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Impact Analysis of Meditation on Physiological Signals

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***Abstract*— Vipassana meditation is a type of mindfulness meditation technique mostly practices in southwest part of the globe, where relaxing but highly awake and alert mind state is achieved. Vipassana Meditation involvement was carried out for a group of mid aged people. This people constantly dealing with high level of stress. This research evaluate advance signal processing methodologies of respiration and electroencephalographic (EEG) signals during Vipassana meditation and control condition to assist in quantification of the meditative state. EEG of respiration and Vipassana Meditation data were collected and analyzed on 40 novice meditators after a 3-weeks meditation intervention. Collected data were analyzed with advanced mathematical tool such as Wavelet Transform for spectral analysis. The Support Vector Machine is used as a classifier for classification of EEG signals to evaluate an objective marker for meditation. We analysed and observed Vipassana meditation and control condition differences in the different frequency bands such as (alpha, beta, theta, delta and gamma) for EEG signals of subjects. Moreover, we confirmed a classifier with a higher accuracy (92%) during respiration and EEG signals for discrimination between meditation and control conditions, rather than EEG signal alone (85%). Classifier based on respiration and EEG signal is feasible objective marker for verifying ability of meditation. Different level of meditation depth and experience can be studied using this classifier for future studies. The main objective of this work is to develop a physiological meditation marker as a medication (mind-body medicine field) to advance by nourishing severity of methods.**

***Keywords*— Meditation, EEG signal, Stockwell Transform, SVM.**

I. INTRODUCTION

Vipassana Meditation is a mindfulness meditation which acts as a type of medication in the field of mind-body medicine [1]. This meditation is Buddhist practice that involves focusing with a calmness and most active mental state. But, there is no exact method to measure strength and insufficient controls of brain. Also there are no particular criteria to judge the potential of meditation which acts in the mind-body medicine [2].

Some of the previous research studies have suggested for meditation's potential using self-decided criteria [3]. But these self-decided criteria are always influenced by the practitioner's self-observation. The available literature for all type of meditation practice lacks any attached aim or potential measures.

EEG signals are one of the best physiological measures to assess fruitful meditation's potential since it is reactive to mindfulness meditation. Changes in EEG signals are well-reported during meditation [2,4]. The features extracted from spectral analysis can be utilized to design a dedicated classifier, once the parameters are set up using spectral analysis. These parameters are sensitive to overall brain activity during meditation. Hence, designed classifier can classify meditation and control conditions.

Respiration is again one of the prominent and reliable physiological markers for meditation. Some of the previous research studies reveal that breathing rate becomes slow during meditation automatically [8]. Literature also reveals that expert and experienced meditators have low breathing rate during meditation as compared to controls state at rest [9]. Hence, slow breathing rate within the same subject is also one more physiological criterion to judge meditation and controlled condition.

The main aim of this work was to set up different objective measures to evaluate strength of Meditation. The focus was to design objective measures to differentiate meditation and controlled condition using respiration and EEG Signals. The subjects chosen for this research work were novice meditators. They have been told to complete three-week VM intervention at Vipassana Research Institute (VRI) Dhammagiri using three quantitative methods. VM is one of the popular mindfulness meditation practices that teach skills to deal with day to day life circumstances.

Two statistical signal processing methods have been used for classification of meditation and control conditions using respiration and EEG signals which were as follows:

1. Spectral analysis of respiration and EEG signal at several scalp locations were carried out using Stockwell transform during meditation and control condition. The

frequency components was extracted from EEG and respiration signals using Stockwell transform[13];

2. Support vector machine (SVM) as a classifier is designed using various features extracted during spectral analysis of respiration and EEG signal individually. A joint classifier is also designed with the help of respiration and EEG signal together to classify both meditation and control conditions.

