively.**

Keywords— EEG, EMD, sleep stages, Chi-square, Hjorth parameter.

I. Introduction

Electroencephalograms (EEGs) are important bio-signals used to analyze and diagnose different health-related problems. Sleep stage detection is one of the applications where EEG signals are used. The efficient detection of sleep phases contributes to the identification and treatment of different problems linked to the brain. The definitions Rech-tschaffen and Kale's (R&K) [1] and the American Academy of Sleep Medicine (ASAM)[2] are two methods for identifying sleep phases. The R&K criterion is used for the analysis in this article. Six sleep phases are awake (A), stage 1, 2, 3, 4 termed as S1, S2, S3, S4 and fast eye movement (REM). In five stages of sleep detection, S3 and S4 as combinationtermed as slow wave sleep (SWS). In four steps, the five phases S1 and S2 are combined to form a single stage. In three stages, S1, S2, S3 and S4 are combined to form a non-rapid eye movement (NREM) and two stages consist of awake and all remaining sleep periods. The expert scorer will provide the sleep stage scoring. But such scores also have human error and variation from scorer to scorer [3]. Less time and better accuracy can be accomplished with the aid of a computer-based automated sleep stage scorer. Various data were used by various authors to predict sleep phases. Electroencephalogram (EEG), Electromyogram (EMG) and Electrooculogram (EOG) are primarily used for this purpose. It's Charbonnieret. Al. [4] used a multilayer sensor for stage detection. Spectral and statistical attributes have been extracted from single channel EEG, EOG and EMG data. The precision obtained for the five-phase detection is 85.5 percent. Agrawalet. Al. [5] the two EEG channels, two EOG channels, one single channel EMG data were used to extract spectral attributes. These attributes were used with the K-mean clustering for classification. After this method, a precision of 80 percent was achieved.

Authors also used data from a single channel to detect the different stages. Most of them used a single EEG channel for this purpose. Rozhinaet. Al. [6] used a single channel EEG signal for two stages, three stages, four stages and six stages. Spectral and statistical attributes have been extracted and used in the ANN. It's Zhu et. Al. [7] used the visibility graph of the single channel EEG data for the extraction of the attribute.

The best attributes have been chosen and transmitted via SVM with the RBF kernel. The two-stage, three-stage, four-stage, five-stage and six-stage accuracy rates were 97.9%, 92.6%, 89.3%, 88.9% and 87.5% respectively. Hassan and Hassan et. al. [8] Single channel EEG data were also used for two phases of classification, three phases, four phases, five phases, six phases. Bagging has been extracted and graded for the spectral and statistical features In the two-stage classification, maximum accuracy of 95.5% was achieved.

In our proposed method, single channel EEG attributes are derived by statistic attributes, Hjorth parameters, and zero levels of empirical decomposition mode. The attributes will then be chosen using the chi-square evaluation [10]. Finally in the AdaBoost classification, the selected attributes are used with the REP tree as the basis user. Two phases, four phases, five phases and six phases have been identified and the exact findings indicate that our system has yielded the best results from past plays. The results are reliable.

2. Proposed Methodology and Datasets:

2.1 Datasets

The data sets used are taken from the sleep-EDF Physionet database [9]. The experiment was randomly chosen for four healthy subjects (ST4001e0, ST4002e0, ST4022e0 and ST4112e0). The databases are comprised of 2 EEG channels (Fpz-Cz and Pz-Oz) and one EOG channel. For high-precision sleep-stage detection, the Pz-Oz single channel data is used. The cumulative data was collected in 11055 epochs. The epoch details are shown in Table I below.

TABLE I: Epochs in Different Sleep Stages

SLEEP STAGES	EPOCHS COUNT
AWAKE	7880
SLEEP STAGE 1	225
SLEEP STAGE 2	1555
SLEEP STAGE 3	365
SLEEP STAGE 4	370
REM	655

2.2 Methodology

The EEG Pz-Oz cycles of the 30s are primarily used in this experiment. Every time is then used with the assistance of the statistical parameters of EMD for extraction of attributes via MATLAB. In the next step, a Chi-square calculation was made for the extracted attribute. In addition, these attributes for the training and classification of data are used in machine learning. AdaBoost is used in this experiment as a machine learning algorithm. The data was split into two classes. The first collection contains 60% of all data sets used for instruction. The second collection covers 40% of data and is used for data processing. This is achieved with the use of the WEKA algorithm.

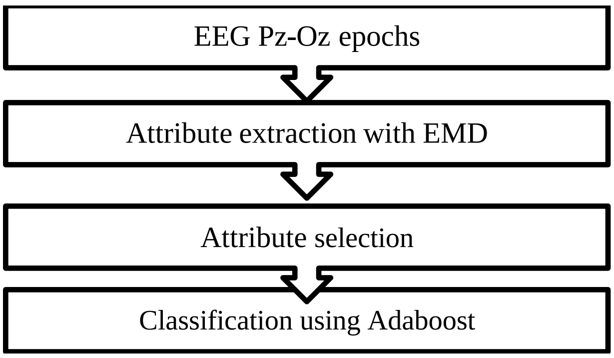

Figure: 1. Flow diagram of experiment

The method for decomposing the signal into the time frequency approximation of the signal is the empirical mode decomposting (EMD). The decomposed estimate is called the IMF function. Minimum modes requirements

- The overall difference between total minimum numbers and overall numbers should be one.
- The total of the local maximum and minimum amount produced should be zero at any time.

