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***Abstract*—One interpretation of breathing exercise is to enforce mind-body harmony, when someone feels well and healthy, different organs of our body function harmoniously. One dysfunctional organ may disturb the resonating mechanism across multiple organs. There are different breathing techniques, and recent scientific evidence encourages understanding the neural correlates of breathing. This research investigates breathing exercises at two paces: Rapid and Deep Slow using neural signals. We collect Electroencephalography (EEG) recordings of 14 participants performing breathing tasks. EEG signals are primarily decomposed in frequency bands that designate different cognitive functions. We extract six primary frequency bands, including delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), low beta (13-20 Hz), high beta (21-30 Hz), and gamma (30-40 Hz). Two different techniques are utilized to report the findings encompassing power spectral analysis and employing machine learning classifiers to discriminate features among different stages of inhalation and exhalation with the significance of different frequencies bands. Lowered beta power in Slow Deep breathing is observed compared to Rapid Breathing, which may suggest increased relaxation, calmness, and anxiety reduction. Differences between the two conditions observed in the fronto-parietal cortex may be attributed to differences in voluntary control between the two tasks. We observed classification accuracy of 72% using low beta between Rapid and Deep Slow breathing using Decision Tree. Several interesting findings are observed in different scalp regions suggesting future direction for further investigation. This study contributes to the understanding of neural signatures for different breathing practices. The implication of this research in health care is to design personalized therapies and to design better breathing mobile applications for daily use.**

***Index Terms*—Machine Learning, Breathing, EEG**

I. Introduction

Breathing exercises have been an integral part of yogic practices and spiritual activities in eastern cultures, such as Indo-Tibetan and Buddhist cultures. Some examples of breathing exercises are breathing in and out in a predetermined pace, breathing with alternate nostrils, forced inhalation and exhalation, and holding of breath for a longer duration. It was based on the principle that mind and body are interconnected, where breathing exercises increase oxygenation of body to improve physical and mental well-being. Several studies have supported the effectiveness of breathing exercises as an intervention for mental illnesses like anxiety and depression, in reducing stress, and in promoting performance on cognitive tasks. [1], [2].

Breathing exercises reduce the activity of sympathetic nervous system and increase the activity of parasympathetic nervous system [3]. Voluntary control of breath, with underlying neural areas like cerebellum, supplementary motor area, somatosensory and motor cortices, helps in functional modulation of the autonomic nervous system including vagal tone, vigilance and attention [4]–[6]. Performing breathing exercises regularly brings about long-term changes in neural activity. Bhatia et al. reported that beta1 and beta2 activity increases in the left frontal, midline and occipital regions in Sudharshan Kriya Yoga (SKY) practitioners in comparison to non-SKY practitioners [7].

Recently, several researchers have investigated electrophysiological changes as a result of paced breathing. An increase in beta-power when participants engaged in paced breathing at a frequency of 0.2 Hz and 0.25 Hz was found by Stancák et al [8]. They also found a drop in alpha band variability in the right parietal and occipital regions during paced breathing at 0.1 Hz when compared with normal breathing in the rest phase. An increase in alpha-power and decrease in theta power during paced breathing has also been found [9]–[11]. Satyanarayana et al. (1992) showed that the increased coherent and synchronous activity of the alpha-band (8-10 Hz) slowly merged into theta waves (6-8 Hz) as participants performed a paced breathing exercise for a short duration [12]. However, Tsuji did not find any differential activity in the aplha-band during slow breathing and spontaneous breathing [13]. Unlike previous studies showing a decrease in theta power, Cheng et al found an increase in this activity at central areas in the paced breathing group [14]. In [15], the effect of altered breathing rate , slow breathing (bradynpea) and fast breathing (tachynpea) and its effect on EEG was studied. Fast Breathing resulted in increased theta power in frontal parietal and occipital areas Slow Breathing did not result in an increase in theta power.

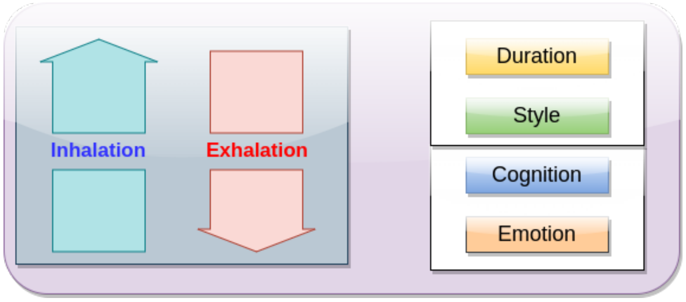

Fig. 1. Several factors to be in account during breathing. Duration of inhalation and exhaltion with certain style, for instance, closing one nostril and allowing other to inhale. The impact of this exercise on our cognition and emotion.

