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Change in physiological signals during mindfulness meditation

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Abstract

Mindfulness meditation (MM) is an inward mental practice, in which a resting but alert state of mind is maintained. MM intervention was performed for a population of older people with high stress levels. This study assessed signal processing methodologies of electroencephalographic (EEG) and respiration signals during meditation and control condition to aid in quantification of the meditative state. EEG and respiration data were collected and analyzed on 34 novice meditators after a 6-week meditation intervention. Collected data were analyzed with spectral analysis and support vector machine classification to evaluate an objective marker for meditation. We observed meditation and control condition differences in the alpha, beta and theta frequency bands. Furthermore, we established a classifier using EEG and respiration signals with a higher accuracy at discriminating between meditation and control conditions than one using the EEG signal only. EEG and respiration based classifier is a viable objective marker for meditation ability. Future studies should quantify different levels of meditation depth and meditation experience using this classifier. Development of an objective physiological meditation marker will allow the mind-body medicine field to advance by strengthening rigor of methods.

I. INTRODUCTION

Meditation is a type of complementary medicine treatment [1]. However, there is no definite way of measuring efficacy and several problems such as inadequate controls, inappropriate and highly variable outcome measures, and lack of measures for intervention adherence are involved [2] [3]. Also there is no measure to evaluate the practitioners ability to engage in the mind-body medicine.

Previous studies have attempted to analyze meditation ability using self-rated measures [4] but self-rated measures are always biased by the practitioners self-observation. The meditation intervention literature lacks any sort of objective adherence or meditation ability measures.

Physiological measures such as EEG offer promise as objective measures to assess meditation ability because of their sensitivity to meditation. EEG changes are well-documented during meditation state changes and from long-term meditation cross-sectional trait differences [2] [5]–[9]. Once spectral analysis parameters sensitive to meditation on

overall brain activity are found, the spectral coefficients can be employed to build a classifier to distinguish between meditation and control conditions.

Respiration may also be a reliable physiological marker of mediation. Some studies have shown that meditation slows breathing rate without a direct instruction to do so [10]. Experienced meditators are reported to have slower respiration rates compared to controls at rest and slower minute ventilation during meditation [11]. Slow breathing may be a simple physiological marker within subject to assess whether a person is meditating or not.

The overall goal of this project was to establish an objective measure of meditation ability. The objective of this study was to develop this objective measure by analyzing EEG and respiration signals from novice meditators during meditation and a control condition after they had completed a six-week mindfulness meditation intervention (MMI) using three quantitative methods. MM is one meditation approach that is popular and teaches skills applicable to everyday life situations. The two statistical processing methods were: 1) spectral analysis of EEG signal during meditation and a control condition to determine the effect of meditation on frequency behavior of EEG data at different locations over the scalp and time-frequency analysis of respiration using Stockwell transform [16] ; and 2) a support vector machine (SVM) classifier constructed to perform classification using EEG frequency coefficient, respiration signal and a joint classifier with both the EEG and respiration signal to assess the classifier ability to distinguish between meditation and control conditions.

II. METHODS

A. Participants

Participants were recruited with newsletters, email list serves, and flyers at Oregon Health and Science University (OHSU) and around Portland, Oregon Metro Area. The participants were generally healthy adults 50-75 years of age who self-reported being stressed. Inclusion criteria were: age 50 -75 years old; baseline Perceived Stress Scale (PSS) [13] score ≥ 9 ; and willing to follow the study protocol. They also could not have prior experience with meditation classes or other mind-body classes (e.g., yoga or tai chi) within the last 24 months or more than 5 minutes daily practice in the last 30 days. The study was approved by the OHSU Institutional Review Board, and written informed consent was obtained from all participants.

B. Intervention

The complete MMI curriculum adapted from Mindfulness-Based Stress Reduction (MBSR) and Mindfulness-Based Cognitive Therapy (MBCT) programs has been more fully described elsewhere [14]. In brief, training includes a one-on-one 60-minute session weekly for six weeks taught by a trained and experienced teacher. The in-lab sessions included three components: 1) didactic instruction and brief discussion concerning stress, relaxation, meditation, and mind-body interaction; 2) practice in meditation and other mindfulness exercises that the subjects perform both in session and daily at home; and 3) discussion about problem-solving techniques regarding their successes and difficulties in practicing and applying the exercises in daily life.

