INT. J. BIOAUTOMATION, 2019, 23(4), 391-402 doi: 10.7546/ijba.2019.23.4.000505

Towards an Automated Detection of Alcohol Dependence Using EEG Spectral Power Estimates

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Received: August 08, 2017 **Accepted: April 09, 2019**

Published: December 31, 2019

Abstract: *The study utilized spectral power estimates evaluated from the Electroencephalogram (EEG) of alcoholics and control participants to attempt an automatic detection of individuals suffering alcohol dependence. Power estimates were obtained for non-overlapping consecutive EEG segments of 0.5-second duration while using a 5th order Burg Autoregressive estimator. EEG power was averaged within δ (1-4 Hz), θ (4-8 Hz), α_1 (8-10 Hz), α_2 (10-12 Hz), β_1 (12-20 Hz), β_2 (20-30 Hz), γ_1 (30-40 Hz), and γ_2 (40-50 Hz) rhythms and used as features in the "k nearest neighbors" classifier. A leave-one-out cross-validation procedure was implemented to evaluate the classification performance. The highest classification accuracy was observed for power estimates for α_1 and α_2 EEG rhythms. Depending on the number of neighbors included into classification, Sensitivity of the classifier was ranging between 90.91% and 98.70%, while Specificity was between 91.11% and 95.56% for these rhythms. Compared to other reported classification approaches, present work utilizes simpler and more robust data analysis techniques that, perhaps, may be preferred for practical applications. We conclude that it is possible to detect (with reasonably high accuracy) the individuals, who suffer alcohol dependence by analyzing their EEG.*

Keywords: *Alcohol dependence, Autoregressive spectral estimates, k-NN classifier, EEG.*

Introduction

The World Health Organization pronounces alcohol as one of the leading health threats, attributing approximately 2.5 million deaths per year worldwide to alcohol abuse. "320,000 young people between the ages of 15 and 29 die from alcohol-related causes, resulting in 9% of all deaths in that age group." Additionally, many serious social and developmental problems are linked to alcohol abuse [23].

Studies suggest that acute intake of ethanol alcohol may produce short-term effects on a subject including impaired judgment and coordination, increase in aggressiveness and are often lead to dizziness, nausea, stomach dysfunctions, etc. Continued consumption of alcohol may also cause long-term (permanent) effects that include (although not limited to) high blood pressure, permanent impairments of vital organs, cancers, nutritional deficiencies, epigenetic changes, severe damage to cognition and memory, etc. [23].

The diagnostics of alcoholism may be difficult and time-consuming, especially in its mild cases, thus various tools have been employed to study alcoholism. One such tool is Electroencephalography (EEG), a brain imaging technique offering superior temporal resolution – compared to other imaging techniques such as PET and fMRI – at a significantly lower cost. For instance, the U.S. Food and Drug Administration (FDA) recently approved a medical device for an assistive EEG-based assessment of Attention Deficit Hyperactivity Disorder (ADHD) [4]. Perhaps, similar tools can be developed for other disorders – including alcohol dependence – to provide a quick, inexpensive, yet fairly accurate tool for preliminary diagnostics.

Studies indicate that both short-term and long-term effects of ethanol alcohol consumption may be related to specific alterations in the subject's EEG. Considering the spectral analysis in particular, an increase in the α-rhythm power (8-12 Hz) related to moderate doses of alcohol was reported as one of the ***short-term*** effects of alcohol on spontaneous EEG [10]. Additionally, a significant increase in the α_1-rhythm (8-10 Hz) power was determined as induced by alcohol administration [3]. An increased power of lower EEG rhythms (below 8 Hz) was associated with larger doses of alcohol [13]. Studying the ***long-term*** effects, EEG of alcoholics in the resting state has been linked to an increased power in δ-rhythm (1-4 Hz) [12], an increased power in θ-rhythm (4-8 Hz) [21], a reduced power in α-rhythm (8-12 Hz) [3, 5, 6, 11, 13, 14, 18], and an increased power in β-rhythm (12-30 Hz) [2, 7, 12, 15, 18]. Interestingly, similar alterations in the EEG of the offspring of alcoholics were also reported [5, 18]. Other EEG processing techniques, such as connectivity measures, have also been used in studies of alcohol dependence [8, 12].