II. Methods

1. Selection of Subjects

Subjects were recruited from Educational field working as teacher as well as students from VJTI Mumbai and working professional in and around Mumbai city. The subjects were generally healthy of age between 21-70 years who themselves-reported being stressed by examinations, job and business. Subject recruitment criteria were: age 21-70 years old; and have Perceived Stress Scale (PSS) [13] score ≥ 9 as a baseline score; and self willing to follow all the protocol related with this Research. They were not having prior meditation experience or any other mind sharpening body exercise (e.g., Zen or yoga) within the last 24 months. They were even not having 5 mins of practice of breathing exercise in the last one month. The Research was approved by the Vipassana Research Institute (VRI), Mumbai, Ethical Committee of VJTI Mumbai and written informed accord was taken from all subjects participated in this Research.

The Functional modules in a typical computerized classification of any Physiological signal are given in Fig.1.

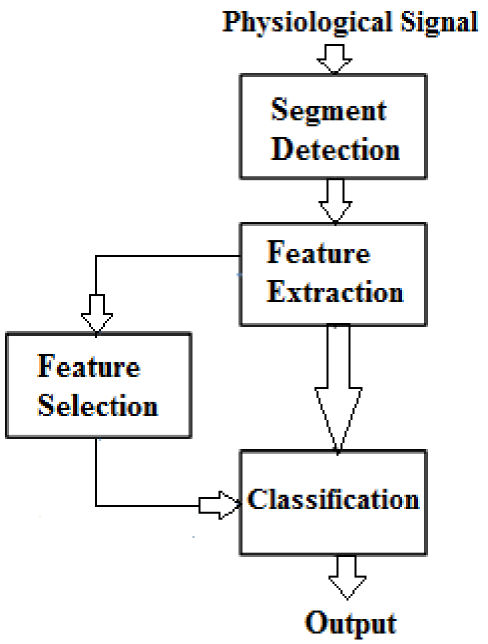

Fig.1. Functional Blocks for classification of Physiological signal.

2. Intervention

The whole VM Intervention measure modified from Mindfulness-Based Cognitive Therapy (MBCT) and Mindfulness-Based Stress Reduction (MBSR) course has been wholly explained somewhere else. In concise, training is given at VRI, Mumbai which includes a group seating of atleast twelve hours daily with a break of two hours in between this session. This session was taught by a trained, expert & experienced meditator. The meditation session in VRI's centre had three components:

1. Instructional and concise discussion about relaxation, VM, mind-body interaction, working and educational stress;
2. Daily practice of VM and other mindfulness exercise such as breath control during session at VRI centre and their living place.
3. Discussion related with different problem-solving techniques along with their success and failure rate and difficulties in practicing daily life exercises.

3. Protocol and Data acquisition for EEG signal

Physiological EEG signals were acquired from the subjects in two situations.

1. While listening to a fifteen minutes silent song from Bollywood movies (participants had chosen the song from the given list) with eyes closed;
2. Fifteen minutes session of VM learned at VRI's Centre for three week of ten hours daily. The EEG signals were recorded using 8-channel Enobio EEG acquisition device (Enobio NE, The Barcelona Spain) which have sampling frequency of 500 Hz as shown in Fig.2. Respiration signal were also recorded using piezoelectric belt which has light elastic nature. It was attached near the diaphragm around the subject's chest. Signals from other channels (Except EEG) were also recorded as the measuring parameters for VM because EEG signal may be unsuccessful in differentiating VM state and control state alone.

Fig. 2. EEG signal recording during VM Practice (courtesy: Vipassana Research Institute, VRI Mumbai).

