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(RESEARCH ARTICLE)

A novel application of dry-electrode EEG Device for knowledge discovery in emotional-behavioral disorder studies

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Abstract

As per World Health Organization (WHO), emotional and behavioral disorders affect 10.7% of global population. Studies have shown emotional-behavioral problems having significant positive correlation with obesity and overweight (P<0.01). It has been established in published body of knowledge that obesity and overweight are negatively correlated with psychological comorbidities, emotional and behavioral disorders, and self-esteem. There is an increasing interest in studying the psychological and cognitive neuroscience aspects of obesity. Lately there has been an increase in the number and availability of consumer grade low-cost EEG (electroencephalographic) devices. The objective of this study is two-fold i.e. exploring the research potential of a consumer grade EEG device (Muse) and analyzing the relationship between EEG electrical activity, depression and obesity. The level of depression was quantified through filling the PHQ-9 (patient health questionnaire) and students BMI (body mass index) noted. The EEG experiment consisted of displaying high and low-calorie visual stimuli along with non-food stimuli; with eyes closed in-between. This process was repeated, first in the hunger state and subsequently after taking a high sugar drink. During both experimental states EEG of the 10 student subjects was continuously recorded. On clustering the EEG recordings, sub clusters were discovered among minimally depressed students, but strong clustering was discovered among mildly and moderately depressed obese/overweight students with lower grades. Thus, mood and food-related information was found to be processed differently among subjects requiring monitoring vs. clinical judgment and consumer grade EEG device was found to have the potential to be used for practical research work.

Keywords: Cognition; Depression; Obesity; Clustering

1. Introduction

Depression has developed as a major health liability worldwide, and positive recognition of such disorder is an enormous challenge requiring latest scientific tools, such as Electroencephalography (EEG). Using a consumer grade EEG device, this EEG-based research endeavors to discover prominent brain regions that are generally related to depression-obesity combination. Electroencephalogram (EEG) is an effective tool having research and clinical applications in many scientific fields, and is in use for the last 90 years. The fundamental technology of employing "wet" electrodes positioned on the scalp with conductive paste or gel paste has not essentially altered over decades. A "dry" electrode EEG system that does not need conductive gel and readying the skin characterizes a major development and could significantly escalate the usefulness of such systems for numerous human factor uses. Traditional EEG devices typically cost thousands of dollars. Recently, there has been an enormous growth of low-cost (i.e., less than US$500) EEG recording systems. The procedure for experiment preparation is also laborious and using the device is not a pleasant experience. It would be advantageous, if the contemporary consumer grade devices, which are considerably

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cheaper and straightforward to use, might also be used for research. The consumer grade systems mostly available in the market provide software developer kits permitting researchers to access raw data. In this paper, we will explore the research applications of one such device i.e. Muse, by clustering raw electrical signals at AF7 and AF8 locations in a block-design paradigm with visual stimuli.

2. Background

2.1. EEG

Electroencephalogram (EEG) is a non-invasive monitoring method that gauges the brain's electrical activity. Electrodes are positioned at specific positions on the scalp. The general positions and terminologies as defined by the American Clinical Neurophysiology Society are shown in Figure 1. The red dotted circles in Fig-1 are the locations at which raw EEG electrical signals are recorded by the device used in our work. Conventional EEG devices use wet electrodes to enhance the conductivity of the entire system that typically cost thousands of dollars. Furthermore, individual electrodes are connected to distinct wires making the preparation procedure laborious and rather uncomfortable in application. A typical EEG system with upto 256 electrodes/channels can cover most of the subject's skull, and allows for taking care of skulls of different shapes and sizes.

2.2. Consumer-grade EEG

Lately, diverse types of dry electrode EEG systems have become available as substitute to the traditional wet electrode systems [1]. In the absence of the conductive gel, these devices have fast turnaround time and are easy to use. These devices have wireless sensors, thus eliminating clutter of wires resulting in more consumer-friendly usage. These devices are also considerably low cost i.e. from hundred to a few hundred dollars only. These newer devices, frequently called brain-computer interface (BCI) devices deliver neurotherapy or EEG biofeedback to the user to coach the brain to operate more effectively, such as; for example, how to respond to stress, and emotional state or improve attention, [2, 3]. These newer low-cost EEG devices have fewer electrodes as compared to typical EEG devices and systems, therefore, cannot cover all of the 10-20 or 10-10 system electrode locations. Some of the consumer grade EEG devices presently in the market are Muse from InteraXon, Epoc from Emotiv, and MindWave from Neurosky.