Considering the gravity of the alcoholism problem and bearing in mind the corresponding alterations in EEG mentioned above, attempts to aid the detection of alcohol dependence by EEG analysis have been recently made. For instance, Palaniappan has reported optimistic results (up to 98.71% of correct classifications) of automated discrimination between alcoholics and control participants [15]. However, while presenting promising results, the analysis implemented in the work may suffer noticeable limitations: the author's definition of frequency ranges of EEG rhythms is inconsistent with the traditionally accepted ones; the "root MUSIC" algorithm used in the study, while being a frequency estimation technique, may generally produce biased power estimates [9]; applications of low-order (8 and 28) FIR filters to reduce unwanted frequency components seem questionable. Additionally, γ-rhythm spectral estimates were chosen as classification features with no discussion of the reasons for such a selection.

Acharya and colleagues [1] have recently published their work, reporting classification of alcoholic subjects with an accuracy of 91.7%. Nonlinear features, such as sample and approximate entropy and Lyapunov exponents, were employed in the data analysis with a support vector machine classifier [1]. Ping and coworkers [17] considered a three-class classification problem discriminating between epileptic, alcoholic, and control subjects. The authors implemented two non-linear methods –recurrence plots and recurrence quantification analysis – to produce EEG features that were classified according to six different algorithms. The highest classification accuracy, exceeding 98%, was reported for the Gaussian mixture model classifier [17]. However, when aiming towards automated classification, more robust and established techniques may be preferred.

One such technique, an autoregressive spectral estimator, has been successfully utilized in EEG research for last decades. Specifically, as we demonstrated recently, while implementing autoregressive estimation, "spectral power evaluated for low-frequency EEG rhythms – i.e., δ through α_2 – was generally lower for alcoholics than for control participants. More pronounced changes between alcoholics and controls arose from the right hemisphere; Kruskal-Wallis's one-way analysis of variance indicated these alterations as statistically significant" [22].

While utilizing the same EEG data and the results obtained in the previous study (the same EEG data as used in [1, 15, 17]), present work specifically targets an automated classification between alcoholics and control individuals, as our previous work indicated that such classification may be possible. While more sophisticated data processing methods may be implemented for the same task, the novelty of current work stems from the selection of more robust and computationally efficient signal analysis techniques that, perhaps, are more suitable for practical applications.

Materials and methods

Participants and EEG data

This project consists of a secondary analysis of available data. EEG data were obtained from an open database available to the public, and the set was originally donated by Dr. Henri Begleiter of the Neurodynamics Laboratory at the State University of New York Health Center in Brooklyn. The data set was downloaded from http://sccn.ucsd.edu/~arno/indexeeg.html in 2008. EEG data have been collected from 77 male alcoholic subjects of the average age 35.83 with a standard deviation of 5.33 and a range of 22.3-49.8 years, and from 45 male controls of the average age 25.81 with a standard deviation of 3.38 and a range of 19.4-38.6 years who were used previously in studies of alcohol dependence [1, 15, 17, 21, 24, 25]. The alcoholic participants were fully detoxified prior data acquisition; therefore, only the long-term alcohol effects are assessed in the present study.

The participants were exposed to visual stimuli exerted from the Snodgrass and Vanderwart picture set [20] during the data collection. EEG was recorded from a set of 61 electrodes placed according to the extended 10/20 International montage; trials with an excess of eye and body movement were not included. The duration of recordings varied from 41 to 120 seconds, while most recordings were between 110 and 120 seconds. More details regarding the EEG acquisition may be found elsewhere [21]. The Cz channel was excluded in the present study, since it was used as the recording reference.

EEG analysis

Unlike in Palaniappan's work [15], we implemented no additional artifact removal. Spectral estimates were obtained for consecutive 0.5 second-long EEG fragments using a parametric technique (Burg Autoregressive Estimator). Our previous study indicated that selection of EEG fragments whose duration exceeds 0.5 seconds increases the risk of including non-stationary sequences into the analysis. Since the original sampling rate was 256 Hz, applications of traditional nonparameteric (i.e., DFT-based) spectral estimation techniques for such short sequences (i.e., 128 samples) might lead to biased results [9] and, therefore, they were not considered.

As previously reported, prior to spectral estimations, the sampling rate of EEG data was reduced by the factor 3 "to decrease the effects of data pre-filtering at the acquisition stage and to eliminate high frequency noise. Also, a common average reference (CAR) spatial filter was applied" to mitigate surface currents, and DC components were removed from each data fragment [22]. The order of an autoregressive model was selected as 5 – a trade-off between the spectral resolution and spurious spikes. Additionally, a low AR order reduces computational complexity. More details on the EEG processing implemented in the study may be found elsewhere [22].