Therefore, the current studies seem to be limited and more research is required in this direction. The variations in the frequency of breathing, cues to indicate paced breathing, participant demographics, practice in performing these exercises, and duration of paced breathing in these experiments could be a source of inconsistent results. Accordingly, we investigated the electrophysiological changes underlying paced breathing using a within-subject design to substantiate the current literature. We also compared the electrophysiological activity as participants inhaled and exhaled while performing these breathing exercises.

To the best of our knowledge, previous studies have not studied the EEG correlates of breathing respective to variation in the inhale: exhale ratio using spectral and machine learning techniques. Hence this study explores the differences in EEG spectral powers in rapid breathing of 500ms of inhale with 500ms of exhale, and Deep Slow breathing of 1s inhale with 2s exhale.

II. Motivation

Personalized breathing modules may be designed for individuals with a growing scientific understanding of breathing techniques. The rapid advancement of neurotechnology has led to the development of consumer EEG headsets that can provide insight into individual's neural rhythms [16]. Breathing techniques can therefore be suggested according to the characteristics of individual neural rhythms. As shown in Fig. 1, Breathing has several variations depending on its style and duration. A variety of breathing styles are available, including three-part alternate nostril breathing, complete breath, post-exhale pause, and skull shining [17]. Breathing generates relaxation, optimal bodily function, emotional balance, self-awareness, and cognitive modulation [18].

III. EEG Dataset and Preprocessing

A. Participants

A sample of 14 healthy participants (13 males) pursuing postgraduate or undergraduate degree programs at the Indian Institute of Technology Gandhinagar was recruited for this experiment in the age group of 17-27 years (mean age = 22.79 years, SD = 2.75). Neither had any known motor, learning, or other neurophysiological deficits. Before beginning the experiment, all the participants provided their consent.

B. Procedure

Participants performed breathing exercises at two paces. In the first pace, participants had to breathe with an inhalation and an exhalation time of 500 ms each, such that each breathing cycle was 1 second long. In the second pace, they had to maintain a breathing pattern with an inhalation time of 1 second and an exhalation time of 2 seconds, making one breathing cycle last for 3 seconds. Breathing exercise at each pace was performed for a duration of 5 minutes. The order of these two paced breathing exercises were counterbalanced across participants. The participants were guided by visual cues to maintain the pace of breathing. The experiment was designed and conducted using E-prime. EEG data was recorded as the participants performed this task.

C. EEG Data Acquisition

High density Geodesic Net of 128 channels was used to acquire the EEG data. EEG caps are available in different sizes therefore before beginning a experiment, we measured the circumference of the head to identify the appropriate cap size for each participant. The reference electrode was decided between nasion (point in between eybrows) and inion (middle point of skull ending at the backside) as mentioned in this article [19]. To enhance the quality of the data, one liter of distilled water was used to prepare the electrolyte solution, followed by immersing the EEG cap in the solution. The electrode impedance was set to below 50 kiloohms with a sampling rate of 250 Hz.

D. EEG Data Processing

We performed the data processing steps and statistical analysis using EEGLAB and MATLAB [20]. Low pass and high pass filtering at 2 and 40 Hz were applied to remove noise and linear trends. Bad channels were removed and interpolated, and finally data were re-referenced from Cz to the mastoid (channel E129). We segmented the data into two groups corresponding to the breathing paces: Slow Deep breathing and Rapid breathing. Then the epochs for each of these segments were extracted. For the paced breathing data, we defined the epoch from 100 milliseconds prior to the onset to 3 seconds after the onset of the breathing cycle. Similarly, for the normal breathing data, we defined the epoch from 100 milliseconds prior to the onset of the breathing cycle to 1 second after its onset. Once the epochs were extracted, the data was re-referenced to the mastoid (channel E129). In addition, we removed all artefact epochs from the dataset. Large fluctuations were also detected and rejected.

