Predictive model of quality of mental behavior quality

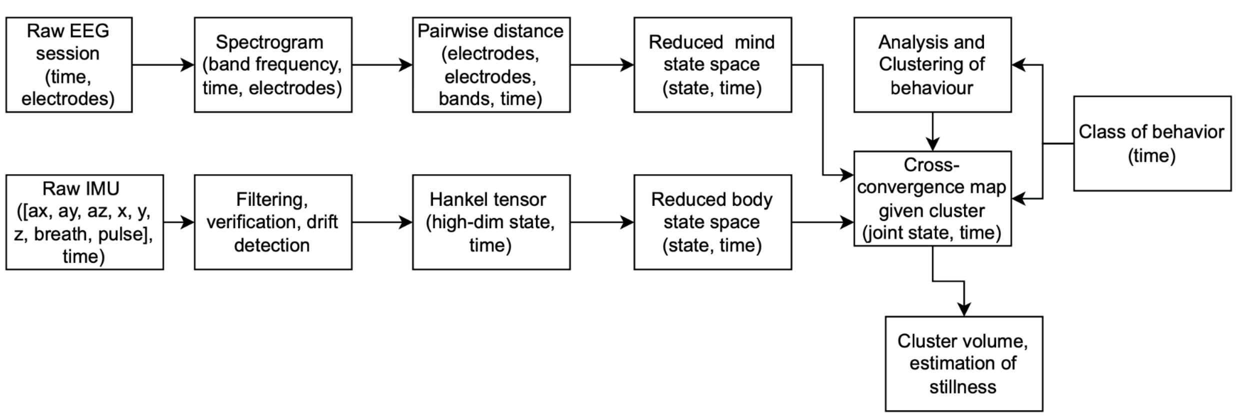
We investigate a series of a participant's mind states during meditation. The mental state and mental processes affect the participant's body position. The goal of modeling is to estimate the desired degree of attention using a wearable device with IMU only. At the model selection and optimization stage an EEG cap delivers additional information to ensure the predictive model's estimations are based on pertinent information from body state. So the main hypothesis is to test the relation between mind and body states using EEG and IMU signals.

One session of a participant's measurement behavior lasts up to one hour. It has several stages of the patient's behavior. Each stage has its timelapse and a label of behavior class. An experienced participant differs from a novice participant in the quality of mental behavior, which is expressed in the linguistics scale. It is registered in the questionnaire. Also, it is observed in measurements of brain activity and body position.

The goal of the predictive model is to estimate the quality of mental behavior using a wearable device with an IMU sensor. To boost the quality of this estimation, at the modeling state, an EEG recording device is used. The EEG data is used as privileged, or teacher, information to set a structure and parameter of the predictive model properly. The EEG signals are well-studied in their spectral domain. So as the initial approach, their visual representation sets the basic classes of the mind state. it reinforces the IMU data and sets the parameters of the predictive model in the modality of privileged information.

The following diagram establishes the following procedure to set the computational experiment. Label the class of behavior using the linguistic scale. Construct a mind-state space. Construct a body state space. Find the relation between mind and body state trajectories in two spaces given class. Analyze clusters of trajectory, and set dimensionality. Estimate related cluster volume, and estimate stillness.

Define the mind state and the body state with the following models.



Styles of meditation affect the spectral and power description of the signal. Each signal has its spectrogram, computed by the wavelet transform at each time point. The spectrogram splits into recommended bands. We compute the pairwise distance between electrode signals at a given band and each time point. It forms a four-way tensor. This tensor is the phase trajectory of the mind state.

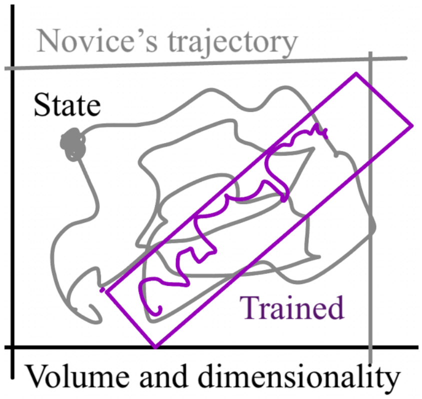
The body position is described by a vector of accelerometer and gyroscope samples of the body-mounted IMU. This vector also includes the breath wave and the pulse wave. The trajectory of the body state is defined by the Hankel matrix, for this list of signals it is a three-way tensor.

The body position plays a key role in this methodology, so the robust representation of the body state is important. The body position is defined by the pelvis and vertebral column positions. It is a mechanical system. So we describe the body position with the physical or physics-informed model. We use the Hamiltonian principle of the Least Action to model the Lagrangian of the body position using the Physics-Informed Neural Networks. So to make a robust model of the body state we verify the measured state with the Lagrangian of the system.