Therefore, a data set consisting of spectral estimates obtained from two groups – alcoholics and controls – was used. Since each spectral estimate was obtained for 60 EEG electrodes, estimates were treated as 60-dimensional vectors during the classification stage. As a result of EEG segmentation into 0.5-s epochs, multiple spectral estimates were obtained from each participant. Thus the alcoholic group contained 13,935 data samples (vectors) for each EEG rhythm and each EEG channel, while the control group included 7,994 such samples for the classification.

We have previously observed that applications of traditional statistical classification methods, such as Euclidean distance-based, Fisher, and regression analyses, did not contribute to reliable classification between alcoholics and controls using their EEG power estimates as classification features [8]. Therefore, an instance-based cluster analysis algorithm, the *k* nearest neighbors (*k*-NN) classifier, was implemented in the present work. The unknown sample (vector of features) was assigned to the class (i.e., either alcoholics or controls), to which belonged the majority of its *k* "neighbors" [19]. The *k* nearest neighbors were determined by their distances with respect to the sample point. During the decision process, the neighbors' contributions might be weighted by their distances: i.e., the closest neighbors influence the decision more than the distant ones. The *k*-NN classifier implementing such a weighting rule is referred to as a weighted *k*-NN classifier; otherwise, the non-weighted *k*-NN classifier was realized. We note that, for a non-weighted *k*-NN, only the odd numbers of neighbors, *k*, were considered to avoid ambiguity. No such restrictions were implemented for the weighted *k*-NN classification. Various distance metrics may be used in classification. Unlike Palaniappan, who implemented the Manhattan distance, the Euclidean distance was selected in the present work as the most commonly used and intuitive [19]. While the Manhattan/taxicab metric is used to assess differences in frequency distributions, this distance does not appear justified for the problem on hands – comparing two multidimensional continuous distributions. Perhaps, the Mahalanobis distance that is often used in classification problems could be utilized instead. However, the uncertainties associated with estimation of the covariance matrices might introduce an additional and unwanted bias in the analysis. Therefore, we have opted in favor of the Euclidean distance. Such distance, D, between two N-dimensional points with coordinate vectors x_1 and x_2 is evaluated as the second norm of their coordinates' difference:

$$D = \sqrt{\left|x_2 - x_1\right|^2} = \left\|x_2 - x_1\right\|_2 . \tag{1}$$

Therefore, the feature space of the classification problem considered here consisted of 13,935 and 7,994 60-dimensional vectors of averaged EEG power estimates for the alcoholic and control groups respectively. Both non-weighted and weighted *k*-NN classifications were implemented for various values of *k* and for each EEG rhythm: δ (1-4 Hz), θ (4-8 Hz), α_1 (8-10 Hz), α_2 (10-12 Hz), β_1 (12-20 Hz), β_2 (20-30 Hz), γ_1 (30-40 Hz), and γ_2 (40-42 Hz). The distances between the sample (unknown) point and the points forming the classifier's training set were evaluated according to (1). Data analysis was implemented using MATLAB. Fig. 1 illustrates a simplified block-diagram of the proposed EEG signal processor.

DC removal should be implemented twice, since individual EEG fragments (epochs) may have minor DC offsets that could affect power spectrum estimation. In evaluating the classifier's performance, the alcoholic group was designated as the unusual class and the control group as the normal. Therefore, the classification problem reduced to the detection with the unusual class being positives and the normal class being negatives. In assessing the classifier's correct detections of an abnormal condition (True Positive) and of a normal condition (True Negative), the classifier's performance (i.e., percentage of correct classifications) may be described by the following characteristics [19]:

$$Sensitivity = \frac{True\ Positive}{Total\ Abnormal} \cdot 100\%\ , \tag{2}$$

$$Specificity = \frac{True\ Negative}{Total\ Normal} \cdot 100\%\ . \tag{3}$$

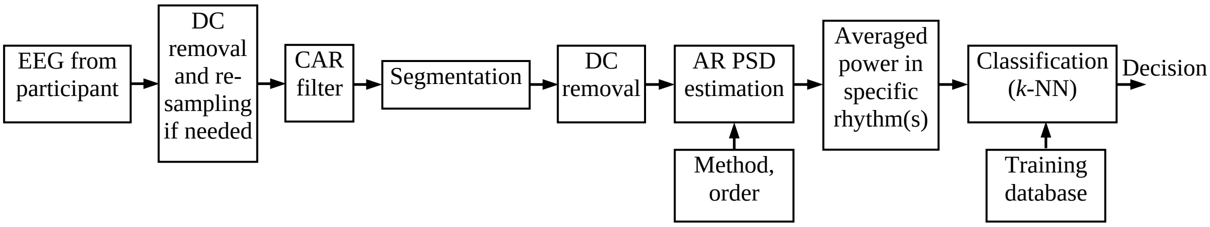

Fig. 1 Block-diagram of the proposed EEG signal processor

For reliable classification, both Sensitivity and Specificity must be as high as possible. To evaluate the classifier's performance, a leave-one-out cross-validation was implemented and the classification accuracy was estimated according to Eqs. (2) and (3).

Initially, while implementing the validation procedure, the performance results (not included) were consistent with the results reported by Palaniappan and the highest classification accuracy (both Sensitivity and Specificity) was approximately 95% for γ_1-rhythm power estimates. However, one questionable assumption was originally implicitly accepted, while assessing the classification accuracy. Power estimates were obtained for the EEG of each participant for multiple, non-overlapping time frames. These power estimates (evaluated for the same individual) were assumed as uncorrelated during classification. In other words, both training and validation data included features extracted from the EEG of the same subject. Since the validity of this assumption is arguable, a corrected leave-one-out validation procedure was implemented next: all power estimates obtained for a particular participant were excluded from the classifier's training set during the validation.

Results

Fig. 2 illustrates the percentages of correct classifications of the non-weighted *k*-NN classifier as functions of EEG rhythms. The left panel presents the classifier's Sensitivity, while the right panel illustrates Specificity. Values of *k* (the number of neighbors) are indicated in the legends. The corrected leave-one-out validation procedure was implemented.

Compared to the results of the non-modified validation (not shown), we observed, in general, degraded classification performance, when using the corrected validation. Therefore, we hypothesize that the correlation between EEG spectral power estimates evaluated for non-overlapping time intervals and for the same subject cannot be neglected. The Sensitivity and Specificity reported in Fig. 2 reflect, perhaps, more accurate results.

Another important observation is that γ_1 rhythm EEG power estimates no longer contribute to the highest classification accuracy as it was observed by Palaniappan [15]. Instead, classification with α_2 rhythm EEG power estimates yields, overall, better results.

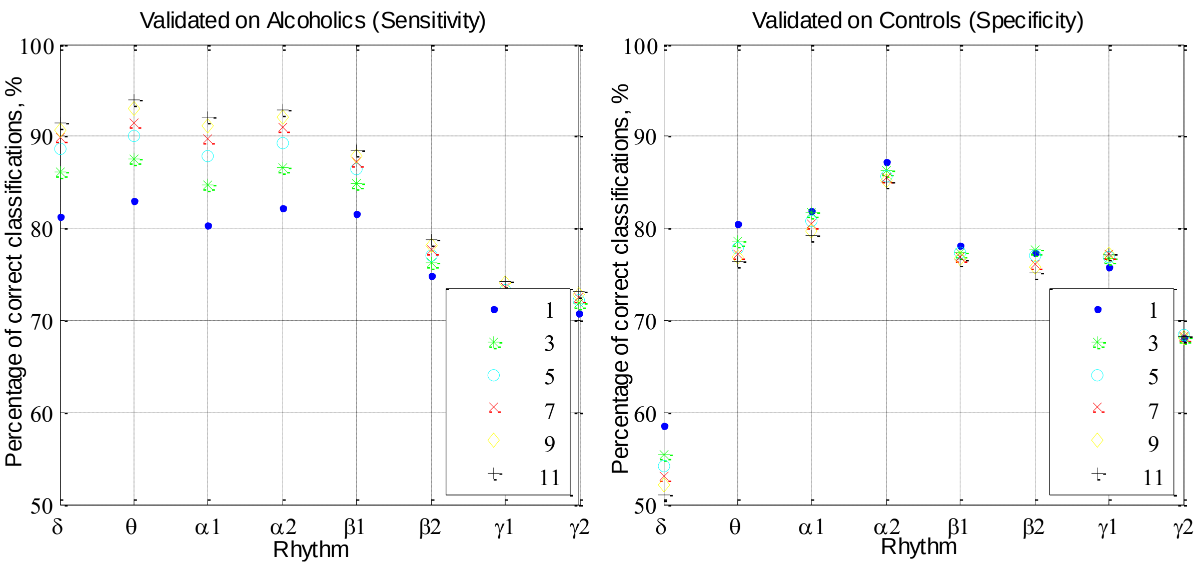

Fig. 2 Percentages of correct classifications of a non-weighted *k*-NN classifier for different values of *k* as indicated in the legend