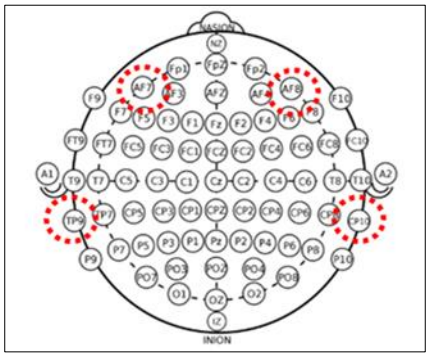

Figure 1 Common locations and nomenclatures as specified by American clinical neurophysiology society. Dotted circles are the four electrode locations accessed by the headband used

In this work, we choose the Muse device designed as a headband having 7 EEG electrodes reading data at four channels/locations i.e. AF7 (left side of forehead) AF8 (right side of forehead), TP9 (left ear) and TP10 (right ear). The EEG signals are over/down-sampled resulting in sampling rate of 220 Hz. Additionally, the headband has a 3-axis accelerometer and gyro for activity input and measuring head movements. The headband connects with the smartphone through Bluetooth. Figure-2 shows the Muse headband worn by a subject for the experiment discussed in this study. The Muse application provides overall brain activity signals as an image without any units; therefore, we used Muse Monitor that provides time series location specific EEG data as a CSV (comma separated value) file.

(a) Muse headband

(b) Subject wearing Muse headband

Figure 2 Muse headband and its usage in the experiment reported in this paper

2.3. Emotional Behavioral Disorder, Obesity and Brain

Emotional and behavioral disorders (EBD) are unsuitable emotions/actions in usual situations or learning problems not caused by health reasons or difficulty with interpersonal relationships, including relationships with peers and teachers or a general feeling of depression or unhappiness. There are many types of EBDs, such as eating disorders; bipolar disorder; conduct disorders; anxiety disorders; psychotic disorders; obsessive-compulsive disorder. EBD can be a result of number of reasons, such as biological (genetics, chemical imbalance, brain injury), Environment (exposure to violence, extreme stress loss of an important person) and Family (relationship with parents, child abuse).

Obesity and overweight have shown an increasing tendency in most developed countries and obesity causing several health-related problems. In [4] a study was conducted to establish the association of overweight and obese with emotional-behavioral problems in school-age primary school girls. The mean scores in all scales were greater in obese and overweight girls as compared to normal weight girls and the emotional-behavioral problems had considerable positive correlation with obese and overweight ($P<0.01$). Although our study is about adults, but childhood emotional-behavioral issues are unlikely to vanish in adolescence.

In [5] a cross-sectional study consisting of 4,361 adult Iranian health-care workers was reported who were analyzed for general obesity and 3,213 workers analyzed for central obesity. Gender-based stratified analysis for male workers did not revealed any significant association between general obesity, depression and anxiety. However, for males, an inverse relationship was found between abdominal obesity (WC > 102 cm) and severe depression. For females, before and after taking confounders into consideration abdominal obesity was considerably correlated with anxiety. No substantial relationship was observed amongst either sex for abdominal obesity and psychological distress after controlling for potential confounders.

Mood disorders are often found to be correlated with abnormal feeding behaviors. Mood states such as depression and anxiety affect the choice of food and energy or calorie consumption. Overeating and obesity is frequently correlated with depression and anxiety in humans, but has also been published in animal models. For example, depression and anxiety co-occur with obesity [6-10]. Further investigation of the association between mood, food, and obesity is beyond the scope of our work. The seminal 1954 articles by Goor [11] and subsequently the 1955 publications by Martin [12] commenced a novel study domain of neurological bases of anorexia nervosa. In 1973, the Royal College of Physicians (London, UK) arranged a clinic-opathological conference on a case of anorexia nervosa and, through the period of the conference, the need for EEG-based cases was realized thus initiating the EEG-eating disorder studies [13]. It was largely in the 1980s that a succession of investigations were conducted employing EEG for analyzing eating syndromes.

3. Related work

In [14] a prototype dry electrode system was authenticated and compared with standard wet electrode system. An objective authentication study of dry vs. wet electrodes was undertaken and in general, the results established that the data collected by the prototype system were equivalent to traditional wet technology. The system discussed in [14] is now commercially available and the company is developing wearable sensor suite for US Air force for measuring such varied physiological signals as EEG, ECG, fNIR etc.