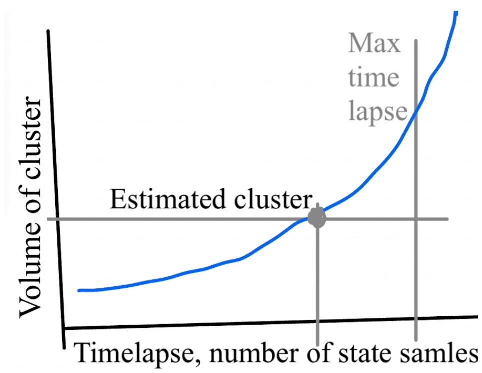
To determine the dependency between mind state and body state, we use the Convergent cross-mapping. It tests a cause-and-effect relationship between mind and body states. The principle is the following. There exists a relationship between mind and body states if a cluster of body states maps (with a given Lipshits constant) to the corresponding cluster of the body states and vice versus. This map shall hold all the time segments of the given class of the participant's attention.

For cohort research, one has to introduce three models of participant behavior: short-term, long-term, and cross-participant models. The cohort research is a very challenging part. The short-term model investigates the state trajectories and clusters of one participant during one session. The long-term models model investigates the trajectories and clusters (behavior) of a given participant in the sequence of sessions during the period of training. Conditions of the participant’s body, weather conditions, and details in measurement may vary drastically. So the model parameters may be renewed. It complicates estimations of long-term changes. The cross-participant model investigates invariants in modes for participants of various ages, sexes, and health conditions. An additional challenge of this research is the assumption that there is no stimulus presented. So there is no ERP expected, and state samples in the space shall be selected according to additional signals like breath and pulse wave.

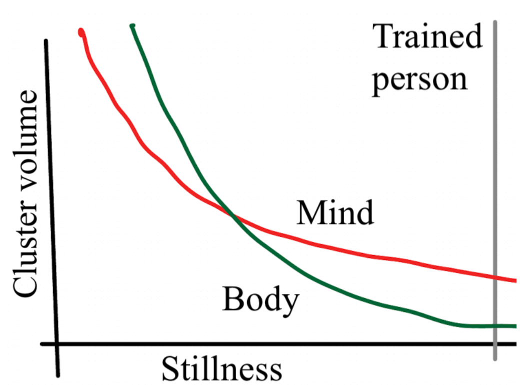
The quality of meditation during one session is estimated using the trajectory of the body state. The quality of training after a series of sessions is estimated as a change in the cluster that collects trajectories of a participant’s body trajectories.



This figure shows the difference between the state trajectories of a trained person and a novice. The axes show the space basis. Changes in behavior form a continuous-time trajectory. Assume this trajectory lies in a compact subspace. One has to cluster the trajectory, separating different clusters from each other for given classes of patient behavior. Assume the dimensionality and the volume of a cluster describes the experience in training and quality of stillness. The most trained person's state lies in a cluster of lesser volume in low-dimensional space.



This figure shows the idea of cluster dimensionality and volume computation. The x-axis shows the timelapse of a fixed behavior class. If the state trajectory has high variance or shows breaks in its behavior class, the x-axis shows the number of trajectory samples that belong to the cluster. Augmentation of timelapse inflates the cluster. The y-axis shows the volume of the cluster. One has to find a stable cluster to estimate its volume.



This figure shows the principle of stillness estimation using the body and mind state spaces. The x-axis shows the desired estimation of stillness in the mind and body states. The y-axis shows the observed volume of state trajectories. These volumes are computed after the clustering of a given behavior class. We assume that the lower volume and dimensionality of the participant's state trajectory leads to a higher quality of stillness.

Overall to demonstrate the ability of a participant to reach stillness, one has to demonstrate the progress of miniming the volume of both clusters. Since each cluster is a compact set of states, separated from the rest of the clusters and non-classified behavior, one selects a particular class of mental behavior.

Technological details

The pipeline and parameter optimization procedure
EEG, spectral, distances, tangent space, dimensionality reduction, state space with phase trajectory
IMU, Hankel, ICA dimensionality reduction, state space with phase trajectory
Class of behavior, timeline, starting clusters
Tune all models for classification, check the CCM
Fix the classification parameters, and maximize the convergent value.

Variants of models
Attention in the transformer mode, IMU is the request.
Seq2seq with privileged information from EEG, the output is meditation quality.

Data available to check hypotheses

At the moment there are no meditation EEG-IMU open data sources available. However, the system can be developed (but can not be tested for the feasibility of the main hypothesis) with synthetic or quasi-synthetic data. This data mimics the desired data from a group of 30-60 participants of persons for the 3-month training period, one-hour session, at least one time in two days (expected frequency of training).
Additional data includes a video of the eye movement and the skeleton position, the breath wave, and the pulse wave.

