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SURA Research Proposal

Using EEG to Derive Neural Signatures of Meditation

Background

During the past two decades, mindfulness meditation has received accelerated interest from scientists, healthcare professionals, and the general public. Part of this growth in interest stems from the increasing number of scientific studies linking mindfulness meditation with a variety of psychological (e.g., improved emotion regulation) and physical (e.g., lower blood pressure) health benefits (Carlson, 2012; Keng et al., 2011). Although much is now known about the salutary effects of mindfulness meditation, it remains unclear exactly how mindfulness meditation works. Part of the problem is that although mindfulness is commonly defined as nonjudgmental attention to present moment experience (Kabat-Zinn, 1991), the term "mindfulness meditation" or "mindfulness training" can refer to a multiplicity of meditative practices (Davidson & Kaszniak, 2015; Lutz et al., 2015).

For example, mindfulness-based interventions (MBIs), a class of psychotherapeutic interventions predicated on the training of mindfulness skills, often involve a core curricula of varying meditation practices colloquially subsumed under the umbrella term "mindfulness meditation". These practices include focused attention (FA), open monitoring (OM), loving-kindness (LK), and body scan (BS) meditation (Britton et al., 2018; Santorelli et al., 2017). Briefly, FA meditation involves sustaining attention on a target object of concentration (e.g., the breath), whereas OM meditation involves nonjudgmental monitoring of present moment experience encompassing thoughts, emotions, and physical sensations. On the other hand, BS meditation involves systematically directing attention to various parts of the body, while LK meditation promotes the cultivation of compassion towards self and others (Hofmann et al., 2011; Sevinc et al., 2018). Importantly, it is evident that these meditative practices contain substantial technical differences and are putatively thought to yield differential effects (Lippelt et al., 2014). Therefore, as other contemplative scientists have suggested before, it may be valuable to appropriately differentiate these practices so as to better understand their underlying mechanisms and functional effects (Lutz et al., 2015).

In line with this idea, neuroscientific research involving electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) have sought to comparatively investigate the neural underpinnings of different meditation practices. Although this line of research is relatively nascent, findings show that several of the aforementioned meditations (i.e., OM, FA, LK) exhibit distinct neural correlates, which ostensibly contribute to unique functional outcomes (Fox et al., 2016; Lee et al., 2018; Manna et al., 2010). However, these reported neural patterns are not always uniformly generalizable and are likely to vary depending on the characteristics of sample cohorts (e.g., experts vs. novice meditators) and design parameters (e.g., inclusion of active control conditions; see Lin et al., 2020). The field may therefore benefit from deriving robust approaches that can more reliably differentiate meditative states across groups and within individuals.

The research topic of my proposal is to address this need by evaluating whether an EEG machine learning classifier approach can be used to distinguish neural markers/signatures associated with different types of meditation. Instead of examining EEG spectral power profiles during meditation as others have done before (Lee et al., 2018; Lomas et al., 2015), we will explore the use of a novel geometric classifier to decode meditative states. This classifier was recently developed and validated to show superior performance relative to standard pattern classifiers for EEG, and also has the advantage of providing instantaneous predictions (i.e., at each timepoint) among an arbitrary number of categories (Singh et al., 2018). However, this EEG classifier, has never before, to our knowledge been used in the meditation domain. Thus, investigating the utility and performance of this geometric classifier will be an important first step toward deriving more robust neural measures of meditation. Over the longer-term, such measures will be highly useful in developing a better understanding of the neural mechanisms underlying different meditative practices as well as the psychotherapeutic benefits of MBIs more broadly.

By completing the proposed project, I will obtain valuable research experience that will greatly benefit me in my pursuit of becoming a research psychologist. Moreover, the topic and scope of the project aligns particularly well with my research interests and existing skill set. Specifically, as a math major, the focus on method development and use of machine learning algorithms fit well with my quantitative background, and I am very interested to explore the intersection between applied math, computer programming, electrophysiology, and cognitive neuroscience. Some of the more essential learning objectives such as EEG set-up and running participants can only be achieved if I am able to work in the lab in-person. Due to the financial constraints as a low-income student, I will not be able to relocate to campus without funding. Therefore, funding support from SURA is essential for me to obtain the training I need to contribute substantively to the project.

Methods

Participants will be adults (age 18-85) recruited from Washington University and around the greater St. Louis area. Although there will be no formal eligibility criteria involving meditation experience, we will aim to recruit relatively equal numbers of novice and experienced meditators. Experienced meditators in particular will be actively recruited from local meditation communities. Adopting the criteria from Payne et al. (2019), novices will be operationalized as individuals with less than 2 years of meditation experience; whereas experienced meditators will be operationalized as individuals with more than 2 years of meditation experience, including a period of active practice with at least 2 hours per week over a minimum of 3 months.