In [15] the goal was to measure the capability of a smartphone-based EEG application i.e. Smartphone Brain Scanner-2 (SBS2), to discover epileptiform abnormalities contrasted against usual clinical EEG. The SBS2 system consisted of an Android-based wireless tablet linked to a 14-electrode EasyCap headset (cost about US$300). SBS2 and typical EEG were conducted on subjects with expected epilepsy in Bhutan (2014–2015). Regardless of shortcomings in sensitivity,

it was established that the SBS2 may become a practical helpful test for discovering epileptiform aberrations, and provide low cost EEG access to particularly resource-restricted populaces.

In [16] some limitations of a consumer-grade EEG device have been outlined, such as i) the data collected by the headband are of inferior quality in noisy settings, such as a public lecture; we conducted our experiments in a quite isolated room and had minimal problems ii) EEG signal appears very noisy just by observation; however, we performed noise removal before using the data and got good results iii) time variation between succeeding samples is unpredictable and there is a lot of omitted values; we used raw EEG electrical signal values instead of EEG frequency bands and there were hardly any missing values iv) eye movement, muscular activity etc. include artifacts to the signal and interrupt the measurement of authentic brain waves; we used gyro and accelerometer X, Y and Z values to minimize and mitigate the artifacts.

In [17] meditation brainwaves were investigated using the Muse headband. The researchers examined the recordings and confirmed that a low-cost device had sufficient functionality to be used as a research tool. However, the consumer device was expected to have more errors in relation to the conventional device due to the diversity of design and fewer sensors. However, the initial results indicated that the consumer grade device can successfully record an EEG signal and might possibly be used as a research tool.

The concerns about ERP (event related potential) for consumer grade EEG devices as described in [18] and other sources are well founded. However, a more consequential test of data quality is quite explicit i.e. collect data from a low-cost consumer grade system and straightforwardly ascertain if the said EEG system can deliver data that visibly delivers consistent results and statistically measureable ERP components. The current studies that have scrutinized the usefulness of consumer grade EEG systems for ERP research propose that it was possible to collect enough data of right quality for ERP studies [19, 20].

4. Experimental methodology

In our experiments EEG data is recorded using a Muse EEG headband with preset 500Hz sampling rate, no onboard data processing performed. Graduate students participated in the experiment for bonus points and signed written informed consent and necessary approval received from concerned ethical research committee. All subjects had normal or corrected-to-normal vision, no known neurological deficiencies, not under the influence of any sedative medication. The 10 student subjects were selected based on stratified random sampling from among the 40+ subjects who participated in the study answered the PHQ-9 questionnaire prior to the EEG experiment. The inclusion criterion was adolescent or young adult, normal vision and classification into obese/overweight (OW) or control normal weight (NW), the exclusion criterion being history of eating disorder and inability to fast due to illness or medication. Before the experiment, participants' height and weight were noted, however, due to cultural considerations, subjects waist circumference, and hip circumference were not measured.

PHQ-9 is the depression segment scoring each of the 9 DSM-IV (Diagnostic and Statistical Manual of Mental Disorders, 4th Edition) criteria as "0" (not at all) upto "3" (nearly every day); we used the scoring rubric for PHQ-9 based on [21]. PHQ-9 has been authenticated for primary care applications. PHQ-9 is not a screening tool for depression, instead used to monitor severity of depression and reaction to treatment. Table-1 shows the academic and non-academic demographics of the 10 student subjects including their depression severity and BMI category. Here "Course score" is the final semester score of the student who took part in the experiment reported in our work and BMI category calculated based on BMI (body mass index) i.e. weight (in kilograms) divided by height squared (in meters).

Table 1 The demographics of the 10 student subjects

Subject	Course score (100)	Course grade	PHQ-9 score	BMI category	Depression severity	Grading Rubric
1	66	B	7	control	mild	> 75 A- <= 80
2	63	B-	9	obese	mild	> 70 B+ <= 75
3	75	B+	4	control	minimal	> 65 B <= 70
4	65	B-	5	control	mild	> 60 B- <= 65
5	69	B	3	obese	minimal	> 55 C+ <= 60
6	72	B+	4	control	minimal	> 50 C <= 55
7	64	B-	11	obese	moderate	
8	56	C+	4	obese	minimal	
9	53	C	3	control	minimal	
10	58	C+	8	obese	mild	