Appendix

Review

Investigating EEG Biomarkers for Attention with Deep Learning: Final Report by Ziad Ali
Reports overtraining, Acc=0.67,0.80, data probably available at s41597-019-0027-4
Code is not found, Model Spectr-Conv-Gru-NN

Effect of Brief Meditation Intervention on Attention: An ERP Investigation by Manvi Jain
Data https://pubmed.ncbi.nlm.nih.gov/21584256/ promised not found, no model, no code (but methodology could be useful)

Attentional processes in typically developing children as revealed using brain event-related potentials and their source localization in Attention Network Test (83 children record direction of swimming fish) /10.1038/s41597-019-0027-4 data promised, there is metadata to ask for download, no model, no code

Self-supervised learning for human activity recognition using 700,000 person-days of wearable data by
Hang Yuan (wrist-watch data are available on request) in fact, it is a paper on transfer learning.
Code https://github.com/OxWearables/ssl-wearables, not sure it fits see https://github.com/OxWearables

Machine learning of brain-specific biomarkers from EEG by Philipp Bomatter, predicts sex and age by EEG 0.9, model wavelets, and riemann. TUAG and TDBRAIN https://brainclinics.com/resources/ 120Gb 1274 psychiatric patients, and this is work of 2024, this shows the challenges

EEG in meditation

The useful table with features
https://www.hindawi.com/journals/apm/2015/614723/tab1/
From https://www.hindawi.com/journals/apm/2015/614723/

A long list of papers, and no EEG features
A systematic review of the neurophysiology of mindfulness on EEG oscillations
https://doi.org/10.1016/j.neubiorev.2015.09.018

Temporal and Spatial Characteristics of Meditation EEG
https://www.drfredtravis.com/Papers/Char%20of%20Meditation%20EEG%20final.pdf

A Critical Analysis on Characterizing the Meditation Experience Through the Electroencephalogram (spectral features freq alpha-beta, list of regimes of Mindfulness CDM-FA/OM) https://www.frontiersin.org/articles/10.3389/fnsys.2020.00053/full#B89

A BRIEF REVIEW OF RESEARCH AND CONTROVERSIES IN EEG BIOFEEDBACK AND MEDITATION
https://www.atpweb.org/jtparchive/trps-19-87-02-161.pdf

EEG-Guided Meditation: A Personalized Approach
https://www.bm-science.com/images/bms/publ/art83.pdf

EEG-fMRI for meditation
Noninvasive Strategies to Optimise Brain Plasticity: From Basic Research to Clinical Perspectives
https://downloads.hindawi.com/journals/np/2013/653572.pdf

Case Study of Ecstatic Meditation: fMRI and EEG Evidence of Self-Stimulating a Reward System
https://downloads.hindawi.com/journals/np/2013/653572.pdf

Elbow Motion Trajectory Prediction Using a Multi-Modal Wearable System: A Comparative Analysis of Machine Learning Techniques
(hand-made feature extraction EEG)
https://www.mdpi.com/1424-8220/21/2/498

Quadratic Programming Feature Selection for Multicorrelated Signal Decoding with Partial Least Squares by Isachenko and Strijov (Canonical Correlation Analysis for EEG-IMU with code)

A multimodal-signals-based gesture recognition method for human-machine interaction
10.1109/ICUS50048.2020.9274853 (EEG-IMU, EEG part is vague)

Tools requested

Faster ICA under orthogonal constraint https://arxiv.org/pdf/1711.10873
https://github.com/pierreablin/picard a deep learning version is welcome!

Reducing the leakage of signals from non-brain generators into the EEG
https://www.biorxiv.org/content/10.1101/2023.12.15.571864v5.full.pdf

CCM for high-dim spaces

Density estimation over time

A cap
https://bio-medical.com/accessories/eeg-caps.html?_=1715030260057&price=378.99-695.99

EEG-IMU datasets

Mobile BCI dataset of scalp- and ear-EEGs with ERP and SSVEP paradigms while standing, walking, and running https://www.nature.com/articles/s41597-021-01094-4
Open dataset https://osf.io/r7s9b/

Multi-channel EEG recordings during a sustained-attention driving task
https://www.nature.com/articles/s41597-019-0027-4
Open dataset

MobileBCI_Data
https://github.com/youngeun1209/MobileBCI_Data?tab=readme-ov-file

Miscellaneous

Teach knowledge workers to breathe and meditate and measure how much their productivity increases. No AI is required here. If it is impossible without AI, then why AI should help?
So how to scientifically show and prove that meditation positively impacts productivity? The A/B test will work: measure the amount of delivered product before and after deployment or compare to a control group.

Also, an aggregated plot of select EEG signals does not mean one could see this patterin in any of these signals

Put MEG electrodes on the **muscles of the spine** to check the connection EEG-MEG-IMU.
For long-term processes in the brain, fMRI data must bring more valuable information than EEG