We have also implemented weighting of neighbors' contributions by the Euclidean distances; however, both Sensitivity and Specificity appear very similar whether weighting is implemented or not. Therefore, we conclude that weighting by the Euclidean distance does not seem to contribute to improving classification accuracy in our case, so it shall not be considered in the following experiments.

We observe that both Sensitivity and Specificity differ by varying the number of neighbors, *k*. Perhaps a sub-optimal number of neighbors can be found in the *k*-NN procedure. Fig. 3 illustrates classification performance of a non-weighted *k*-NN classifier when using α_2 rhythm EEG power estimates as classification features. The number of neighbors, *k*, was varied between 1 and 41.

We observe in Fig. 3 that, while Sensitivity generally increases as more neighbors are included in classification, Specificity is relatively persistent for a wide range of *k*. The highest Specificity of 93.33% is obtained for $k = 21$ (Sensitivity is 93.51% for this number of neighbors), and the highest Sensitivity of 97.40% is observed for $k = 31$ (Specificity is 91.11% for this *k*). The smallest number of neighbors, for which Sensitivity and Specificity are approximately equal (i.e., 90.91% and 91.11%), is 11. Based on the last observation, we suggest that to obtain reasonably high and less biased discrimination results, no fewer than 11 neighbors should be included in classification when using α_2 rhythm EEG power estimates as classification features.

We have also observed that classification accuracy can be further improved by including α_1 rhythm EEG power estimates (in addition to α_2 rhythm estimates) into classification features. The corresponding Sensitivity and Specificity are illustrated in Fig. 4.

We observe in Fig. 4 that, while Sensitivity generally increases as more neighbors are included in the classifier, Specificity degrades as *k* increases. For instance, for 3 and 9 neighbors, Sensitivity is 92.21% and Specificity is 95.56%. For 11 neighbors, Sensitivity increases to 96.10% and Specificity reaches 93.33%. The highest Sensitivity of 98.70% is observed for $k = 37$; Specificity is 91.11% for this number of neighbors.

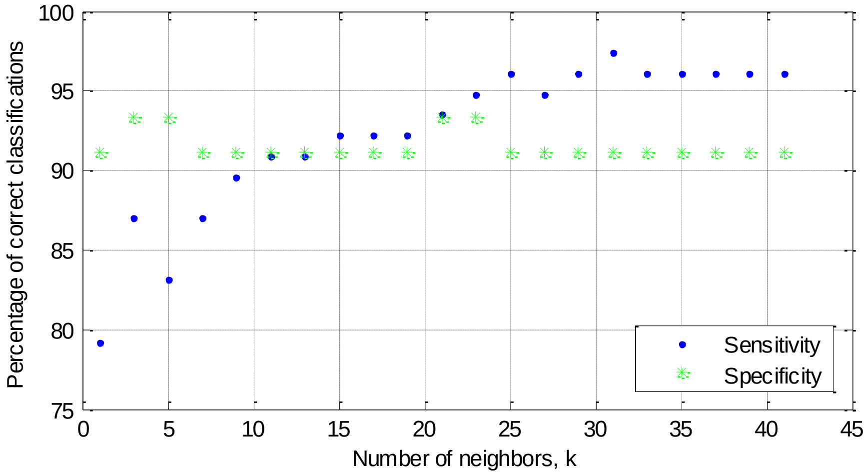

Fig. 3 Percentages of correct classifications of a non-weighted *k*-NN classifier with α_2 rhythm EEG power estimates and for different values of *k*