Figure 2 shows the produced IMFs.

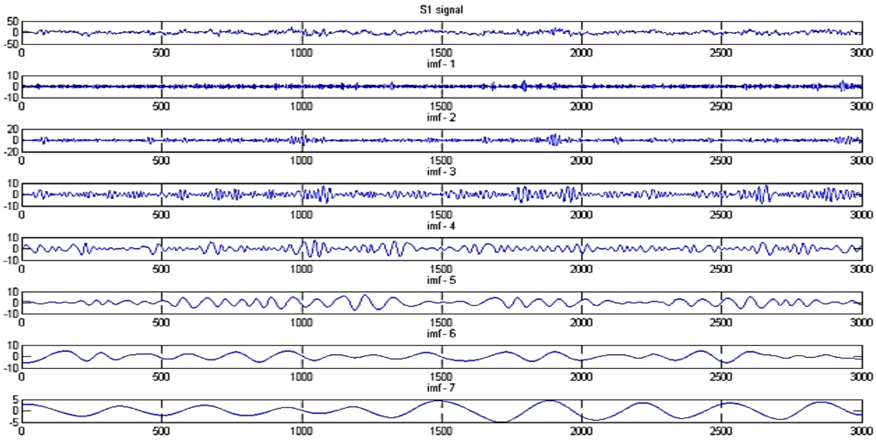

Fig. 2: The IMF generated with EMD algorithm.

Different attributes used in this experiment are Skewness (s), Kurtosis (k), Mean (m) and Variance (v2).

Skewness (s) offersirregularity of the diverse signal. S of each N IMF with mean (m) and variance can be calculated as given in eqn. (1):

$$s = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{p_i - m}{v}\right)^3 \tag{1}$$

Kurtosis (k) offers the peak value of signal. Kurtosis of each N IMF with mean (m) and variance (v) can be calculated as given in eqn. (2):

$$k = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{p_i - m}{v}\right)^4 \tag{2}$$

Total 44 attributes were extracted from each IMF's at different moments.

Mean (m) demonstrates the central propensity of any data. m can be intendedby eqn. (3).

$$m = \frac{1}{N}\sum_{i=1}^{N} p_i \tag{3}$$

Variance (v2) gives the spreading of signal contrary to mean value (m). This variance is supportive for classification sleep stages, REM from S1 and S2. Variance of each N IMF can be intendedby eqn. (4):

$$v^2 = \frac{1}{N}\sum_{i=1}^{N}(p_i - m)^2 \tag{4}$$

2.3 Chi-square evaluation

The attributes generated after EMD process are passed through the Chi-square distribution. ThisChi-square distribution is defined as in equ. 5.

$$\chi^2 = \frac{(O-E)^2}{E} \tag{5}$$

We get different χ^2value for the different attribute. The ranking is provided based on this value in decreasing order. Subsequently, the best attributes are selected from the list which provides the best result.

2.4 AdaBoost

The algorithm AdaBoost or Adaptive Boost, developed by the Freund and Schapire in 1996 is a meta-learning, automated learning algorithm. In this algorithm, the learner is improved by increasing the weighted value to improve performance. The REP tree was used for the learner method during the classification method. The REP tree gives a fast learning algorithm which provides the tree with an information gain or variance of the instances based on the regression or decision. A 10-fold validation is the classification method for Adaboost.

The batch size is 100, the iteration number is 100 and the threshold is 100. For the author, i.e. The batch size of the REP tree is 100, while the seed number is 2.

3. RESULTS AND DISCUSSION

This experiment is performed on the computer with Pentium Quad core processor, 2.17 Ghz clock speed and 4 GB RAM on Windows 10 platform.

TABLE II: COMPARISON TABLE OF ACCURACY

	Zhu *et. al.* (2014)[**Error! Reference source not found.**]	Hassan *et. al.*(2016) [**Error! Reference source not found.**]	Proposed method
2-stages	97.9%	95.05%	**98.01%**
3-stages	92.6%	89.77%	**94.78%**
4-stages	89.3%	87.49%	**92.66%**
5-stages	88.9%	86.53%	**92.15%**
6-stages	87.5%	85.57%	**90.78%**

The proposed AdaBoost method is compared with the state-of-the-art research work for the classification of the sleep period. The sleep-EDF data from Physionet is also taken into account in this study and Zhu. al. [7] used the EEG channel visibility disparity map and the single channel horizontal visibility map. Those included the attributes used for the classification in SVM. The two-stage, three-stage, four-stage, five-stage and six-stage [12] precisions are 97.9%, 92.6%, 89.3%, 88.9% and 87.5% respectively. Hassan and Hassan.et. Al.[8] used the properties of statistics and scope for the bootstrap aggregation classification.