The subjects were asked not to have breakfast before the experiment i.e. to be in the hunger state with the last meal being dinner. The experiment consisted of visual stimuli and then closing their eyes, this process was repeated for food and non-food stimuli and during the entire experiment EEG of the subjects was recorded. Subsequently the subjects were given identical volume of identical high sugar drink and the entire experiment was repeated with raw EEG signals recorded. EEG recording of each subject consisted of upto 656 samples, there were two AF (frontal lobe) recordings for each subject i.e. AF7 and AF8 before and after taking the drink, thus for 10 subjects 40 recordings. Raw EEG electrical signal recordings of the student subjects captured using the consumer grade EEG device as per the experimental paradigm are shown in Fig-3, and Fig-4. In Fig-3 and Fig-4, y-axis is μV and x-axis is the EEG raw signal sampling in seconds (upto 656 samples taken in 300 seconds).

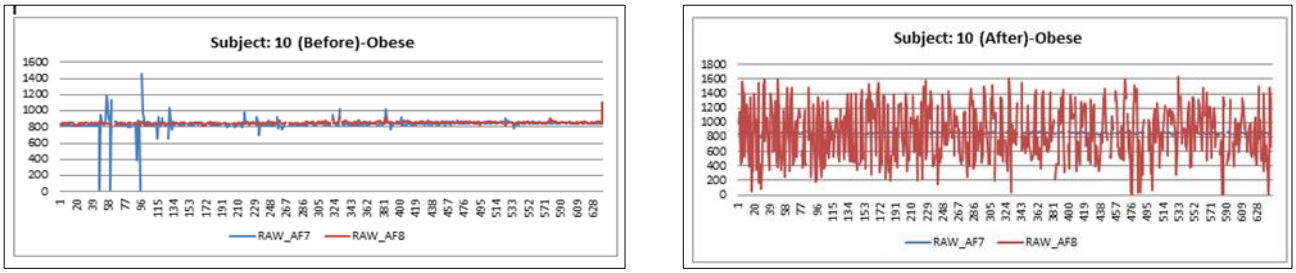

Figure 3 Raw EEG signals of Mildly depressed OW subject before and after consuming the high sugar drink in response to the expereimnetal paradigm

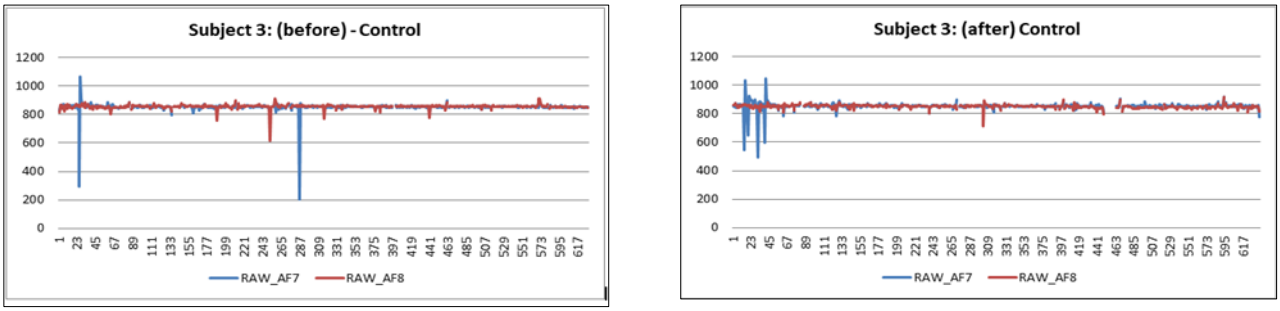

Figure 4 Raw EEG signals of Minimal depressed Control NW subject before and after consuming the high sugar drink in response to the expereimnetal paradigm

The EEG recordings of subjects were not made in any particular order, actually recordings made on first come first served basis. Note that subjects BMI data along with severity of depression was not used in any knowledge discovery technique used in this study, as we did not wanted our results to be influenced in any way by BMI or depression score.

4.1. Noise Removal

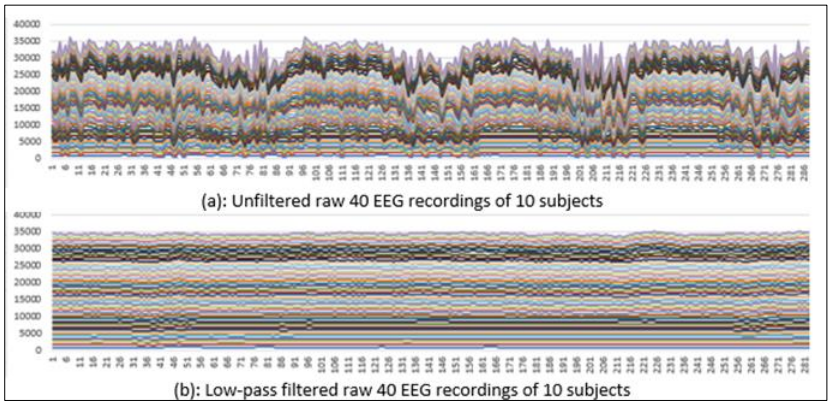

Figure 5 Raw and filtered EEG recordings of the 10 subjects for AF7 and AF8 locations before and after consuming high sugar drink as per the experimental paradigm

