

Feature Extraction to Identify Depression and Anxiety Based on EEG

Laura Minkowski
Biomedical Engineering
Ryerson University
Toronto, Canada

Kristiina Valter Mai
Electrical, Computer and Biomedical
Engineering, Ryerson University
Toronto, Canada

Dharmendra Gurve
Electrical, Computer and Biomedical
Engineering, Ryerson University
Toronto, Canada

Abstract—Biomarkers in neurophysiological signals can be analyzed to determine indicators of mood disorders for diagnosis. In this paper, EEG signals were analyzed from a public database of 119 subjects ages 18 to 24 performing a cognitive task. 45 subjects had moderate to severe anxiety and/or depression and the remaining 74 subjects had minimal or none. A subject's level of depression and/or anxiety was classified by standard psychological tests. EEG signals were preprocessed and separated into frequency bands: beta (12-30 Hz), alpha (8-12 Hz), theta (4-8 Hz) and delta (0.5-4 Hz). Features were extracted including Higuchi Fractal Dimension, correlation dimension, approximate entropy, Lyapunov exponent and detrended fluctuation analysis. Similarities, and asymmetry can be examined between the left and right brain hemispheres as well as the prefrontal cortex channels. ANOVA II analysis showed a significant difference ($p < 0.05$) for topographical region comparisons of several features between the affected and unaffected subjects for specific features. The results demonstrate physiological asymmetry between high scoring subjects indicating a mood disorder, with low scoring, to be used as an indicator of illness. Understanding the complexities of how depression and anxiety are manifested physiologically including its comorbidities, is critical for accurate and objective diagnosis of mood and anxiety order disorders.

Index Terms—EEG, depression, anxiety, biomarkers, features, asymmetry, BCI

I. INTRODUCTION

EEG detects neural activity in the brain and the signals can be analyzed to show indicators of stress and mood disorders. The objective is to analyze EEG signals to detect and delineate the presence of depression and/or anxiety validated by the results of psychological tests. Using EEG, features were extracted and changes in subjects were compared during a testing protocol for both groups with and without mental illness. Non-linear features can be extracted and used to discriminate EEG signals [1]. Several studies have examined whether greater left or right anterior EEG activity can predict psychopathology of depression or anxiety. Greater relative left frontal EEG activity is associated with positive emotion whereas greater

relative right frontal EEG activity is associated with negative emotions. Previously depressed individuals exhibited greater relative right anterior EEG activity. Consequently, when there was greater right anterior EEG activity (depression indicator), there was relatively less right posterior activity [2]. In addition to and similar to depressed subjects, greater right relative anterior as well as posterior EEG activity has been associated to anxiety. Similarly, subjects with comorbid anxiety and depression exhibit higher right anterior and posterior activity. These neurophysiological patterns are not conclusive and consistent across all studies on this matter, however it is clear that asymmetry indicates underlying psychopathology and requires further investigation. It has been suggested that asymmetry fits into the diathesis-stress model serving as a risk factor for developing a mood or anxiety disorder [3].

II. DEPRESSION AND ANXIETY

Major depressive disorder (MDD) is characterized by persistent sadness, emptiness, irritability and anhedonia while also influencing cognitive changes and the ability to function [4]. MDD is a serious mental disorder characterized by at least one depressive episode lasting for two or more weeks [4]. Varying presentations of symptomatology can lead to over-diagnosis or under-diagnosis. This trend highlights the need for depression diagnostic indicators of depression based on physiological biometrics.

Anxiety disorders are characterized by unrealistic, irrational fears or anxieties that cause significant distress or impairments in functioning [4]. It is often coupled with bodily responses such as worried facial expressions, increased muscle tension, restlessness, impaired concentration, sleep disturbances and irritability. Generalized anxiety disorder (GAD) is considered to be excessive anxiety and worry occurring more days than not for at least 6 months with respect to a variety of causes (school, work, family) [4]. The overlap of symptoms of GAD and other mood disorders is common and many people with one type of anxiety disorder will often experience at least one more anxiety disorder or depression concurrently or at a different time in their life. However, the phenotypical overlap of disorders may be due to diagnostic unreliability.