4. EEG signal analysis in time frequency domain

Initially, the EEG signals were passed through band pass filter which had cut-off frequency in the range of (2-40 Hz) to remove DC biasing and Noise frequency greater than 40Hz using a linear phase FIR filter. The Enobio device had a provision to remove 50Hz line frequency disturbances from Electrical Signal. In the next step after filtering, the EEG signal was processed further to down-sampled upto 64 Hz. The Gamma activity of EEG signals have not been included in the analysis because of known fact that, EMG signals interfere in gamma activity during EEG Signal recording from scalp [12]. For avoiding filter transient impact on EEG signal, we have discarded initial few samples from the recorded EEG signals. Power Spectral density (PSD) is estimated from EEG signals for meditation conditions. PSD was also calculated during normal condition while listening silent Bollywood song during spectral analysis from various electrodes placed on scalp sites. All frontal Electrodes was averaged and converted entire frontal reading into single averaged Electrode. Similarly other Electrodes placed on different regions averaged into single Electrode reading (central, occipital, right and left temporal region; Fig.3) for various frequency bands (such as delta [0-3Hz), theta [4-8 Hz), alpha [9-12 Hz) and beta [13-30 Hz)). Once Power Spectral Density (PSD) is calculated for all the electrodes and frequencies, and then it is clustered based on the location of the Electrode on the scalp and according to frequency bands.

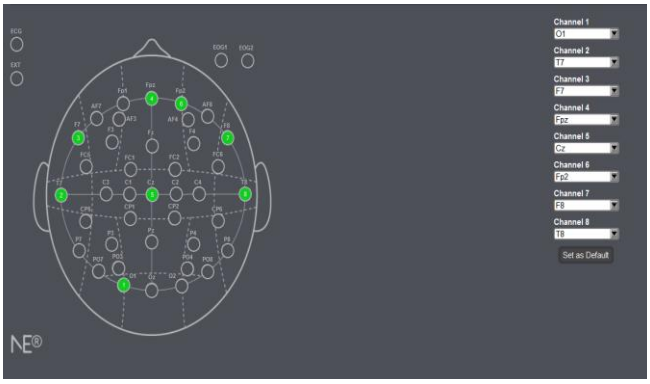

Fig.3. Electrodes placement on different positions of the scalp such as central, frontal, occipital, right and left temporal.

5. Time frequency analysis of Respiration

Respiration signal is acquired using piezoelectric belt. This signal is then passed through band pass filtered of 0.01-20 Hz range to remove the DC biasing, noise and baseline wandering using linear phase FIR filter. Since, Respiration signal have much lower frequency as compared to EEG signals. Hence, low pass filter having lower cut-off frequency than EEG signal is needed for Respiration signal. Respiration signal was then analysed Time-frequency analysis. Time frequency Analysis is a mathematical tool to study signal behaviour in the original domain and its counterpart separately. In real sense, all physiological signals varies their frequency content with time, while most of the frequency transforms such as FFT consider that the signal is stationary in nature. The Stockwell transform which is also called as S-transform) [13] was applied to these signals, since it has a similar feature like Wavelet transform for time-frequency representation of the signal and is found to be a good method for Time frequency Analysis, since it uses a window length dependent on the frequency. Assuming:

$$x(n) = \left\{ x(0), x(1), ..., x(N-1) \right\} \quad (1)$$

being the signal, in this case the respiration signal, the S-transform is computed as:

$$S\left(f,n \right) = A\left(f,n \right) e^{j\phi\left(f,n \right)}$$

$$= \sum_{m=-\infty}^{\infty} x(m) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(n-m)^2 f^2}{2}} e^{-i2\pi fm} \quad (2)$$

This output *S* (*f*, *n*) is called Stockwell Transform. The output was in Matrix form. This Stockwell matrix contains coefficients of time domain samples and target frequency range which is called as Stockwell coefficients. S-Transform was then applied to EEG and respiration Signals after filtering. After Application of S-Transform, Stockwell coefficient was extracted from time frequency matrix which is then plotted as an image. In the next step, Stockwell coefficients were analysed using statistical method called *Analysis of Variance (ANOVA)* with a factor for the meditation or Control condition. This was applied to find out the difference in respiration signal during normal and meditation states.

6. Classification using Support Vector Machine

Feature selection is the initial step of classification. Best selected features from the available list of features were used for classification. For constructing a joint classifier for EEG and Respiration signal, the feature vectors were combined and normalised in [0,1] before applying it to classifier.