IV. Methodology

The complete processing pipeline is shown in the Fig. 2

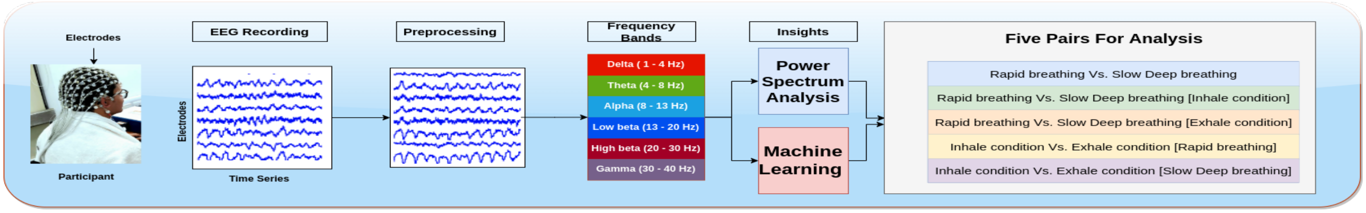

Fig. 2. EEG recordings are pre-processed, followed by decomposition of 6 primary frequency bands, and the last stages involve spectrum analysis and classification using machine learning.

A. Power Spectrum Analysis

We performed a two-way paired-sample t-test to compare the difference between the mean spectral power of the following five pairs of breathing conditions.

1) Rapid breathing Vs. Slow Deep breathing
2) Rapid breathing Vs. Slow Deep breathing [Inhale condition]
3) Rapid breathing Vs. Slow Deep breathing [Exhale condition]
4) Inhale condition Vs. Exhale condition [Rapid breathing]
5) Inhale condition Vs. Exhale condition [Slow Deep breathing]

We computed the spectral power for each frequency band as shown in the Fig. 2, for each electrode site as well global spectral power (Spectral power averaged over all 128 electrode sites) and the mean spectral power averaged over particular electrodes in a particular zone, such as fronto-parietal, left frontal, right temporal etc. After conducting a two way paired sample ttest, for all 128 electrodes, between the pairs of the 5 condition. The t test score was plotted on a topographical plot of the cortex. So extremely positive values of t test score (indicated by dark red color) indicate a statistically significant greater spectral power in condition one compared to condition two, similarly, extremely negative values of t test score (indicated by dark blue color) indicate a statistically significant lesser spectral power in condition one compared to condition two, green indicates no statistically significant difference in power between the two conditions.The results stated in the results section were based upon our observations of the t score topoplots as well as observations p values shown by t tests of spectral power differences between the breathing conditions at individual electrodes.

B. Machine Learning Classification of Breathing States

Machine learning classifiers were used to observe classification accuracy in classifying breathing conditions based on spectral power of frequency bands at different electrode sites. Machine Learning analysis was performed in python using the scikit-learn library [21]. Classifiers employed were K Nearest Neighbors (KNN), Support Vector Machine (SVC), Decision Tree Classifier, Random Forest Classifier, Multi-Layered Perceptron (MLP), Ada Boost Classifier, Gaussian Naive Bayes, and Quadratic Discriminant Analysis (QDA) classifiers and these classifiers are found to be significant in various EEG literature [22], [23]. Similar to spectral analysis, binary classification was performed on five breathing pairs. The features used for classification were the mean spectral powers at electrode sites for each spectral band. Each classification between two breathing conditions was completed using data from each band trained separately. Hence, every classification between two different breathing conditions used six different sample-feature matrices. Accuracy was tested using every classifier, and the classification with the best accuracy was considered.

Feature Selection and Cross Validation: The significance of electrodes was determined during performing spectral analysis, which provided an electrode arrangement in increasing order of p-value. We sequentially considered the electrodes for classification. For instance, the first iteration evaluated the first electrode with a minimum p-value. The second next iteration included the next electrode with the second least minimum p-value. Similarly, all 128 electrodes were considered for classification. The electrode data features were selected in decreasing order of their significance (as measured by their p-value. The permutation test score method developed in the scikit-learn library was used to test the statistical significance of the classification with 1000 different permutations of the dataset [21].