Laura M. is with the Department of Biomedical Engineering, Ryerson University, Toronto, ON, Canada e-mail: lminkowski@ryerson.ca

Kristiina V. M., IEEE Senior Member, is with the Department of Electrical, Computer and Biomedical Engineering, Ryerson University, Toronto, ON, Canada e-mail: kvmai@ryerson.ca

Dharmendra G., IEEE, Student Member, was with the Department of Electrical, Computer and Biomedical Engineering, Ryerson University, Toronto, ON, Canada e-mail: dgurve@ryerson.ca

III. METHODS

A. Data Acquisition

The dataset used in this study was acquired from a public database from PRED+CT originally published by Cavanaugh et al. in 2019 [5]. EEG signals were acquired from 119 subjects between the ages 18 to 24 who were asked to perform a probabilistic learning task requiring subjects to pair Japanese characters correctly. EEG signals were measured using a Synamps2 system (Neuroscan) using 66 electrodes in total referenced to FCz. Positioning followed the 10-20 international system. Two electrodes were placed on the mastoid and two were EOG. The sampling frequency was 500 Hz and impedance was less than 10 k Ω . For more information, please refer to the original paper [5].

Beck's Depression Inventory (BDI) is a psychological test used for the evaluation and diagnosis of depression severity. BDI-II is a questionnaire consisting of 21 questions to which the respondent selects the statement that best describes the way they have felt in the previous two weeks [6]. Test scores can be used to classify minimal depression (BDI < 13), mild depression (14 < BDI < 19), moderate depression (20 < BDI < 28) and severe depression (BDI > 29). The Spielberger Trait Anxiety Inventory (TAI) is a psychological questionnaire developed to differentiate anxiety from depression [7]. There are 20 questions each with a 4-point scale of response. Scores can be used to classify minimal anxiety (TAI < 37), moderate anxiety (38 < TAI < 44) and severe anxiety (TAI > 44). Psychological tests are subjective scales of measurement of mood disorders. These tests have been proven to be reliable, however there are limitations. Subjects may misinterpret the question or not respond accurately based on their own experiences. The tests are generic and comorbid mood disorders may have different manifestations in diverse populations.

Demographic data on participants included gender, age, symptomology and psychological test scores. 122 subjects participated in the study, however there was incomplete data for 1 subject (ID 507), and missing data for 2 (ID 599, ID 600) and were therefore excluded from this analysis. All subjects who met the depression criteria also met the anxiety criteria. These participants (meeting both criteria) were used as the affected subjects for analysis. See [5] and table I for participant data.

IV. ANALYSIS

The purpose of this analysis was to determine whether there is a detectable disparity between affected subjects classified as having depression and/or anxiety (possessing a BDI score greater than 13 and/or with a TAI score greater than 38) and unaffected subjects (BDI score less than 13 and TAI score less than 38) signifying minimal signs of both. The ANOVA II statistical analysis was performed on two groups: affected and unaffected. The affected group consisted of 45 subjects with anxiety and depression and the unaffected group included the remainder of the subjects. Several studies have examined whether greater left or right anterior EEG activity can predict psychopathology of depression or anxiety [1] [8].

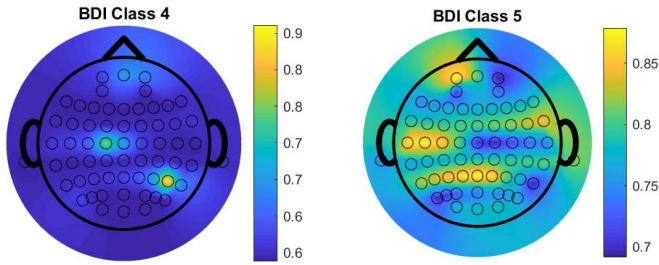
TABLE I: Participant Demographics and Symptom Scores

Affect	Sex	No. of Participants*	Mean BDI Score (>13)	Mean TAI Score (>37)
Depression	Female	33	22.15	55.79
	Male	12	23.17	55.79
	All	45	22.42	55.73
Anxiety	Female	40	19.08	53.63
	Male	11	18.36	49.45
	All	51	18.92	52.73
Unaffected	Female	34	1.21	29.09
	Male	30	1.87	30.27
	All	64	1.52	29.64

* Note that the statistical analysis was performed on two groups: affected vs. unaffected. The affected group consisted of 45 subjects with moderate to severe anxiety and depression and the unaffected group consisted of 74 subjects with minimum to no mood or anxiety disorder.