Support vector machine (SVM) is supervised machine learning algorithm for classification of data [14]. SVM contains several Kernels functions. But Radial Basis Function (RBF) was selected after trial and error method, since better results were obtained using RBF kernel as compared to other kernel functions. Radial basis function (RBF) kernels were used to map real time data (nonlinear in nature) into a large dimensional space. This kernel has the formula given as:

$$K(x^{(i)}, x^{(j)}) = \phi(x^{(i)})^T \phi(x^{(j)})$$

$$= e^{\left(-\gamma \left\| x^{(i)} - x^{(j)} \right\|^2\right)}, \ \gamma \succ 0 \quad (3)$$

Then feature vectors derived from this method were categorised into meditation or control state. A process of 10-fold cross validation was applied on the categorised data to acquire the hyper parameters (optimized) for the kernel of Radial basis function (width of standard deviation σ, overlap penalty of error function c). Accuracy calculated using this process was averaged for all subjects. For Classification of EEG Signal, the classifier constructed with the above derived coefficients was in the range of *4-40 Hz* with intervals of *0.25 Hz*.

Classifier constructed using the coefficients to classify the respiration signal (*0.0625-20 Hz* frequency range). To construct the combine classifier for EEG and respiration signal, feature vectors had frequency range of *4-40 Hz* and *0.0625-20 Hz* for EEG and respiration signals respectively.

III. Real Time Data Analysis

50 healthy subjects selected for this research that includes 25 men and 25 women volunteers. They were willingly participated for this study with a mean age 40 years (with standard deviation of 6.8 and age group ranges between 25 to 55 years). Real time physiological signals were acquired from these subjects. The first data set was recorded from Expert meditator (more than 30 days of mediation experience) using a standard 10-20 electrode placement approach as shown in Fig.2. The subject data were recorded while practising meditation with eyes closed.

The recorded EEG signals during normal (controlled state) and meditation state are shown in Fig.4 and Fig.5 respectively. The recorded Respiration signals are shown in Fig.6 (Blue line indicates controlled state and Red shows Meditation state). The data set were acquired from the same volunteers during normal seating position.

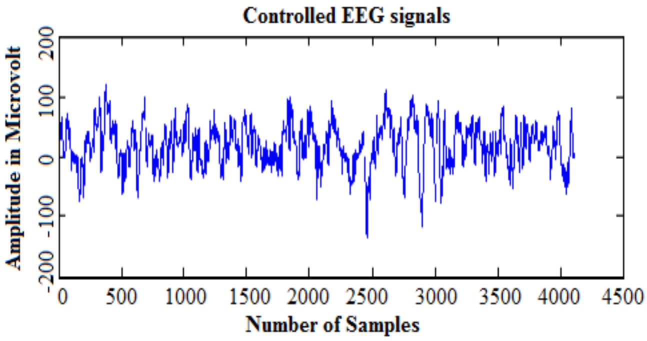

Fig. 4. EEG signals during normal state

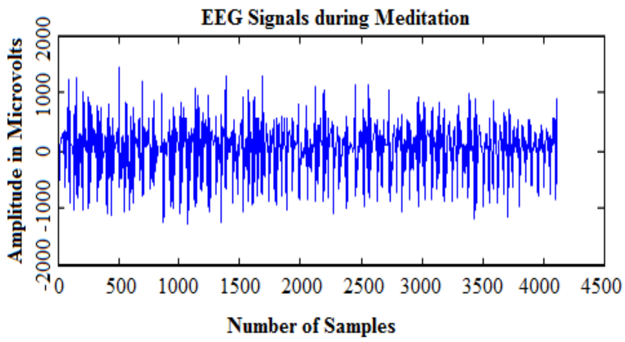

Fig. 5. EEG signals during Meditation state.