C. EEG Recording and Protocol

Physiological data were collected during two conditions 1) listening to a 15 minute National Public Radio podcast (participants chose from a list of four) with eyes closed; and 2) 15 minutes of a sitting mindfulness meditation they learned in the MMI. The physiologic data recorded were 32-channel EEG, EOG, respiration, ECG, and two movement monitors (BioSemi, Amsterdam, The Netherlands). Respiration was measured with a light elastic piezoelectric belt (Ambu-Sleepmate, Maryland) around the participant's chest near the diaphragm. Non-EEG channels were included in the meditation measure because EEG alone may not be successful in distinguishing meditation from control states.

D. EEG Spectral Analysis

First, the EEG data was bandpass filtered in 2-35 Hz to avoid baseline wandering and DC bias and high frequency noise using a FIR linear phase filter (Equiripple, length 2811). Subsequently, the cleaned EEG was further down-sampled to 64 Hz. We did not include analysis of gamma activity in part because of the known contribution of EMG activity to gamma activity in scalp recordings [15]. The first few samples were discarded from the data to avoid filter transient impact on signal. Spectral analysis of EEG data during the podcast and meditation conditions was calculated using power spectrum density (PSD) estimation at different electrode sites (averaged electrodes at frontal, central, parietal, occipital, right temporal and left temporal regions; Fig. 1) for different frequency bands (theta [4-8 Hz), alpha [8-12 Hz) and beta [12-30 Hz)).

Once PSD is estimated for all electrodes and frequencies, it is grouped based on location and frequency bands. The PSD values for all frequencies at each band and different locations were subjected to a two-way within subject ANOVA (analysis of variance), involving factors of Condition (Meditation, Control) and Location (Frontal, Central, Parietal, Occipital, Right Temporal and Left Temporal).

E. Respiration Time-Frequency Analysis

First, the respiration signal was bandpass filtered in 0.01-20 Hz to avoid baseline wandering and DC bias and high frequency noise using FIR linear phase filter; the low frequency filter needed a lower cutoff than for EEG because of the much lower frequency of respiration than EEG. Time-frequency analysis (TFA) was then used to analyze the respiration signal. TFA is a signal processing tool to study the signal and its transform jointly rather than separately. In practice, many physiological signals change their frequency content with time, while most traditional frequency transforms assume that the signal is stationary. The Stockwell transform (S-transform) [16] was used, because it reveals a wavelet-transform-like time-frequency representation of the signal and is found to be a good approach for TFA, since it employs a frequency dependent window length. Assuming:

$$x(n) = \{x(0), x(1), \dots, x(N-1)\} \quad (1)$$

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

$$S(f, n) = A(f, n) e^{j\phi(f, n)} \\ = \sum_{m=-\infty}^{\infty} x(m) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(n-m)^2 f^2}{2}} e^{-i2\pi f m} \quad (2)$$

The output of the S-transform $S(f, n)$ is a matrix containing Stockwell coefficients for all samples in time and in the target frequency range. The filtered data subjected to S-transform and a time-frequency matrix of Stockwell coefficients was extracted and plotted as an image. The Stockwell coefficients were then analyzed with ANOVA with a factor of condition (Meditation, Control) to measure the difference of respiration behavior during meditative and non-meditative states.

F. Support Vector Machine Classification

Feature selection is the first step in classification and pattern recognition analysis. To construct a joint classifier, the feature vectors from EEG and respiration signal were combined and all feature vectors were normalized to the interval [0,1] before applying the classifier.

In machine learning, support vector machines (SVM) are supervised binary classification models that have been extremely successful [17]. A Matlab SVM toolbox that uses Radial basis function (RBF) kernels to nonlinearly map data into a high dimensional space. All feature vectors were labeled as meditation or control classes and a 10-fold cross validation process was performed on the labeled data to obtain the optimized hyper parameters for the RBF kernel (width σ , overlap penalty c). Accuracy was averaged across subjects. For the EEG classifier, the coefficients were in the range of 4-32 Hz with 0.25 Hz intervals. For the respiration classifier, the coefficients were in the range of 0.0625-16 Hz. For the joint EEG and respiration classifier, the vectors of EEG signal were in 4-32 Hz range and the respiration feature vectors were in 0.0625-16 Hz range.

