# Exploring Mental State Changes during Hypnotherapy using Adaptive Mixture Independent Component Analysis of EEG

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***Abstract*—Advancing our understanding of neurocognitive systems impacted by hypnotherapy may improve therapeutic outcomes. This study addresses the challenge of decoding cortical state changes from continuous electroencephalographic (EEG) data recorded during hypnosis. We model changes in brain state dynamics over the course of hypnosis using Adaptive Mixture Independent Component Analysis (AMICA), an unsupervised approach that learns multiple ICA models for characterizing non-stationary, unlabeled data. Applied to EEG from six sessions of hypnosis, AMICA characterized changes in system-wide brain activity that corresponded to transitions between hypnosis stages. Moreover, the results showed consistent AMICA-based models across sessions and subjects that reflected distinct patterns of source activities in different hypnosis states. By analyzing independent component clusters associated with distinctive classes of model probability patterns, shifts in the theta, alpha, and other spectral features of source activities were characterized over the course of the therapy sessions. The AMICA approach offers a promising tool for linking brain-network changes during hypnotherapy with physiological and cognitive state changes brought about by this form of treatment. It can also ignite new research and developments toward brain-state monitoring for clinical applications.**

***Index Terms*—Hypnotherapy, independent component analysis, EEG, brain state monitoring, unsupervised learning**

## I. Introduction

In the 21st century, hypnotherapy has attracted increasing attention both as an integrative treatment modality [1] and a research tool [2]. Guided imagery hypnotherapy (GIH) is a family of hypnotherapy techniques that involve bringing patients into a light, relaxation-based, self-hypnotic trance, then leading them through active visualization processes that support their therapy-related goals. It has been implicated in reducing anxiety, stress, and depression [3]–[6], as well as fatigue and pain [4], [6], [7] in various clinical populations.

Advancing our understanding of the neurocognitive systems impacted by GIH may lead to more individualized and effective therapy. However, a challenge to this goal is parsing from a continuous GIH session a set of experimentally relevant underlying brain states. Although hypnotherapy scripts typically contain distinctive transitions throughout the induction and visualization stages, it is unknown whether these session "landmarks" are accompanied by corresponding shifts in the cognitive or mental states of the patients and the brain-network activities that associate with the states. To address these challenges, we propose to model changes in brain state dynamics over the course of GIH using Adaptive Mixture Independent Component Analysis (AMICA) [8]–[10], which is a general unsupervised-learning approach that uses a mixture of distinct ICA models – each representing a different set of statistically independent sources – to characterize underlying EEG source activities associated with distinct patterns of whole brain engagement. This approach allows the decomposition of the moment-to-moment fluctuations of activation of different brain systems from continuous, unlabeled EEG data recorded during therapeutic sessions. It can then explore how changes in patterns of brain system engagement correspond to the transitions in hypnotherapy stages.

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## II. Adaptive Mixture Independent Component Analysis

Comprehensive formulation and extensive evaluation of the AMICA algorithm have been presented in [8] and [10] respectively. Conceptually, it consists of three layers of mixing processes: AMICA learns a mixture of ICA models (Eq. 1); each model is a mixture of independent components (IC) or sources, and each IC has a probability density function parameterized as a mixture of generalized Gaussians [8].

The first layer assumes that data $\boldsymbol{x}$ ($N$-channels $\times$ $T$-samples) are nonstationary, so that different models may best characterize the data at different times, i.e., $\boldsymbol{x}(t) = \boldsymbol{x}_h(t)$ where $h$ is the model index. In the second layer, a standard ICA model is employed to model the data $\boldsymbol{x}$ as an instantaneous linear mixture $\boldsymbol{A}$ ($N$-channels $\times$ $N$-sources) of statistically independent components $\boldsymbol{s}$ ($N$-sources $\times$ $T$-samples), i.e., $\boldsymbol{x} = \boldsymbol{A}\boldsymbol{s}$. The first two layers constitute the ICA mixture model:

$$\boldsymbol{x}(t) = \boldsymbol{x}_h(t) = \boldsymbol{A}_h \boldsymbol{s}_h(t) + \boldsymbol{b}_h, \quad h = 1, \ldots, H \tag{1}$$

where $h = h(t)$ and $\boldsymbol{A}_h$ is the dominant or active model at time $t$ with source activities $\boldsymbol{s}_h(t)$ and bias $\boldsymbol{b}_h$. Assuming $\boldsymbol{x}(t)$ are temporally independent, the likelihood of data given the ICA mixture model can be written as:

$$p\big(\boldsymbol{X}\big|\Theta\big) = \prod_{t=1}^{T} \sum_{h=1}^{H} p\big(\boldsymbol{x}(t)\big|C_h, \theta_h\big) \cdot p(C_h) \tag{2}$$

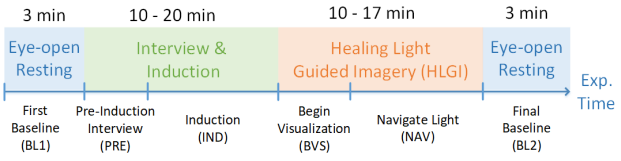


Fig. 1. Experimental paradigm of a Healing Light Guided Imagery (HLGI) session.

where $\Theta = \{\theta_1, \ldots, \theta_H\}$ contains the parameters of ICA models and $p(C_h)$ is the probability of the $h$-model being active that satisfies $\sum_{h=1}^{H} p(C_h) = 1$.

As an unsupervised approach with generative models, the $\Theta$ parameters learned by AMICA provide rich information about the underlying data clusters and their temporal dynamics. Specifically, the activation of each ICA model $h(t)$ can be represented as the data likelihood given the estimated parameters of each model $\theta_h$, i.e., $L_{h(t)} = p\big(\boldsymbol{x}(t)\big|\theta_{h(t)}\big)$. Therefore, the probability of activation of each ICA model at time $t$ can be calculated by normalizing $L_{h(t)}$ across all models and is referred to as "ICA model probability" that indicates the goodness-of-fit of the ICA model to the data samples [10].

The expectation-maximization (EM) algorithm is employed to estimate the parameters $\hat{\Theta}$ that maximize the data likelihood function in Eq. 2. In the M-step, AMICA uses the Newton approach based on the Hessian (matrix of second-order derivatives) to achieve faster convergence. Rejection of data samples based on their posterior probabilities was applied to alleviate the effects of transient artifacts. A sphering transformation of the EEG data was also applied prior to AMICA decomposition to facilitate the learning process. Further, an efficient implementation of AMICA with parallel computing capability by [8] was used in this study. The code for that implementation is available at https://github.com/japalmer29/amica and also as an open source plug-in for EEGLAB [11].

## III. Experiment and Data Collection

Two healthy adults each participated in three GIH sessions based on Healing Light Guided Imagery (HLGI) techniques. One participant (Subject 2) was new to hypnotherapy. Fig. 1 shows the HLGI experimental paradigm. Each session began with an eyes-open resting-state baseline (first baseline) and a short goal-setting interview with the therapist (pre-induction). Next, participants were led through relaxation (induction), then guided imagery and hypnotic suggestions. Although different aspects of the imagery were tailored to each individuals specific goals, continuity was maintained through a consistent framework involving motifs related to descending a staircase, sitting in a chair, and putting on a crown (begin visualization), followed by seeing and navigating light (navigate light). Each session lasted roughly 45 minutes, including the baseline rest periods. High-density EEG (66 channels) were recorded throughout the duration of each session using Biosemi active electrodes placed according to the International 10–20 system.

## IV. Data Processing and Analysis

Raw EEG data were down-sampled to 250Hz and band-pass filtered (1-50 Hz) by the *clean_rawdata()* function from EEGLAB [11] to remove flat-line channels and channels that were poorly correlated (less than 0.85 correlation) with spatially adjacent channels. The number of remaining channels ranged from 52 to 65. Line noise was cleaned with a standard deviation of 4, and high-amplitude artifacts were repaired with a mild threshold (burst repair = 30) using artifact subspace reconstruction [12]. Re-referencing was performed to average channel values including the initial reference channel.