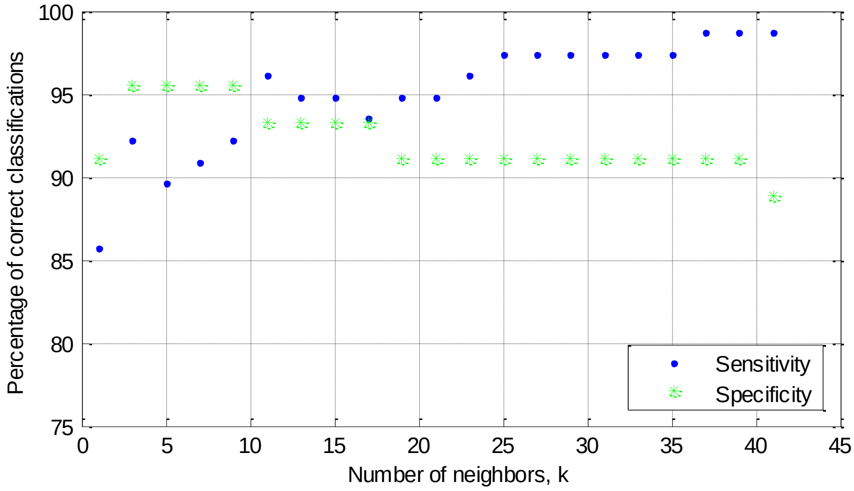

Fig. 4 Percentages of correct classifications of a non-weighted *k*-NN classifier with α_1 and α_2 rhythm EEG power estimates and for different values of *k*

Inclusion of averaged power evaluated for other EEG rhythms did not contribute to an improvement of classification accuracy, according to our observations. Therefore, the corresponding results are not reported.

We have previously concluded that various EEG channels (electrodes) may have different contributions to the classification accuracy. Moreover, channels' selection generally depends on EEG rhythms, within which power was evaluated. Therefore, we next perform discrimination, including only the EEG electrodes that have been deemed as producing power estimates that are the most statistically different between two groups. The channels were selected for inclusion based on the results of Kruskal-Wallis test, as described previously [22]. Table 1 illustrates the EEG channels, whose power estimates were found (ranked in the order of descending significance) as being the most statistically different between two experimental groups; for α_1- and α_2-rhythms, respectively.

Classification was performed next for 9 and 37 neighbors in the *k*-NN algorithm, while using α_1- and α_2-rhythm EEG power estimates as classification features and for the 1 to 60 "most significant" channels selected according to Table 1. For instance, assuming 58 electrodes for the classification, power estimates from all EEG channels, except for AF_8 and AF_7, were included for α_1; while for α_2, all power estimates from all EEG channels, except for AF_8 and FT_8, were included into classification. The classification accuracy is shown in Fig. 5.

Table 1. EEG channels ranking in the descending significance order for α_1-rhythm (channel α_1) and α_2-rhythm (channel α_2) power estimates. Power estimates for PO_2 channel are the most statistically different between the two experimental groups, while the estimates for AF_8 are the least statistically different for both rhythms α_1 and α_2.

Rank	Channel (α_1)	Channel (α_2)	Rank	Channel (α_1)	Channel (α_2)	Rank	Channel (α_1)	Channel (α_2)
1	PO_2	PO_2	21	CP_2	CP_4	41	C_5	TP_8
2	PO_8	PO_8	22	P_3	F_z	42	AF_z	F_4
3	P_4	PO_z	23	CP_4	CP_z	43	AF_2	C_6
4	P_2	P_4	24	C_1	F_1	44	CP_3	CP_3
5	PO_z	P_2	25	F_z	CP_2	45	F_7	CP_5
6	P_z	O_2	26	FC_5	FC_2	46	FT_7	C_5
7	P_6	PO_1	27	FC_2	C_1	47	CP_5	F_6
8	FC_3	P_6	28	F_1	P_5	48	F_6	FC_6
9	PO_1	O_1	29	CP_1	FC_4	49	F_4	FP_z
10	O_2	P_z	30	F_5	CP_1	50	FC_6	F_7
11	FC_z	O_z	31	C_2	AF_1	51	T_8	FT_7
12	FC_1	P_8	32	FC_4	F_2	52	F_8	FP_1
13	CP_6	PO_7	33	C_4	FC_5	53	TP_7	FP_2
14	P_8	FC_3	34	C_3	F_5	54	FT_8	T_8
15	O_1	CP_6	35	TP_8	C_4	55	FP_2	TP_7
16	O_z	FC_1	36	P_5	AF_2	56	FP_1	AF_7
17	P_1	P_1	37	AF_1	C_3	57	FP_z	F_8
18	CP_z	FC_z	38	C_6	C_2	58	T_7	T_7
19	F_3	P_3	39	F_2	AF_z	59	AF_7	FT_8
20	PO_7	F_3	40	P_7	P_7	60	AF_8	AF_8