Participants will first complete a self-report assessment battery, including questionnaires on demographics, meditation experience, cognition, trait mindfulness, and other personality metrics. Participants will then undergo EEG setup and first complete two non-meditative tasks while EEG is recorded: (1) a mind wandering condition during which participants will be instructed to allow their minds to wander freely; and (2) an active control condition during which participants will listen to a TED talk on how to acquire second language proficiency quickly. After these tasks, participants will complete the four meditations in randomized order: FA, OM, BS, LK. At the end of each meditation, participants will be asked to assess state mindfulness using the state mindfulness scale (SMS; Tanay & Bernstein, 2013). All tasks will be completed with eyes closed to minimize known neural oscillatory confounds (Barry et al., 2007).

EEG data will be recorded using a BrainVision ActiChamp recording system and actiCAP active electrodes (Brain Products GmbH, Munich, Germany). The International 10/20 System will be used to mount electrodes on an elastic cap. The sampling rate will be set to 512 Hz. EEG data will be re-referenced, band-pass filtered, and artifact corrected based on established best practices.

In line with the main aim of the proposal, we will subject the data to a conic machine learning classifier to determine the extent to which the task conditions are decodable. This technique was developed in our lab and relies on converting neural time series into temporal derivatives, which can then be used to represent brain dynamics in geometric space (Singh et al., 2018). We will then benchmark the performance of the classifier by using standard cross-validation (CV) procedures, ranging from simple train-test split to more sophisticated k-Fold and time series approaches. Importantly, we will leverage our sample by comparing the performance of the classifier between experienced meditators and novices. This would allow us to test the intuitive hypothesis that meditative states become more distinguishable as a function of practice. A final exploratory aim involves applying the classifier to differentiate experienced meditators from novices using data from the mind wandering condition. This may yield important information about the neural dynamics underlying the effect of long-term meditation practice on mind wandering characteristics.

Implications and Importance to the Field of Study

Developing effective ways to characterize the neural underpinnings of different meditative practices hold great promise for advancing contemplative science. It would allow us to gain a more granular and nuanced understanding of the kinds of practices and meditative states that are subsumed within broader intervention or practice labels (e.g., MBIs, mindfulness meditation). Methodologically, this project represents an important first step toward the broader goal of decoding subjective mental states. Acquiring the means to reliably decode key subjective features of meditation (e.g., mind wandering, concentration, affect) could be instrumental toward the development of novel neurofeedback/brain cognition interface training augmentation programs (Tan et al., 2014). These kinds of technological applications could greatly accelerate mindfulness training and produce substantial public health impact.

References

Barry, R. J., Clarke, A. R., Johnstone, S. J., Magee, C. A., Rushby, J. A. (2007). EEG Differences Between Eyes-Closed and Eyes-Open Resting Conditions. *Clin. Neurophysiol. Off. J. Int. Fed. Clin Neurophysiol*, 118, 2765-2773. doi: 10.1016/j.biopsycho.2017.09.010

Britton, W. B., Davis, J. H., Loucks, E. B., Peterson, B., Cullen, B. H., Reuter, L., Rando, A., Rahrig, H., Lipsky, J., Lindahl, J. R. (2018). Dismantling Mindfulness-Based Cognitive Therapy: Creation and Validation of 8-Week Focused Attention and Open Monitoring Interventions Within a 3-Armed Randomized Controlled Trial. *Behaviour Research and Therapy*, 101, 92-107. doi: 10.1016/j.brat.2017.09.010

Carlson, L. E. (2012). Mindfulness-Based Interventions for Physical Conditions: A Narrative Review Evaluating Levels of Evidence. *International Scholarly Research Notices (ISRN) Psychiatry*. doi: 10.5402/2012/651583

Davidson, R. J., Kaszniak, A. W. (2015). Conceptual and Methodological Issues in Research on Mindfulness and Meditation. *American Psychologist*, 70(7), 581-592. doi: 10.1037/a0039512

Fox, K. C. R., Dixon, M. L., Nijeboer, S., Girn, M., Floman, J. L., Lifshitz, M., Ellamil, M., Sedlmeier, P, Christoff, K. (2016). Functional Neuroanatomy of Meditation: A Review and Meta-Analysis of 78 Functional Neuroimaging Investigations. *Neuroscience & Behavioral Reviews*, 65, 208-228. doi: 10.1016/j.neubiorev.2016.03.021

Grootendorst, M. (2019). Validating your Machine Learning Model. https://towardsdatascience.com/validating-your-machine-learning-model-25b4c8643fb7

Hofmann, S. G., Grossman, P., Hinton, D. E. (2011). Loving-Kindness and Compassion

Meditation. *Clinical Psychology Review*, 31(7), 1126-1132. doi: 10.1016/j.cpr.2011.07.003

Kabat-Zinn, J. Full Catastrophe Living: Using the Wisdom of Your Body and Mind to Face Stress, Pain, and Illness. (Pub. By Dell Publishing, a Division of Bantam Doubleday Dell Pub. Group, 1991).