Next, a six-model AMICA decomposition was applied to the pre-processed datasets, each obtaining six ICA models (i.e., mixing matrices $\boldsymbol{A}_h$ in Eq. 1) and their model-probability time courses (i.e., normalized data likelihood). Since brain activity is non-stationary throughout the hypnotherapy, we expect the probability time course of each model would fluctuate, reflecting changes of EEG patterns captured by different models.

To quantify the relationship between ICA models and GIH stages, we reported the mean model probability during each stage for each model. To further identify the consistent models across the 6 sessions, we calculated the correlation matrix ($\rho$) of the mean-probability-across-stages feature vectors for each pair of the 36 models and performed hierarchical clustering (8 clusters) on the distance matrix (1-$\rho$) using *linkage()* (with group average) and *dendrogram()* functions in MATLAB.

After finding the model clusters across all sessions, we again performed the hierarchical clustering (60 clusters) on independent components (IC) of all models in the same model cluster to identify consistent IC clusters. The distance matrix used was the pairwise absolute-valued correlation matrix of IC scalp maps (i.e., spatial projections of each IC onto scalp topographies using nonlinear interpolation) among all ICs in the model cluster. The IC scalp maps in the same IC cluster were averaged with their polarity corrected by the signs of the correlation.

To examine the power spectral density (PSD) of the IC clusters, we first computed the source activities $\hat{s} = A^{-1}x$ according to Eq. 1 for all ICs. Next, for each IC we segmented its source activity into 6 subsets according to the GIH stages and then calculated the PSDs of each subset using *spectopo()* function in EEGLAB. We further weighted the 6 PSDs by the average model probability associated with that stage, then summed the 6 PSDs to arrive at a single PSD for each IC. Last, we obtained a mean PSD for each IC cluster by averaging all the weighted IC PSDs within that cluster.

## V. Results and Discussion

Fig. 2 plots the probabilities (normalized data likelihood) of each of the six AMICA models over experimental time. Shifts in model probabilities and transitions of dominant models (e.g. with the highest probabilities) were clearly observed during all sessions, indicating changes in the patterns of EEG activities during hypnosis. The timing of the model transitions corresponded to the timing of the therapists instructions, as noted by the dotted line and event descriptions. For example,

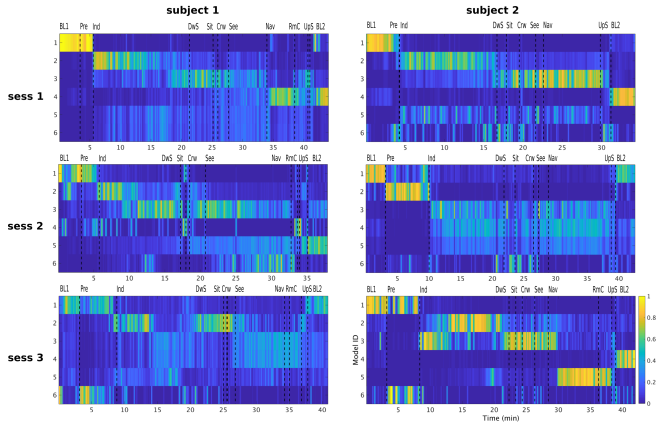


Fig. 2. Activations of ICA models (i.e., model probabilities) of 6-model AMICA decompositions on EEG data recorded from three hypnotherapy sessions for two subjects. BL1: Baseline. Pre: Pre-induction. Ind: Induction. Begin Visualization (BVS) = Down Stair (DwS) + Sit in Chair (Sit) + Crown (Crw). Navigate Light (NAV) = See Light (See) + Navigate Light (Nav). BL2: Final Baseline. For simplicity, Remove Crown (RmC) and Up Stair (UpS) stages were excluded for further analysis.

there are noticeable transitions from the first baseline (BL1) / pre-induction (Pre) to the induction (Ind) stage, from the induction to the begin visualization (BVS) stage, and before and after the onset of final baseline (BL2). In addition, there was a transition of dominant models in the middle of the induction stage for all sessions, which might suggest a shift of mental state (e.g. into a trance state).