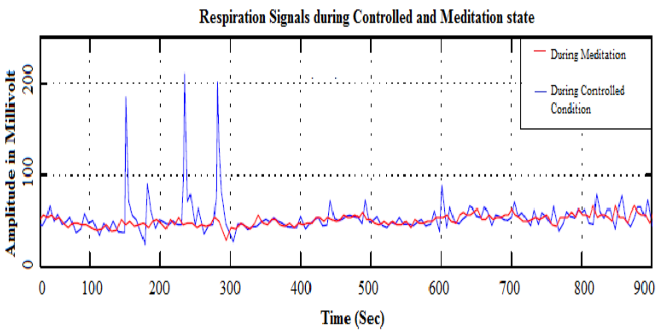

Fig.6. Respiration signal during controlled state shown by Blue Color and during Meditation state shown by Red Color.

IV. Results

1. Spectral Analysis of EEG signals

Fig.7, Fig. 8 and Fig. 9 shows the impact of meditation on different frequency bands and locations. During Meditation state, overall power has been increased significantly in Theta and Beta bands. But in Alpha band, power is increased in occipital and Right temporal part of the scalp during meditation. Fig.7, Fig.8 and Fig.9 Shows the Value of Power Spectral Density over scalp for controlled and meditation state for several frequency bands.

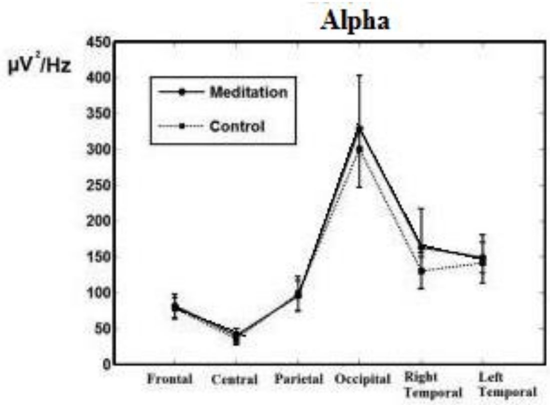

Fig.7. Power Spectral Density (PSD) calculation for alpha band for EEG signal at several Scalp locations for meditation and control states.

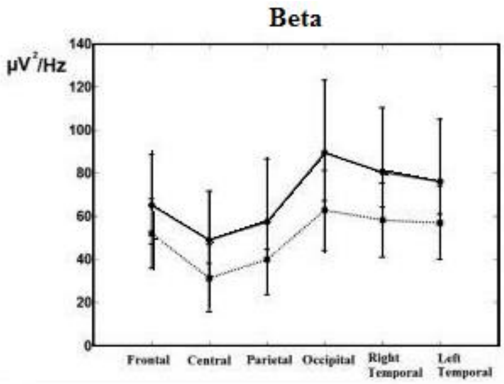

Fig.8. Power Spectral Density (PSD) calculation for Beta band for EEG signal at several Scalp locations for meditation and control states.

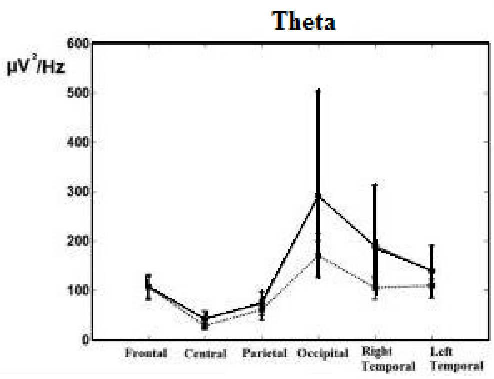

Fig. 9. Power Spectral Density (PSD) calculation for Theta band for EEG signal at several Scalp locations for meditation and control states.

2. Spectral Analysis of Respiration Signal

The distinction between Meditation and Control Condition using Stockwell coefficients is shown in Figure 10. During Meditation lower frequency ranges shows greater activity. While during control condition, higher frequencies shows greater activity. Statistical analysis of Stockwell coefficients was then carried out. One of the popular Statistical parameter which was applied to Stockwell coefficient was Analysis of variance (ANOVA). Vipasanna Meditation shows a significant effect on respiration Signal's Spectral Coefficient using ANOVAs of Stockwell coefficients.