We see in Fig. 5 that Sensitivity generally exceeds 90% even for the small number of EEG channels included into classification. On the other hand, Specificity decreases considerably when reducing the number of available electrodes. For instance, assuming that 30 "most significant" EEG electrodes were selected, Specificity is 82.2% for both 9 and 37 neighbors. Assuming 43 electrodes, Specificity improves to 84.4% and 86.7% for 37 and 9 neighbors, respectively. Also, including more neighbors in the *k*-NN algorithm generally leads to an improvement in Sensitivity, while Specificity may decrease. Based on the results illustrated in Fig. 4, we conclude that to achieve higher classification performance, all available EEG channels should be used to produce classification features. On the other hand, sufficiently accurate classification may still be possible, even when fewer EEG channels are available. Perhaps the latter may be of interest, for instance, when developing a classifier by utilizing a less expensive, portable EEG acquisition system with fewer electrodes more suitable for clinical applications.

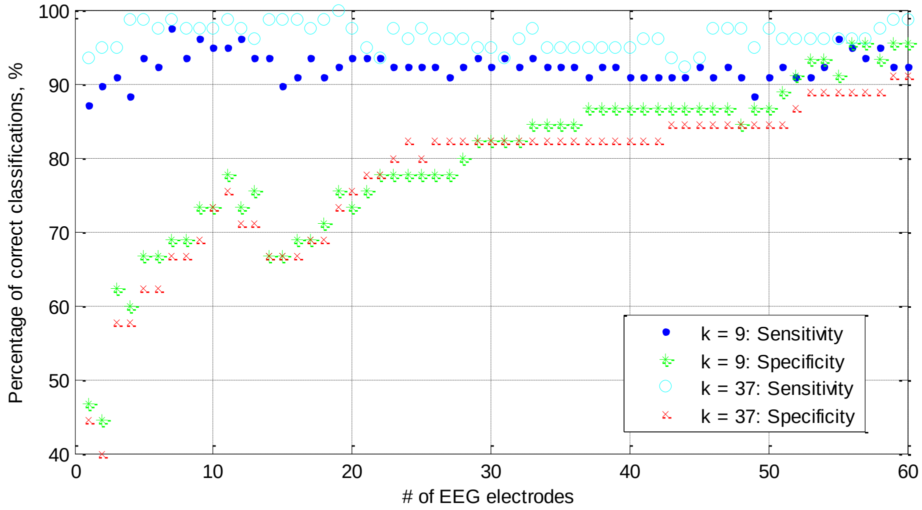

Fig. 5 Percentages of correct classifications of a non-weighted *k*-NN classifier with α_1 and α_2 rhythm EEG power estimates and for 9 and 37 neighbors and different number of EEG electrodes

Sometimes, leave-one-out cross-validation technique is criticized for possible overfitting the model. To address this critique, 45 out of 77 alcoholic participants were randomly selected next and power estimates of their EEG contributed to the training set together with the corresponding estimates for the control group. The rest of the alcoholic group produced the validation set. The classification accuracy (Sensitivity) was observed nearing 80 percent for the combined δ-θ rhythm. Perhaps, this reduction in classification performance may be related to the considerable shortening of the training set. Still, the results appear optimistic.

Discussion

The present work was devoted to an automated detection of individuals suffering alcohol dependence, while using the averaged spectral power estimated from their EEG as classification features for the "*k* nearest neighbors" classifier. We conclude that such detection is possible with a high practical accuracy.

We observed that discrimination performance is greatly affected by the selection of EEG rhythms used for evaluation of classification features. Based on our preliminary results, we expected higher detection accuracy when EEG power estimated for lower rhythms (i.e., θ through β_1) was used in classification. On the other hand, another report [15] indicated high detection accuracy of alcohol dependence when using γ-rhythm EEG power for classification.

However, we have observed that, when using γ-rhythm EEG power as the classification feature, the corrected validation procedure (when all spectral estimates evaluated for the test individual are excluded from the training set) leads to significant degradation of classification performance. On the contrary, neglecting correlations between power estimates evaluated for the same individual leads to the highest classification accuracy when γ_1-rhythm power was used. Perhaps this observation may be attributed to a high consistency of γ_1-rhythm EEG power within an individual. We hypothesize that γ_1-rhythm EEG power might be utilized if the subject's identification is assessed.