Keng, S. L., Smoski, M. J., Robins, C. J. (2011). Effects of Mindfulness on Psychological Health: A Review of Empirical Studies. *Clinical Psychology Review*, 31(6), 1041-1056. Doi: 10.1016/j.cpr.2011.04.006

Lee, D. J., Kulubya, E., Goldin, P., Goodarzi, A., Girgis, F. (2018). Review of the Neural Oscillations Underlying Meditation. *Frontiers in Neuroscience*, 178(12), doi: 10.3389/fnins.2018.00178

Lin, Y., Fisher, M. E., Roberts, S. M. M., Moser, J. S. (2016). Deconstructing the Emotion Regulatory Properties of Mindfulness: An Electrophysiological Investigation. *Frontiers in Human Neuroscience*, 10, 451. doi: fnhum.2016.00451

Lin, Y., Eckerle, W. D., Peng, L. W., Moser, J. S. (2019). On Variation in Mindfulness Training: A Multimodal Study of Brief Open Monitoring Meditation on Error Monitoring. *The Neuroscience of Mindfulness*, 9(9), 226. doi: 10.3390/brainsci9090226

Lin, Y., Gloe, L. M., Louis, C. C., Eckerle, W. D., Fisher, M. E., Moser, J. S. (2020). An Electrophysiological Investigation on the Emotion Regulatory Mechanisms of Brief Open Monitoring Meditation in Novice Non-Meditators. *Scientific Reports*, 14252(10), doi: 10.1038/s41598-020-71122-7

Lippelt, D. P., Hommel, B., Colzato, L. S. (2014). Focused Attention, Open Monitoring and

Loving Kindness Meditation: Effects on Attention, Conflict Monitoring, and Creativity – A Review. *Frontiers in Psychology*, 23(5), 1083. doi: 10.3389/fpsyg.2014.01083

Lomas, T., Ivtzan, I., Fu, C. H. Y. (2015). A Systematic Review of the Neurophysiology of Mindfulness on EEG Oscillations. *Neuroscience and Biobehavioral Reviews*, 57, 401-410. doi: 10.1016/j.neubiorev.2015.09.018

Lutz, A., Jha, A. P., Dunne, J. D., Saron, C. D. (2015). Investigating the Phenomenological Matrix of Mindfulness-Related Practices from a Neurocognitive Perspective. *American Psychologist*, 70(7), 632-658. doi: 10.1037/a0039585

Manna, A., Raffone, A., Perrucci, M., Nardo, D., Ferretti, A., Tartaro, A., Londei, A., Del Gratta, C., Belardinelli, M.O., Romani, G. L. (2010). Neural Correlates of Focused Attention and Cognitive Monitoring in Meditation. *Brain Research Bulletin*, 82, 46-56. doi: 10.1016/j.brainresbull.2010.03.001

Orrù, G., Monaro, M., Conversano, C., Gemignani, A., Sartori, G. (2019). Machine Learning in Psychometrics and Psychological Research. *Frontiers in Psychology*, 2970(10). doi: 10.3389/fpsyg.2019.02970

Payne, J. R., Baell, O., Geddes, H., Fitzgibbon, B., Emonson, M., Hill, A. T., Van Dam, N. T., Humble, G., Fitzgerald, P. B., Bailey, N. W. (2019). Experienced Meditators Exhibit No Differences to Demographically-Matched Controls in Theta Phase Synchronisation, P200, or P300 During an Auditory Oddball Task. *Journal of Cognitive Neuroscience*, 31(8), 1184-1204. doi: 10.31231/osf.io/9a4yd

Santorelli, S. F., Kabat-Zinn, J., Blacker, M., Meleo-Meyer, F., Koerbel, L. (eds) (2017). Mindfulness-Based Stress Reduction (MBSR) Authorized Curriculum Guide (http://www.umassmed.edu/cfm/training/mbsr-curriculum).

Sevinc, G., Hölzel, Hashmi, J., Greenberg, J., McCallister, A., Treadway, M., Schneider, M. L., Dusek, J. A., Carmody, J., Lazar, S. W. (2018). Common and Dissociable Neural Activity After Mindfulness-Based Stress Reduction and Relaxation Response Programs. *Psychosomatic Medicine*, 80(5), 439-451. doi: 10.1097/PSY.0000000000000590

Singh, M. F., Braver, T. S., Ching, S. (2018). Geometric Classification of Brain Network Dynamics Via Conic Derivative Discriminants. *Journal of Neuroscience Methods*, 308, 88-105. doi: 10.1016/j.jneumeth.2018.06.019

Tan, L. F., Dienes, Z., Jansari, A., Goh, S. Y. (2014). Effect of Mindfulness Meditation on Brain-Computer Interface Performance. *Consciousness and Cognition*, 23, 12-21. doi: 10.1016/j.concog.2013.10.010

Tanay, G., & Bernstein, A. (2013). State Mindfulness Scale (SMS): Development and Initial Validation. *Psychological Assessment*, 25(4), 1286-1299. doi: 10.1037/a0034044