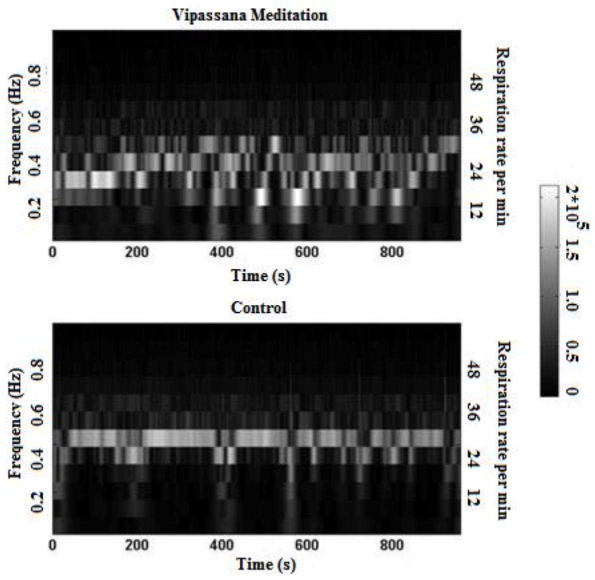

Fig.10. Stockwell coefficients during meditation and controlled conditions.

3 Support Vector Machine (SVM) classification

The Accuracy of EEG Signal, Respiration Signal and jointly Respiration/ EEG signal using SVM classifier is as shown in Fig.11. The analysis using three different conditions such as using EEG signal alone, using Respiration Signal alone and jointly by EEG + Respiration was carried out with the help of *ANOVA.* The classification accuracies derived using these three conditions justify that the joint classifier gives best accuracy. In this way, the effect of several classifiers on accuracy was derived and showed that the combine classifier using EEG and Respiration signals gives best result.

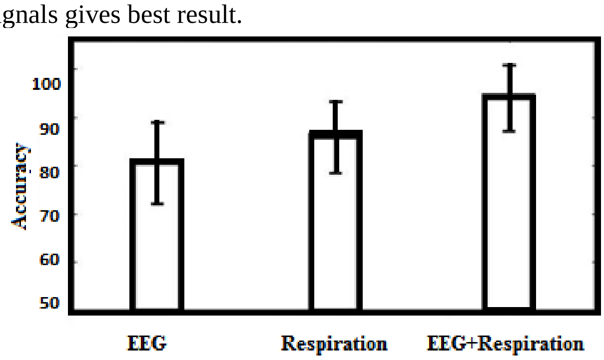

Fig.11. Classification Accuracy using EEG Signal, Respiration Signal and combine (EEG + Respiration).

V. Conclusions

Respiration and EEG signals from 50 novice meditators during control and meditation condition were examined. Spectral analysis was carried out and features are fed through Support Vector Machine (SVM) Classifier for Classification accuracy of these data. Power enhancement in beta and theta frequency ranges of EEG was observed during meditation state over controlled one.

In addition power in Alpha frequency range of EEG signals was also increased in occipital and right temporal part of the scalp during Meditation state as compared to Control state. There is significant reduction in Respiration rate during meditation over control state. The SVM classifier found to be appropriate for fruitful classification of combined signals of EEG and respirations signals.

Respiration signals clearly achieved distinction between control and meditation condition since, meditation state lower the respiration rate. There is variation in meditation practices across globe in regards to regulation of breathing. The Meditation practiced during this research study was a sitting Vipassana meditation, where breath was prime focus of attention, but the instruction was not given to change the frequency of the respiration.

During spectral analysis of EEG signal, alpha and theta EEG power significantly increased during meditation state. There is no significant increased in beta EEG power. Without any specific instruction during meditation, respiration rates get lower. The main cause behind this low breathing rate might be due to meditation state turn up with relaxation response even though relaxation is not the main purpose of meditation [15,16]. In other word, we can conclude that slow respiration rate during meditation suggested significant reduction in stress which ultimately keeps body healthy [17,18]. The SVM classifier will be a milestone for any mindfulness meditation research field.

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