There are different types of noise and artefacts (eye blink, head movement etc.) that can pollute EEG signals, therefore, before proceeding with the clustering of the raw EEG data, we need to minimize. Fig-5(a) shows the raw EEG data of upto 656 samples for 40 recordings, while Fig-5(b) shows the results of 10-value moving average (for each EEG recording) which acts as a low-pass filter.

5. Results and discussion

5.1. Clustering

The 40×656 data matrix of EEG signals is used to create the corresponding 40x40 correlation matrix, which was given as input to the clustering tool. Note that the data used in actual clustering are AF7 and AF8 raw EEG electrical signal recordings (shown in Fig-3 and Fig-4). For the purpose of correlations we have used the Pearson's correlation coefficient defined as follows:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

r = correlation coefficient
x_i = values of the x-variable in a sample
$\bar{x}$ = mean of the values of the x-variable
y_i = values of the y-variable in a sample
$\bar{y}$ = mean of the values of the y-variable

We perform one-way clustering of the EEG recordings using the crossing minimization paradigm [22]. Table-2 shows the clustering results with the four clusters automatically extracted shown by red dotted rectangles. Note that none of the attributes shown in Table-1 i.e. subject ID, electrode location, BMI, depression score and course grade were included in clustering.

Table 2 Ordering of the output of the clustering tool with four clusters automatically extracted with depression severity, BMI category and course grade shown here for reference but not used in clustering

RowID	Subject	Electrode Location	Action Time	BMI category	Depression Severity	course grade		RowID	Subject	Electrode Location	Action Time	BMI category	Depression Severity	course grade	
7	Sbt:5	AF7	before	obese	M0	B		5	Sbt:4	AF7	before	control	M1	B-	
30	Sbt:1	AF7	after	control	M1	B		32	Sbt:8	AF8	after	obese	M0	C+	
19	Sbt:7	AF8	before	obese	M2	B-		3	Sbt:3	AF7	before	control	M0	B+	
27	Sbt:5	AF7	after	obese	M0	B		34	Sbt:10	AF8	after	obese	M1	C+	
10	Sbt:1	AF7	before	control	M1	B		35	Sbt:4	AF8	after	control	M1	B-	
14	Sbt:10	AF8	before	obese	M1	C+		16	Sbt:9	AF8	before	control	M0	C	
13	Sbt:3	AF8	before	control	M0	B+		1	Sbt:2	AF7	before	obese	M1	B-	
17	Sbt:5	AF8	before	obese	M0	B		24	Sbt:10	AF7	after	obese	M2	C+	
12	Sbt:8	AF8	before	obese	M0	C+	SC1	25	Sbt:4	AF7	after	control	M1	B-	SC3
2	Sbt:8	AF7	before	obese	M0	C+		9	Sbt:7	AF7	before	obese	M2	B-	
4	Sbt:10	AF7	before	obese	M1	C+		15	Sbt:4	AF8	before	control	M1	B-	
18	Sbt:6	AF8	before	control	M0	B+		21	Sbt:2	AF7	after	obese	M1	B-	
37	Sbt:5	AF8	after	obese	M0	B		26	Sbt:9	AF7	after	control	M0	C	
20	Sbt:1	AF8	before	control	M1	B		29	Sbt:7	AF7	after	obese	M2	B-	
8	Sbt:6	AF7	before	control	M0	B+		11	Sbt:2	AF8	before	obese	M1	B-	
38	Sbt:6	AF8	after	control	M0	B+		31	Sbt:2	AF8	after	obese	M1	B-	SC4
40	Sbt:1	AF8	after	control	M1	B		39	Sbt:7	AF8	after	obese	M2	B-	
22	Sbt:8	AF7	after	obese	M0	C+		23	Sbt:3	AF7	after	control	M0	B+	
28	Sbt:6	AF7	after	control	M0	B+	SC2	33	Sbt:3	AF8	after	control	M0	B+	
6	Sbt:9	AF7	before	control	M0	C									
36	Sbt:9	AF8	after	control	M0	C									