To quantify the relationship between models and GIH stages, we computed the mean model probability in each stage for each session, as shown in Fig. 3. We observed that some AMICA models modeled EEG activities with high probability in one or two specific states (GIH stages), while others modeled EEG activities that presented across all stages of hypnotherapy. For example, Model 1 (M1) from the three sessions of Subject 1 showed dominantly high probability in the first baseline and pre-induction stages. The second models obtained (M2) from Subject 1 - Sessions 1 (S1-1), S2-1, and S2-3 were more active in the induction stage. However, the results seemed to vary across sessions and subjects.

To assess the consistency of the above results across sessions and subjects, we performed hierarchical clustering to identify eight model clusters that shared similar probability distribution across GIH stages. Fig. 4(a) lists all of the models and the corresponding sessions and subjects, in each model cluster. Fig. 4(b) shows the mean and standard error of the mean (SEM) of the identified model clusters across the six sessions. The SEM within each model cluster was small, indicating that consistent models could be identified across sessions and subjects. Furthermore, each stage of the hypnotherapy could be characterized by distinct model clusters. For example, the EEG activities in the first baseline and pre-induction could be modeled by the Model Cluster F, the induction stage was well characterized by the Model Cluster D, and the begin visualization stage was modeled by the Model Cluster C. This indicates that the EEG patterns in each

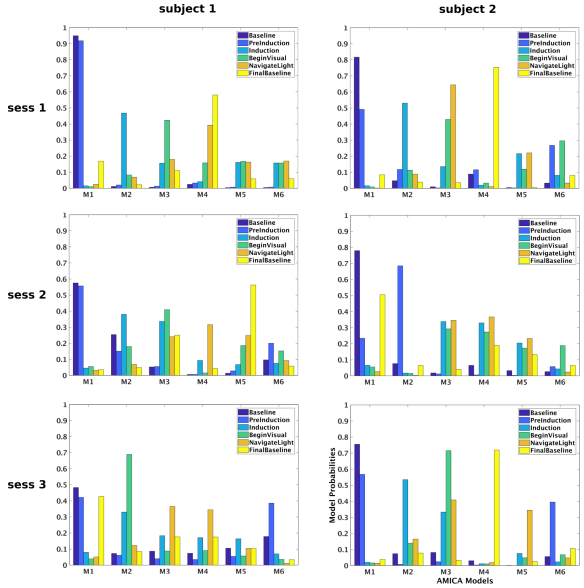


Fig. 3. Mean AMICA model probability in each stage of GIH for each session.

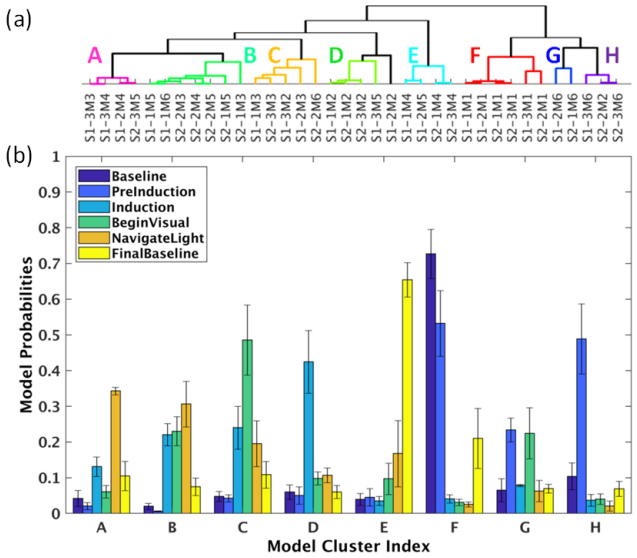


Fig. 4. (a) Identified model clusters based on correlations of model probability across GIH stages between pairs of AMICA models across 6 sessions using hierarchical clustering. "S1-2M3" refers to Model 3 from Session 2 of Subject 1. (b) Mean and standard error of the mean (SEM) of probabilities of clustered models.