EEG signals were preprocessed and filtered. Signals were delineated by their frequency bands of alpha (8-12 Hz), beta (12-30 Hz), theta (4-8 Hz) and delta (0.5 to 4 Hz). Extracted features include Higuchi Fractal Dimension (HFD), correlation dimension (CD), approximate entropy (EN), Lyapunov exponent (LE) and detrended fluctuation analysis (DFA). These features were extracted from each frequency band for a total of 24 parameters per subject. The features were compared based on topographical brain regions and averaged over specified channels. Asymmetry differences was evaluated comparing left and right sides to determine whether there was a significant difference based on statistical analysis. ANOVA II analysis showed significant difference ($p < 0.05$) for topographical region comparisons of several features between the affected and unaffected subjects for specific features. Similarities, and asymmetry can be examined between the left and right brain hemispheres as well as the prefrontal cortex channels. The right and left sides of the prefrontal cortex channels were compared for all subjects and then a statistical analysis was performed to determine if there was a difference between affected and unaffected subjects. This process was iterated a second time to compare the entire left and right hemispheres. See figures 1a and 1b for topographic map showing selected channels used for analysis. The selected channels used for comparison include the left prefrontal cortex (FP1, AF3, F7, F5, F3, F1, FT7, FC5, FC3, FC1) and right prefrontal cortex (FP2, AF4, F2, F4, F6, F8, FC2, FC4, FC6, FT8). In addition, the entire left hemisphere (FP1, AF3, F7, F5, F3, F1, FT7, FC5, FC3, FC1, T7, C5, C3, C1, TP7, CP5, CP3, CP1, P7, P5, P3, P1, PO7, PO5, PO3, CB1, O1) and right hemisphere (FP2, AF4, F2, F4, F6, F8, FC2, FC4, FC6, FT8, C2, C4, C6, T8, CP2, CP4, CP6, TP8, P2, P4, P6, P8, PO4, PO6, PO8, O2) were compared.

Six features were extracted for each frequency band, for a total of 24 features per subject. However, not every feature showed a significant difference between the average of the right and left prefrontal cortex or the right and left hemispheres when comparing affected and unaffected subjects. See table II for significant features.



(a) Moderate ($20 < \text{BDI} < 28$) (b) Severe ($\text{BDI} > 28$)

Fig. 1: Topographic plot showing AppEN feature in the alpha band for subjects classified with a moderate and severe Depression

A. Features

B. Alpha Wave Asymmetry

Alpha waves appear on both sides of the brain, but slightly higher in amplitude on the non-dominant side, generally observed in people who are right-handed. Mumtaz and colleagues (2015) summarize that alpha wave asymmetry in the prefrontal cortex, as well as elevated alpha wave activity, has been indicative of depression [9]. Kemp and colleagues (2010) examined the specificity of brain laterality and found reduced left frontal activity in patients with MDD and overall increased alpha power through EEG acquisition under resting state, eyes closed conditions. In addition, there was greater activity seen in patients with PTSD in the right-parietotemporal region compared to MDD patients [10]. A review by Coan and Allen (2004) shows that positive moods are associated with relatively greater left prefrontal activity and negative moods are associated with relatively greater right prefrontal activity [3]. A meta-analysis reviewed numerous studies that examined alpha wave asymmetry in the frontal cortex and concluded that it is not exclusively an indicator of depression, but also of [11]. Inconsistencies on this subject in the past was attributed to research practices such as short recording periods [12].