III. RESULTS

The participants consisted of 29 women and 5 men, mean age 60 years (std deviation 6.8 and range 50 to 74 years).

A. EEG Spectral Analysis

Within each frequency band, there was a condition effect by location (Alpha: $F(5,165) = 96.24, p = 0.001$, Beta: $F(5,165) = 98.95, p = 0.001$, Theta: $F(5,165) = 64.57, p = 0.001$). Within each frequency band, there was also a condition effect across all locations (Alpha: $F(1,33) = 22.32, p = 0.001$, Beta: $F(1,33) = 56.95, p = 0.004$, Theta: $F(1,33) = 20.35, p = 0.001$). Fig. 2 shows the effect of condition in the different frequency bands and locations. Both Beta and Theta bands show an overall increase in power during meditation. The Alpha band has a slight increase in power in the right lateral and posterior locations during meditation. Fig. 2 shows the Value of PSD over scalp for different conditions and different band.

B. Respiration Time-Frequency Analysis

The Stockwell coefficients (Fig. 3) show a clear distinction between meditation and control conditions. Lower frequencies show greater activity during meditation, while higher frequencies show greater activity during the control condition. ANOVA was applied on Stockwell coefficients involving the factor of state (Meditation, Control). ANOVAs of Stockwell coefficients resulted in a significant effect of meditation on respiration spectral coefficients ($F(1,33) = 10.10$, $p = 0.005$).

C. Support Vector Machine Classification

Fig. 4 shows the accuracy for EEG, respiration and joint EEG/respiration SVM classifier averaged among subjects. The accuracies for three different classifiers were subjected to repeated ANOVA and showed the effect of classifier type on accuracies ($F(2,58) = 59.32$, $p = 0.001$).

IV. CONCLUSIONS

In conclusion, our study examined EEG and respiration data from 34 novice meditators during a control and meditation condition. We conducted two types of analysis on this data, spectral analysis and SVM classification. EEG spectral analysis revealed a generalized increase in beta and theta EEG power during meditation compared to control. Alpha EEG power was also increased during meditation compared to control in the right lateral and posterior locations. Respiration rate was lower in the meditation versus control condition. Finally, the SVM classifier found the greatest accuracy using both EEG and respiration signals to discriminate between the meditation and control condition.

Respiration showed a clear distinction between meditation and control conditions with the meditation condition having a lower respiration rate. There is heterogeneity across meditation practices in regards to regulation of breathing. The meditation done in this study was a sitting mindfulness meditation practice where attention was focused on the breath, but there was no instruction to change the frequency of the breath.

The EEG spectral data supports the already existing evidence that alpha and theta EEG power are increased during the meditative state. The increase in beta EEG power is not as supported in the meditation literature and may be more dependent on participant experience with meditation. The lower respiration rate during meditation supports other literature documenting that respiration rates slows during meditation regardless of whether there is a specific instruction to do so or not. The slowed respiration rate may be because the meditative state overlaps with a relaxation response even though relaxation is not a directed intention of meditation [18], [19]. The slowed respiration rate also provides a mechanism by which meditation reduces stress in healthy adults and multiple chronically ill populations [20], [21]. The SVM classifier is a major step forward for the meditation research field.