When implementing the "*k* nearest neighbors" classifier and the corrected validation procedure, the highest classification accuracy was observed, while using the α_1- and α_2-

rhythms EEG power estimates as the classification features. This result is consistent with our previous observations of averaged power in α_1- and α_2-rhythms being statistically different between alcoholics and control participants [22]. Sensitivity was observed to reach 98.70%, while Specificity ranged between 91.11% and 95.56%. Weighting of neighbors' contributions by the Euclidean distance produced a minor effect on the classification accuracy; therefore, the non-weighted *k*-NN procedure was deemed more computationally efficient and thus preferred. Also, the highest classification accuracy was observed when power estimates evaluated for all available EEG channels were used as classification features in a *k*-NN classifier with either 9 or 37 neighbors.

Perhaps the classification performance may be further improved by implementing EEG artifact removal. We also hypothesize that the classifier's accuracy may be improved by a judicious adjustment of the frequency range over which the averaged EEG power is evaluated. Classification performance could be potentially further improved by implementing a neural network based discriminator. However, such approach would require considerably more resources, while being less computationally efficient compared to the *k*-NN technique. Additionally, EEG re-referencing techniques (such as surface Laplacian, also known as current source density transform, or a linked mastoids approach) may be good candidates for the follow-up studies.

Our observation of α rhythm power estimates contributing to the highest classification performance agrees with the previous reports suggesting a reduced α-rhythm power associated with chronic alcohol consumption [3, 5, 6, 11, 13, 14, 18]. Perhaps, this agreement may further justify the corrected validation procedure that has been implemented.

Considering the results reported for the reduced number of EEG channels, we conclude that it may still be possible to achieve preliminary diagnostics of alcohol dependence in clinical environment (where equipment with large number of EEG electrodes may be non-practical). Such diagnostics would, perhaps, have a tendency to misclassify more non-alcoholic individuals as alcoholics. However, we may predict that the majority of alcoholic participants – more than 90 percent, as we may hypothesize based on our results – would still be correctly detected.

It should be pointed out, however, that the present study did not account for other possible disorders and conditions that might affect EEG characteristics similarly to what was observed for the alcoholics. Similarly, no length of abstinence for alcoholic participants was considered, since this information was unavailable. A considerable age difference between two groups might be another limiting factor of the present study. However, no profound age-related alterations in EEG within the studied age group should be expected. Although study subjects were exposed to visual stimuli during EEG data collection, the resulting EEG was processed as the background activity. However, stimulation-related ERPs might still contribute to the results (see [16], for instance), so it is unclear to what extent the observed effects reflect the background EEG activity or are related to alterations in cortical information processing linked to alcohol dependence. To clarify this, additional experimentation with both specific audio and/or visual stimulations and no stimulation would be needed. Also, as discussed previously [22], the EEG data used in this study were collected from male participants only. Including female subjects may potentially modify classification results. Therefore, collecting more diverse EEG data is still needed for the development of a robust and highly reliable automated EEG-based detector for alcohol dependence.

Nevertheless, despite the mentioned limitations, we have demonstrated that a traditional, well-developed parametric spectral analysis method combined with a robust instance-based classification technique may provide EEG-based detection of alcohol dependence with accuracy comparable to or exceeding the results achieved with more complex non-linear methods [1, 15, 17]. Considering very little EEG preprocessing (segmentation, DC removal, and CAR spatial filter) and the low AR model order implemented in spectral estimation, the techniques that were employed should not require significant computational power for their implementation. We also suggest that the presented approach may be suitable for other EEG-based classification applications due to its robustness and flexibility.

Conclusion

Based on the presented results, we conclude that by using EEG spectral power estimates, the detection of individuals suffering alcohol dependence is possible with high practical accuracy. Utilizing the methods implemented in the present work, building a classifier for such a diagnostic would require comparing (via k-NN, for instance) the subject's α-rhythm EEG power estimates with the database (to be developed) of α-rhythm power estimates for the EEG collected from alcoholic patients and age- and gender-matched controls.

Acknowledgements

The author would like to acknowledge the Henri Begleiter Neurodynamics Laboratory, SUNY, for sharing the EEG data.

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