C. Correlation Dimension

Correlation dimension (CD) is a feature which estimates the correlation of a uniformly sampled time-domain signal in matrix. It is a method to determine the dimension of a nonlinear signal [13] [14].

$$C(r) = \frac{2}{N(N-1)} \sum_{(i \neq j)} \theta(r - |X(i) - X(j)|) \quad (1)$$

D. Lyapunov Exponent

Lyapunov exponent (LE) quantifies the exponential divergence or convergence of initially nearby trajectories in phase space [14]. It characterizes the separation of extremely close

trajectories of a signal. Also, LE can characterize instability or predictability of a system.

$$LE = LE(0)e^{(\lambda \times i \times \delta t)} \quad (2)$$

E. Approximate Entropy

Approximate entropy (AppEN) is a measure of disorder or complexity of a signal. It allows for dynamic analysis of a non-linear signal and measures complexity by statistical computation (computing the conditional probability that two signals are similar within a tolerance) [15]. This algorithm is applied to time series data to quantify its regularity or irregularity. For the length of the data, the algorithm is applied in time windows. Small values of AppEN indicates predictable data whereas higher values indicate unpredictable data.

$$AppEN = \log \frac{\text{correlation}(a)}{\text{correlation}(b)} \quad (3)$$

F. Detrended Fluctuation Analysis

DFA is used in time series analysis to determine the statistical self similarity of a signal [16]. It is useful for non-stationary signals such as for EEG. The fluctuation is repeated over different windows of which the log-log graph indicates self similarity.

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^N (X_k - Y_k)^2} \quad (4)$$

Where X_T of length N is:

$$X_t = \sum_{(i=1)}^t (x_i - x) \quad (5)$$

Where Y_T is X_T divided into time windows of length n and a least of squares is applied.

V. RESULTS

The results of the ANOVA II analysis are given in table 2 highlighting the significant p values.

- 1) CD differs in the delta band and theta band in the right and left hemisphere between the affected (depression/anxiety) and unaffected subjects
- 2) AppEN in the alpha band differs between the right and left prefrontal cortex
- 3) DFA differs in the theta band in the right and left hemisphere between affected(depression/anxiety) and unaffected subjects
- 4) LE in the alpha band differs between the right and left prefrontal cortex
- 5) LE in the theta band differs in the right and left hemisphere

In addition, the topographic heat maps allow for visualization of the channel differences between severe depression and moderate depression.

TABLE II: Summary of Statistically Significant Features

Features	Frequency Band	Prefrontal Cortex		Hemisphere	
		Affected	Unaffected	Affected	Unaffected
CD	Delta	0.930	0.691	0.268	0.002*
CD	Theta	0.029*	0.174	0.000	0.000
LE	Theta	0.629	0.478	0.656	0.021*
DFA	Theta	0.436	0.133	0.033*	0.349
AppEN	Alpha	0.053	0.042*	0.102	0.084
LE	Alpha	0.006*	0.222	0.006*	0.557
LE	Beta	0.000*	0.005*	0.924	0.011*
DFA	Beta	0.863	0.041*	0.236	0.559

*Indicates significant statistical difference ($p < 0.05$)

VI. DISCUSSION

In this paper, extracted features were used for differentiating depressive and anxious subjects from healthy controls. It was found that CD, AppEN, DFA and LE show hemisphere asymmetry differences between affected and unaffected subjects. Where there were differences noted in the right and left hemispheres and not in the right and left prefrontal cortex, it can be concluded that the asymmetry originates from the posterior portion of the brain. The results can be used to discriminate and aid in validating diagnosis of people with depression and anxiety. Visualization of topographic plots (heat maps) of the EEG signals can offer novel insight as opposed to solely evaluating numerical outputs. The heat maps in figures 1a and 1b show channel specific variations that can be easily detected visually when compared to an unaffected condition.

More research is required to confirm these findings as the tests may be sensitive to acquisition methods, the cognitive learning task vs. resting state condition, duration and acquisition techniques, as well as sample population characteristics such as age and gender. Standardized methodologies are required to consistently measure and analyze the signals.