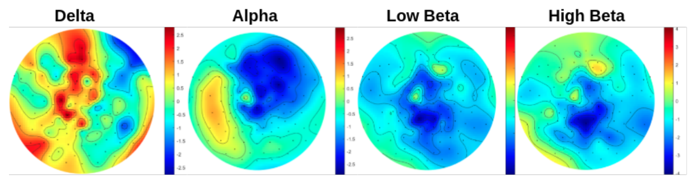

Fig. 3. Differences between Rapid and Slow Deep breathing

V. Results

A. Power Spectrum Analysis

1) Differences between Rapid and Slow Deep breathing: Significant differences were observed in the spectral powers between Rapid and Slow Deep breathing in the delta, alpha, low beta and high beta bands as shown in topograph plots Fig.3. The spectral power differences showed the greatest statistical significance for the low beta band between the two conditions. The low beta power was lower in the Slow Deep breathing

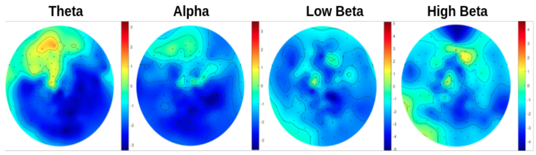

Fig. 4. Differences between Rapid and Slow Deep breathing in the Inhale condition

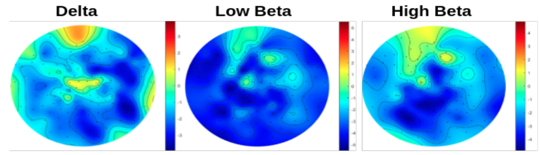

Fig. 5. Differences between Rapid and Slow Deep breathing in the Exhale condition

condition than Rapid breathing.The T-score topoplot showed statistically significantly lower low beta power in the centro-parietal, parietal (more to the left hemisphere than the right), and centro-frontal (more to the right hemisphere than the left). The eight most statistically significant ($p < 0.01$) electrodes were present along the midline and immediately right and left to it, in the left-right and centro-parietal (P1 ($p = 0.00067$) ,Pz ($p = 0.008$) ,P2 ($p = 0.0016$)), centro-parietal (CP1),Central, left and right Occi-Parietal (PO3,POz,PO4), left and right adjacent to the midline electrode sites.

High beta power was significantly lower in the Slow Deep compared to the Rapid breathing condition in the parietal region (extending to the occipital-parietal and right centro-parietal zones), the effect was also present in the frontal midline region. five electrodes showed ($p < 0.01$) respective to the parietal, occipital-parietal (around Pz), right parietal (Cp2) electrodes. There was a statistical significant reduction in power in Slow Deep breathing compared to Rapid breathing.

Alpha power was significantly lower in the Slow Deep breathing than the Rapid breathing in the right frontal,right fronto polar, midline frontal, midline central, midline centro-parietal, right fronto-central regions. The right frontal electrode showed the greatest statistically significant difference, ($p = 0.0157$) and the right fronto temporal electrode ($p = 0.0167$), the other statistically significant electrodes were in the frontal zone, such as Fp2, left frontal. There was a statistically significant reduction in power in the Slow Deep case compared to the Rapid breathing case.The left centro-parietal ($p = 0.0133$) and the left central (P3) ($p = 0.01347$) showed the greatest statistically significant difference in the delta band. There was a statistically significant increase in power in the Slow Deep case compared to the Rapid breathing case.

2) Differences between Rapid and Slow Deep breathing in the Inhale condition: Spectral Power in the six bands were compared between the Slow Deep and Rapid breathing tasks,(Slow Deep-Rapid t test) but only the inhalation period was considered.

The topograph plots are shown in Fig. 4. In low beta power, the right parietal region showed lower low beta power in the Slow Deep condition than the Rapid breathing condition. Sites in that region, to the front of P4 showed ($p = 0.00028$) and to the front of P2 showed ($p = 0.00076$), lowering was observed in the left centro parietal region, at site CP1 ($p = 0.0026$) and the frontal midline zone AFz ($p = 0.0046$). The fronto polar midline region showed significantly high beta power in Slow Deep condition than Rapid breathing. Electrode at this site showed ($p = 0.0098$), and the right temporo-parietal ($p = 0.0057$), the right parietal to occi-parietal zone, electrode at that site showed ($p = 0.006$).

There was significantly lower alpha power in the Slow Deep case as compared to the Rapid breathing case in the right parietal, right centro-parietal zones ($p = 0.0053$), occi-parietal and left occipital zones, site at the right occi-parietal zone showed ($p = 0.006$). There was significantly lower theta power in the Slow Deep case as compared to the Rapid breathing case in the right parietal CP6 ($p = 0.0092$), and occi-parietal zone , site to the right and between PO4 and O2 showed ($p = 0.0077$).