In this experiment, the author has obtained a result of 2 phases, 3 phases, 4 phases, five phases and six phases, with 95.05%, 89.77%, 87.49%, 86.5% and 85.57%. The main explanation for this author's lower accuracy is a smaller number of classification attributes. Chi-Square has obtained a better result with our proposed methodology for the implementation of the Adaboost classification with the EMD statistical attributes. The exactness for all stages, three stages, four phases, five phases and six phases was 98.01%, 94.78%, 92.66%, 92.15% and 90.78%. The proposed research was best performed in each classification criteria.

TABLE III: CONFUSION MATRIX OF SIX STAGES CLASSIFICATION

	Proposed method							
		S1	S2	S3	S4	R	A	**Sen. (%)**
Expert scoring	S1	13	23	0	0	33	22	**14.2857143**
	S2	2	526	35	11	37	13	**84.2948718**
	S3	0	49	56	35	1	3	**38.8888889**
	S4	0	9	24	114	0	1	**77.027027**
	R	4	48	0	0	192	18	**73.2824427**
	A	6	13	2	0	19	3114	**98.7317692**

Table III introduces the six-stage classification uncertainty matrix. From the table above, we may find that sensitivity for S2, S4 and R was good at 84.29%, 77% and 73.28%, but in case of S1 the sensitivity was low at 14%. Most S1 data in the REM stage are malclassified. S1 from REM is a boring job in the real scenario. The problem is the same. In addition, the S2 data were mistreated at stage S2 and A. The other trigger is the smaller number of the sample given for the training collection. The signal is less sensitive. For the S3 level, average sensitivity is achieved. Specificity of the S1 is better from all other shows that the lesser number of data from other stages are misclassified in this category. The awake (A) stage shows the least specificity as compared to others.

Table IV shows the confusion matrix of five stage classification. In this stage, the data of S3 and S4 are combined to form the SWS. In this table, we can see that when the data of SWS gave the better sensitivity than the S3 and S4 in table III. In the five stage classification, the sensitivity for the S1 is poor. For the S2, R, and A stages, better sensitivities can be observed. Also, specificity is best for the S1 stage and the improvement in specificity when S3 is added with the S4.

TABLE IV: CONFUSION MATRIX OF FIVE STAGE CLASSIFICATION

	Proposed method						
		S1	S2	SWS	R	A	Sen.
Expert scoring	S1	13	22	0	31	24	14.54 %
	S2	3	524	45	40	11	84.09 %
	SWS	0	52	236	1	4	80.80 %
	R	5	46	0	188	22	71.87 %
	A	5	15	3	17	3114	98.72 %

We get the better sensitivity when the numbers of stages are less for the classification. From table III and IV, we can see the improvement in each stage except for the A.

TABLE V: CONFUSION MATRIX OF SIX STAGES CLASSIFICATION

	Proposed method							
Expert scoring		S1	S2	S3	S4	R	A	**Sensitivity %)**
	S1	32	58	0	0	83	54	**14.1**
	S2	6	1312	88	28	93	32	**84.2**
	S3	0	122	142	87	2	7	**39.2**
	S4	0	23	59	284	0	3	**77**
	R	10	119	0	0	479	46	**73.2**
	A	14	32	5	1	47	7787	**98.7**
	Specificity (%)	**0.3**	**3.7**	**1.4**	**1.1**	**2.2**	**4.5**	

The confusion matrix for 5 stages classification is presented in Table V. The SWS stage ifs formed by combining the stages S3 and S4. The misclassification is very less in comparison of correctly classified ata. This can be concluded by observing the expert scoring of Table V and Table VI for 5-stages and 6-satgs respectively.

TABLE VI: CONFUSION MATRIX OF FIVE STAGE CLASSIFICATION

	Proposed method						
Expert scoring		S1	S2	SWS	R	A	**Sensitivity (%)**
	S1	33	56	0	77	61	**14.5%**
	S2	7	1311	113	101	27	**84.1%**
	SWS	0	129	589	2	9	**80.8%**
	R	13	115	0	470	56	**71.9%**
	A	13	37	8	43	7785	**98.7%**
	Specific	**0.3%**	**3.5%**	**1.2%**	**2.1%**	**4.8%**	

	ity (%)						

We get the better sensitivity when the numbers of stages are less for the classification. From table III and IV we can see the improvement in each stage except for the A.

CONCLUSION

we have strengthened our precise approach with a minimum increase of 0.11% in stage 2 from the previous author in our proposed method. For the five-stage grouping, the highest precision increase was observed. In the both five and six stage classifications, the value of stage 1 can be improved by increasing numbers of instances and by choosing certain attributes to boost the disparity between stage 1 and other stages. for six stages, total sensitivity is 90.6% and five steps are 92.2%. Each of them has a strong value in terms of its specificity. The value on the top is the wake-up process. Different factors influence accuracy, flexibility and specificity. The better value of these parameters lists a variety of cases in the training results. The selected data classification attribute is another aspect. Sometimes they work best to identify a certain element and contribute to a mistake. The classification parameter may also be influenced by number of grading levels. Thanks to its greater sensitivity and specificity of different sleep stages, this proposal work would better work for a 5-stage grouping.

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