Table-2 is also the color-coded breakdown of each cluster, with the focus being whether the subject is depressed or not and whether OW or NW. In the clustered results, we consider the relationship between EEG recordings of the subjects to be significant, if four or more adjacent records/subjects are of the same type i.e. depressed or not and OW or NW, note that the probability of such an ordering by chance is very low i.e. 1/16 or 0.0625. Observe that during clustering, the data about type of the subject i.e. depressed or not and OW or NW was not used in automatic ordering of the input. This means that if some records/subjects are clustered together this is purely based on the correlations among their EEG raw electrical signals. In Table-2, four adjacent records of subjects are identified by cyan colored brackets. It can

be observed from Table-2 that there are same number of sub-clusters of minimally depressed subjects in Cluster-1 i.e. SC1 and SC2.

After clustering was performed, the order of rows changes for the 40×656 input matrix as per the intrinsic associations between the EEG recordings, resulting in discovery of sub-grouping/sub-clustering (SC1 to SC4) of student subjects shown by green colored cells. The severity of depression can be observed i.e. in sub-cluster SC3 (mostly obese subjects) with most of the subjects getting B- course grade and SC4 (all obese and depressed subjects) all having B- course grade. On close scrutiny of the records of obese and control subjects, it can be observed that in some cases the multiple records of obese subjects are for the same individual either before or after taking high sugar drink, this result is not considered to be significant.

5.2. Sub-clustering

Among the two hemispheres of the brain, the left hemisphere mainly deals with number skills, text, science and mathematics, while the right hemisphere mainly deals with 3-D forms, music awareness and more. We observe that based on the experiment, the right hemisphere of the brain was more active for depressed/obese as compared to the left hemisphere as evident from the AF8 (prefrontal right-hemisphere) location activities vs. the AF7 (prefrontal left-hemisphere) activities in Fig-3 and Fig-4 and corresponding clustering in Table-2. It has been reported in [23] that the newborn children whose mothers endured depression displayed diminished EEG response of the left hemisphere, generally in the left frontal lobe i.e. AF7. The greater the negative feelings of the mother were, the lower was the EEG response within the newborn's brain. Thus our findings corroborate with the reported findings using the conventional EEG device/system.

We can also observe from Table-2 that neural behavior of mildly and moderately depressed student subjects, who are mostly OW, are similar to each other mostly in the AF7 region as can be observed in SC3 and SC4. However, such clear-cut distinction is not there for minimally depressed subjects as can be observed in sub-clusters SC1 and SC2. A weakness of our study is relatively small sample size and heavy reliance on temporal EEG data with limited spatial coverage i.e. only two electrodes located at AF7 and AF8 instead of more neuroanatomical spatial neural mechanisms for making EEG recordings. Lastly, extracting Person's correlation coefficient is nontrivial under heavy noise conditions, while EEG data has several types of noise associated with it.

6. Conclusion

Depression has developed as a major health liability worldwide. Therefore, positive recognition of depression related disorders is an enormous challenge, requiring latest scientific tools, such as Electroencephalography (EEG). However, traditional wet-electrode EEG devices with 50 to 200 electrodes cost thousands of dollars, are beyond the reach of small research groups, have a long turn-around time and also uncomfortable to use. Lately low-cost dry electrode EEG devices have become available [01], using such a consumer grade dry-electrode EEG device with fewer electrodes, this EEG-depression study has endeavored to identify brain regions that generally respond to depression-obesity combination in a block-design paradigm. Accumulated published evidence indicates that OW individuals have reduced executive functions. Although dry-electrode EEG devices have few electrodes, but executive functionality of the brain is at the frontal lobe. In this study, dry-electrode EEG recordings were made at locations AF7 and AF8 i.e. the frontal lobe. Thus, the number of electrodes of dry-electrode EEG device was not a severe limitation in this particular EEG-depression study. From the sub-clustering results of mildly and moderately but mostly OW subjects, we can conclude that mood and food-related information is processed differently among the two types of subjects i.e. those requiring monitoring vs. clinical judgment. Finally, consumer grade EEG device demonstrate the potential to be used for practical research work, provided the experiments are carefully developed considering the strengths and limitations of the device, the spatial functionality of the brain along with the neural response times.

Compliance with ethical standards

Disclosure of conflict of interest

Authors report no conflict of interest.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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