3) Differences between Rapid and Slow Deep breathing in the Exhale condition: Spectral Power in the six bands were compared between the Slow Deep and Rapid breathing tasks,(Slow Deep-Rapid t test) but only the exhalation period was considered.

Global spectral mean power (mean spectral power averaged over all electrodes) showed differences between the two breathing conditions in the low beta band ($p = 0.0008$), delta band ($p = 0.0327$), and high beta band ($p = 0.044$) as shown in Fig.5. The powers were lower in the Slow Deep condition as compared to Rapid. The greatest statistically significant differences between the conditions in low beta power were observed in the left central temporal-parietal C5 ($p = 0.00016$) and left temporal at T9 ($p = 0.00019$). Apart from these, the left frontal, left temporo-frontal , left parietal, left centro-parietal, and left temporo-occipital sites were also statistically significant, ranging p-value in the range of 0.0002 to 0.0009.

As per the T-score topoplot, significantly lower high beta power was observed in the Slow Deep condition compared to the Rapid condition left occi-parietal zone , PO7 showed ($p = 0.00047$),left parietal P3 ($p = 0.00071$) , fronto central (frontal right electrode to this site $p = 0.0018$, FCz $p = 0.0022$) and right temporo parietal (site right of TP10 showed ($p = 0.003$).As per the T-score topoplot, significantly lower gamma power was observed in the left occi-parietal zone and occi-parietal zone , O1 showed ($p = 0.0034$), POz showed ($p = 0.0055$), PO3 showed ($p = 0.0035$). In alpha power between the two conditions, the right occipital area showed higher alpha power in the slow deep case than the rapid breathing case with O2, which showed ($p = 0.019$).

Theta power between the two conditions, the right frontal and right fronto-temporal area showed lower theta power in the slow deep case compared to the rapid breathing case, F10

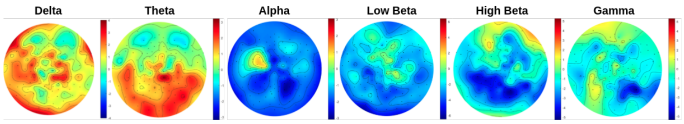

Fig. 6. Differences between inhalation and exhalation during Rapid breathing

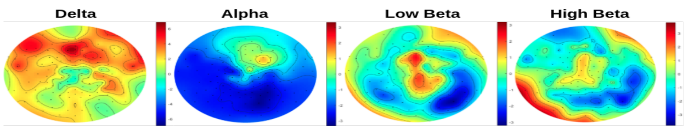

Fig. 7. Differences between inhalation and exhalation during Slow Deep breathing

showed ($p = 0.015$). In delta power, the right temporo-parietal showed significantly lower delta power in the Slow Deep case compared to the Rapid breathing case, TP10 ($p = 0.0047$), (site located near TP8 and TP10 ($p = 0.0028$).

4) Differences between inhalation and exhalation during Rapid breathing: Spectral Power during the inhalation and exhalation period was compared during the rapid breathing task. (inhalation-exhalation t test). The topograph plots are shown in Fig. 6. In the low beta band, it was observed that there was greater power during exhalation compared to inhalation, in the occipital region,parietal region in particular the left occipital region, (electrode at this site showed, ($p = 0.0003$)), right centro-parietal, C5 ($p = 0.00055$)). In the high beta band, it was observed that there was greater power during exhalation compared to inhalation in the right occi parietal zone, electrode at this site showed ($p = 0.00028$),left temporo parietal TP7 ($p = 0.00051$), left parietal zones P3 ($p = 0.0006$), right Temporo Parietal, electrode at this zone showed ($p = 0.001$). In the gamma band, it was observed that there was greater power during exhalation compared to inhalation in the right temporo-occi-parietal zone electrodes at this site showed ($p = 0.00017$) for PO8 and ($p = 0.0014$) at the right occi parietal site.