VII. CONCLUSION

Several indications of stress, depression and anxiety are reflected in EEG signals. Signal processing techniques may be more effective in identifying and classifying mood disorders compared to psychological evaluations. These findings will contribute to further research in classifying features as biomarkers for disease. Biomarkers are yet to be used clinically as a method of diagnosis for mood disorders, however they can be used presently in research settings to provide information on the subject. Future directions may include developing established signal processing algorithms that produce consistent outputs for various subjects and acquisition conditions. The data collected will give insight into how people affected with a mood disorder internalize external stressors and the associated neurophysiological manifestations.

REFERENCES

- [1] Čukić, M., Stokić, M., Simić, S., & Pokrajac, D. *The successful discrimination of depression from EEG could be attributed to proper feature extraction and not to a particular classification method.* Cognitive Neurodynamics, 14(4), 443–455, 2020.
- [2] Blackhart, G. C., Minnix, J. A., & Kline, J. P. *Can EEG asymmetry patterns predict future development of anxiety and depression? A preliminary study.* Biol. Psychol., 72(1), 46–50, 2006.
- [3] Coan, James A., and John JB Allen. *Frontal EEG asymmetry as a moderator and mediator of emotion.* Biol. Psychol., 67.1-2, 7-50, 2004.
- [4] American Psychiatric Association. *Diagnostic and Statistical Manual of Mental Disorders: DSM-5, 5th ed.* DSM-5 Task Force; American Psychiatric Association: Washington, DC, USA, p.xliv.947p, 2013.
- [5] Cavanagh, J. F., Bismark, A. W., Frank, M. J., & Allen, J. J. B. *Multiple Dissociations Between Comorbid Depression and Anxiety on Reward and Punishment Processing: Evidence From Computationally Informed EEG.* Comput. Psych., 3, 1–17, 2019.
- [6] Beck, R. A. Steer, G. K. Brown et al. *Beck depression inventory-II* San Antonio, vol. 78, no. 2, pp. 490–498, 1996.
- [7] Spielberger, “State-trait anxiety inventory,” The Corsini encyclopedia of psychology, pp. 1–1, 2010.
- [8] Debener S, Beauducel A, Nessler D, Brocke B, Heilemann H, Kayser J. *Is resting anterior EEG alpha asymmetry a trait marker for depression? Findings for healthy adults and clinically depressed patients.* Neuropsychobiology. 41(1):31-7, 2000.
- [9] Mumtaz, W., Malik, A. S., Yasin, M. A. M., & Xia, L. *Review on EEG and ERP predictive biomarkers for major depressive disorder.* Biomed. Signal Process Control, Vol. 22, pp. 85–98, 2015.
- [10] Kemp, A. H., Griffiths, K., Felmingham, K. L., Shankman, S. A., Drinkenburg, W., Arns, M., . . . Bryant, R. A. *Disorder specificity despite comorbidity: Resting EEG alpha asymmetry in major depressive disorder and post-traumatic stress disorder.* Biol. Psychol., 85(2), 350–354, 2010.
- [11] Allen, J. J. B., & Reznik, S. J. *Frontal EEG asymmetry as a promising marker of depression vulnerability: Summary and methodological considerations.* Curr. Opin. Psychol., Vol. 4, pp. 93–97, 2015.
- [12] Thibodeau, R., Jorgensen, R. S., & Kim, S. *Depression, anxiety, and resting frontal EEG asymmetry: A meta-analytic review.* J. Abnorm. Psychol, 115(4), 715–729., 2006.
- [13] Natarajan, Kannathal, et al. *Nonlinear analysis of EEG signals at different mental states.* Biomed. Eng. online 3.1, 1-11, (2004).
- [14] Hosseinifard, B., Moradi, M. H., & Rostami, R. *Classifying depression patients and normal subjects using machine learning techniques and nonlinear features from EEG signal.* Comput. Methods Programs Biomed., 109(3), 339–345, 2013.
- [15] Richman JS, Moorman JR. *Physiological time-series analysis using approximate entropy and sample entropy.* Am J Physiol Heart Circ. Physiol. Jun;278(6):H2039-49, 2000.
- [16] Márton, L. F., Brassai, S. T., Bakó, L., & Losonczy, L. *Detrended Fluctuation Analysis of EEG Signals.* Procedia Technology, 12, 125–132, 2014.