GIH stage could be distinct and characteristically modeled by different AMICA models.

Once the model clusters were identified, we can assess the underlying brain networks and activities by examining independent components (ICs) that were consistently found across the AMICA models in each model cluster. Fig. 5 plots the scalp topography and power spectra of the clusters of ICs in each model cluster corresponding to a dominant GIH stage. Notably, in the central and occipital regions, power in the theta (4 - 7 Hz) and alpha (8 - 12 Hz) range declines during post-

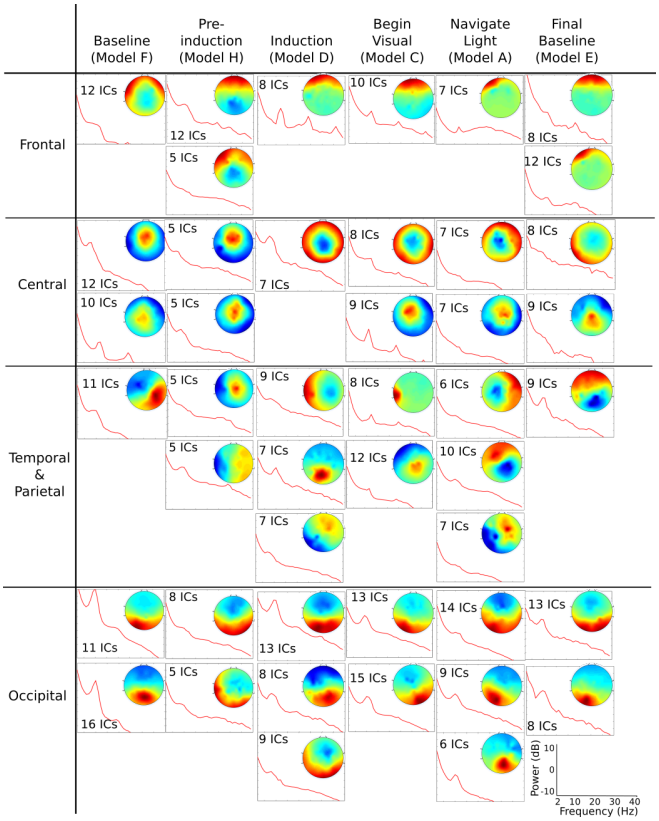


Fig. 5. Scalp maps and power spectra of independent component (IC) clusters in each of the specified model clusters and their corresponding GIH stages. IC clusters with lower power or small numbers of ICs were rejected and were manually categorized into four classes based on their scalp projections.

session relative to pre-session rest baseline. A similar trend can be observed over the course of hypnosis as well - that is, whereas the induction and early visualization stages are characterized by broadly distributed, pronounced peaks in the alpha and alpha harmonic ranges, little indication of these activities is discernible as the visualization process advances, in keeping with the idea that a broad network of brain systems became increasingly engaged as individuals progressed through the visualization sequence. Other studies have reported similar declines in alpha power during hypnosis [13] (but see [14], among others). Importantly, divergence with existing findings may be attributed to differences in research methods, as much existing work in the field has centered on the ways in which high versus low hypnotic susceptibility can modulate brain response - whereas the present study addresses the challenge of parsing continuous EEG into experimentally relevant segments for the purpose of comparing brain responses within different stages of hypnosis.

## VI. Conclusions

AMICA is an effective data-driven approach that learns multiple ICA models for exploring underlying cognitive or mental state changes from continuous, unlabeled EEG data. Applied to the EEG data recorded during guided imagery hypnotherapy, AMICA characterized the changes in EEG patterns that corresponded to transitions between GIH stages. Consistent ICA models across sessions and subjects could be identified that model the EEG activities of distinct states in the GIH. Independent component clusters of the model clusters revealed changes of the independent brain processes underlying the shift of mental states during GIH. The AMICA approach may help advance the understanding of the brain-network changes during hypnotherapy and support the development toward brain-state monitoring for clinical applications and passive brain-computer interfaces.

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