In the delta band, it was observed that there was greater power during inhalation compared to exhalation in the right frontal pole region, electrode in that region showed ($p = 0.00589$),and to a lesser degree left frontal pole region and left occipital. In the alpha band, it was observed that there was greater power during exhalation compared to inhalation in the right parietal to right occi-parietal region, the electrode site at this location showed ($p = 0.012$). In the theta band it was observed that, there was greater power in the inhale condition as compared to the exhale condition, at the central midline zone , a site posterior and to the right of CPz showed region showed (p=0.0076)

5) Differences between inhalation and exhalation during Slow Deep breathing : Spectral Power during the inhalation and exhalation period was compared during the slow deep breathing task. (inhalation-exhalation t test)

In the delta band, greater power was observed in inhalation compared to exhalation in the frontal, fronto polar, and right and left fronto-polar regions, right and left fronto-temporal regions, for AFz ($p = 0.0000256$), site left of AFz and below FP1 ($p = 0.0000329$) , FPz ($p = 0.000076$),right fronto temporal (site to extreme right fronto temporal showed, ($p = 0.000090$) Fz ($p = 0.0002$) F9 ($p = 0.00023$) as shown in topograph Fig. 7. In the alpha band, greater power was observed in exhalation compared to inhalation in the right occipital, right occi-parietal region, O2 showed ($p = 0.0072$), the electrode at the right occi-parietal temporal junction showed ($p = 0.0085$).

In the low and high beta bands, there was a higher power in the exhale condition as compared to the inhale condition in the right occi-temporo parietal zone electrode at that site ($p = 0.0091$) for low beta, ($p = 0.00992$) for high beta.

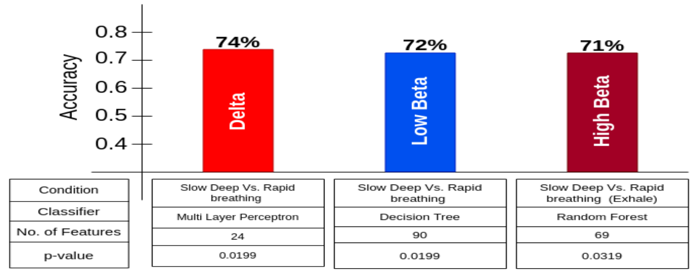

Fig. 8. Accuracy of Machine Learning Classification

B. Machine Learning Classification

Permutation testing was applied to evaluate the significance of classification accuracy. Using the mean spectral delta power of the 20 most significant electrodes, we achieved 74% (p=0.0199) classification accuracy between Slow Deep and Rapid breathing using Neural Network Multilayer Perceptron. Decision tree showed 72% accuracy (p=0.0199) using the mean spectral low beta power of the 90 most significant electrodes between Slow Deep and Rapid breathing. Mean spectral high beta power of 69 most significant electrodes classified Slow Deep and Rapid breathing in the exhale condition with 71% accuracy (p=0.0319) using Random Forest. The classification accuracies of other bands between the other breathing condition pairs were not significant and significant results are shown in Table 8.

VI. Discussion and Conclusion

Both the Deep Slow Breathing and Rapid Breathing exercises performed by the participants require voluntary control because they had to maintain the necessary inhale to exhale ratio (1:2 or 1:1). This suggests that slow deep breathing inhale: exhale ratio (1:2) may require more voluntary control, attention, and alertness than the rapid (1:1) breathing task as more cognitive effort is needed to maintain the 1:2 inhale to exhale compared to a 1:1 ratio. Slow Deep Breathing during meditation and otherwise is known to have a relaxing effect, increase comfort, alertness, mindfulness, and decrease anxiety. We hypothesize that the differences in spectral power observed between the two breathing tasks in this study can be explained by the effect of voluntary and cognitive control in executing the tasks and the impact of Slow Deep breathing on psycho-physiological aspects such as mindfullness and alertness [18]. The effect of any voluntary task, voluntary control over breathing speed, and inhale: exhale ratio will involve the primary supplementary and premotor area. And can be discussed with spectral power differences being observed in the frontal, fronto-central, centro-parietal and parietal zones. Previous fMRI studies confirm the activation of frontal and parietal regions during volitional control of breathing [24]. An Intracranial EEG study found activation of the fronto-tempolar insular network during voluntary control of breathing [25]. Fronto temporal regions showed differences in activation in this study between the two breathing conditions considered in this study as well. Lowering of beta powers in the Slow Deep breathing conditions as compared to the Rapid breathing case can be explained by the fact that lower beta power results in increased relaxation, calmness, and reduction of anxiety [26]. The increase in delta power may be a predictor of increased relaxation.

VII. Limitation

In this study, we did not have a normal, natural breathing control condition performed by the participants. Therefore, the state during the two breathing conditions could not be compared to a control, the default mode of normal breathing. We also filtered the data at 40 Hz, which limited the analysis of gamma band. Further investigation needs to be done with more participants to make stronger inferences with measurement of respiratory activity. However, this study presents a detailed analysis of two breathing techniques and suggests further investigation.

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