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References

1. Barnes PM, Bloom B. Complementary and alternative medicine use among adults and children: United States. 2007:2008.
2. Ospina MB, Bond K, Karkhaneh M, Tjosvold L, Vandermeer B, Liang Y, et al. Meditation practices for health: state of the research. *Evid Rep Technol Assess (Full Rep)*. 2007 Number 155, Publication No. 07-E010:1-263.
3. Wahbeh H, Elsas SM, Oken B. Mind-body interventions: applications in neurology. *Neurology*. 2008; 70:2321–2328. [PubMed: 18541886]
4. Lau MA, Bishop SR, Segal ZV, Buis T, Anderson ND, Carlson L, et al. The Toronto Mindfulness Scale: development and validation. *Journal of Clinical Psychology*. 2006; 62:1445–1467. [PubMed: 17019673]
5. Cahn BR, Polich J. Meditation states and traits. EEG, ERP, and neuroimaging studies. *Psychological Bulletin*. 2006; 132:180–211. [PubMed: 16536641]
6. Farb NA, Anderson A, Mayberg H, Bean J, McKeon D, Segal ZV. Minding one's emotions: mindfulness training alters the neural expression of sadness. *Emotion*. 2010; 10:25–33. [PubMed: 20141299]
7. Brefczynski-Lewis JA, Lutz A, Schaefer HS, Levinson DB, Davidson RJ. Neural correlates of attentional expertise in long-term meditation practitioners. *Proc Natl Acad Sci U S A*. 2007; 104:11483–11488. [PubMed: 17596341]
8. McCollough A, Hild K, Wahbeh H, Oken B. A machine classification measure of meditation ability. *BMC Complementary and Alternative Medicine*. 2012; 12(suppl 1):P3.
9. Lutz A, Greischar LL, Rawlings NB, Ricard M, Davidson RJ. Long-term meditators self-induce high-amplitude gamma synchrony during mental practice. *Proc Natl Acad Sci U S A*. 2004; 101:16369–16373. [PubMed: 15534199]
10. Ditto B, Eclache M, Goldman N. Short-term autonomic and cardiovascular effects of mindfulness body scan meditation. *Ann Behav Med*. 2006; 32(3):227–234. [PubMed: 17107296]
11. Wolkove N, Kreisman H, Darragh D, Cohen C, Frank H. Effect of transcendental meditation on breathing and respiratory control. *J Appl Physiol*. 1984; 56(3):607–612. [PubMed: 6423589]
12. Jerath R, Edry JW, Barnes VA, Jerath V. Physiology of long pranayamic breathing: neural respiratory elements may provide a mechanism that explains how slow deep breathing shifts the autonomic nervous system. *Med Hypotheses*. 2006; 67(3):566–571. [PubMed: 16624497]
13. Cohen S, Karmarck T, Mermelstein R. A global measure of perceived stress. *J Health Soc Behav*. 1983; 24:385–396. [PubMed: 6668417]
14. Wahbeh H, Lane JB, Goodrich E, Miller M, Oken BS. One-on-one mindfulness meditation trainings in a research setting. *Mindfulness*. 2012 published on-line October 31, 2012.
15. Whitham EM, Pope KJ, Fitzgibbon SP, Lewis T, Clark CR, Loveless S, et al. Scalp electrical recording during paralysis: quantitative evidence that EEG frequencies above 20 Hz are contaminated by EMG. *Clin Neurophysiol*. 2007; 118(8):1877–88. [PubMed: 17574912]
16. Stockwell RG, Mansinha L, Lowe RP. Localization of the complex spectrum: the S transform. *IEEE Transactions on Signal Processing*. 1996; 44(4):998–1001.
17. Cortes C, Vapnik V. Support vector networks. *Machine Learning*. 1995; 20:273297.
18. Benson, H. *The relaxation response*. Morrow; New York: 1976.
19. Lazar SW, Bush G, Gollub RL, Fricchione GL, Khalsa G, Benson H. Functional brain mapping of the relaxation response and meditation. *Neuroreport*. 2000; 11:1–5. [PubMed: 10683819]
20. Grossman P, Niemann L, Schmidt S, Walach H. Mindfulness-based stress reduction and health benefits. A meta-analysis. *J Psychosom Res*. 2004; 57(1):35–43. [PubMed: 15256293]
21. Chiesa A, Serretti A. Mindfulness-based stress reduction for stress management in healthy people: a review and meta-analysis. *J Altern Complement Med*. 2009; 15(5):593–600. [PubMed: 19432513]

Fig. 1.

(a) Electrodes divided into six regions over scalp as frontal, central, parietal, occipital, right temporal and left temporal.

Fig. 2.

PSD estimation of EEG signal over Alpha, Beta and Theta bands at different location over scalp for meditation and control conditions averaged across subjects (N=34).

Fig. 3.

Time frequency Analysis of respiration signal shows more activity in lower frequencies during meditation. The figure shows the Stockwell coefficients amplitude averaged across subjects (N=34) in meditation and control conditions.

Fig. 4.
SVM classification accuracy using EEG, Respiration and joint (N=29).