Toward Real-time Mental State Assessment using Electrophysiology

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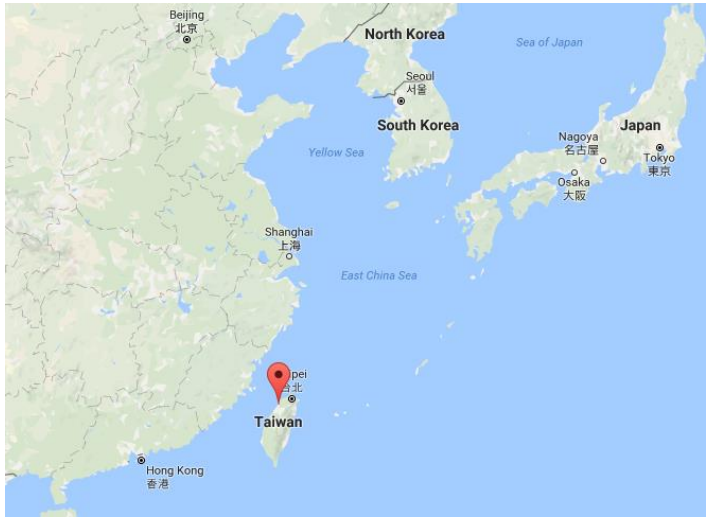
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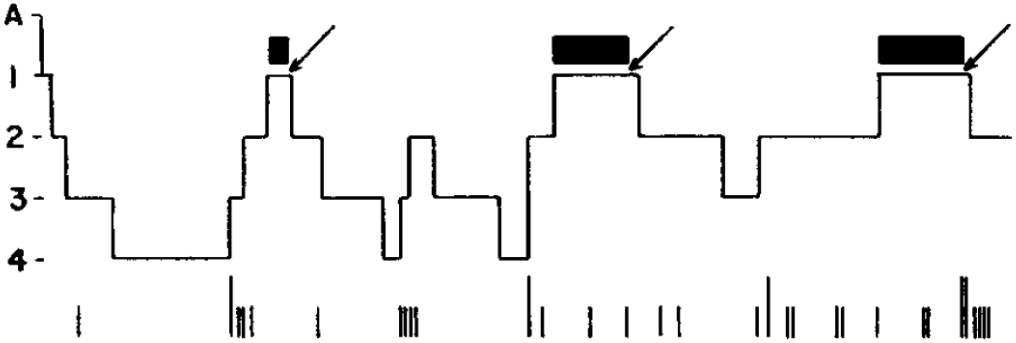
I. Background
II. Source models for alert and drowsy states
III. Adaptive source model for online applications
IV. Conclusion

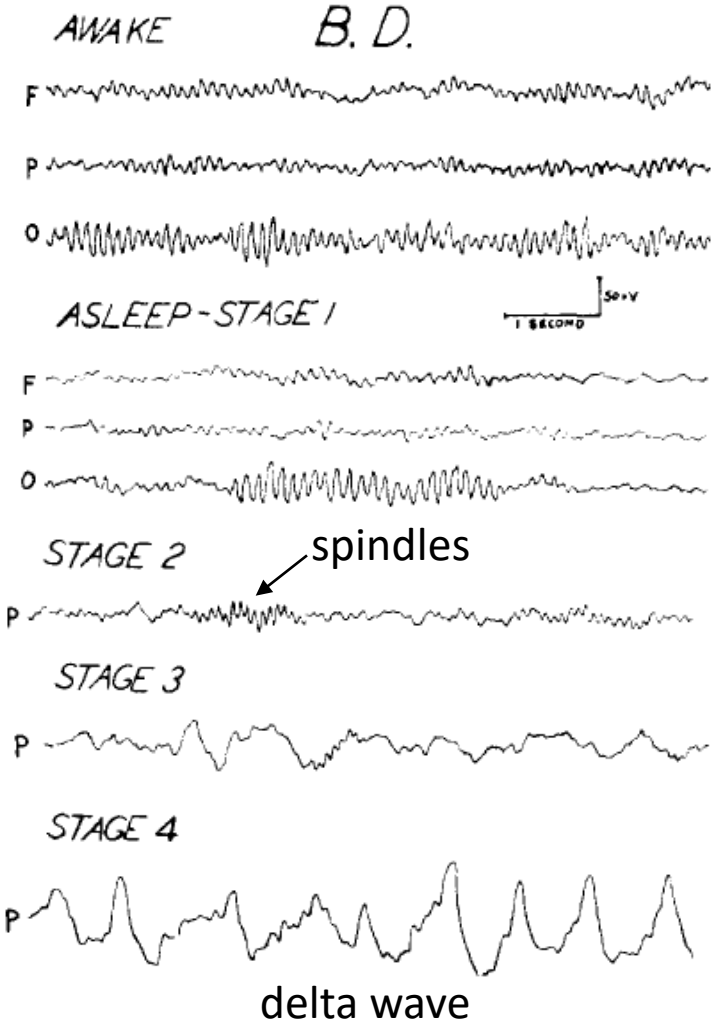




What are states of the brain?

Sleep stages (Dement & Kleitman, 1957)





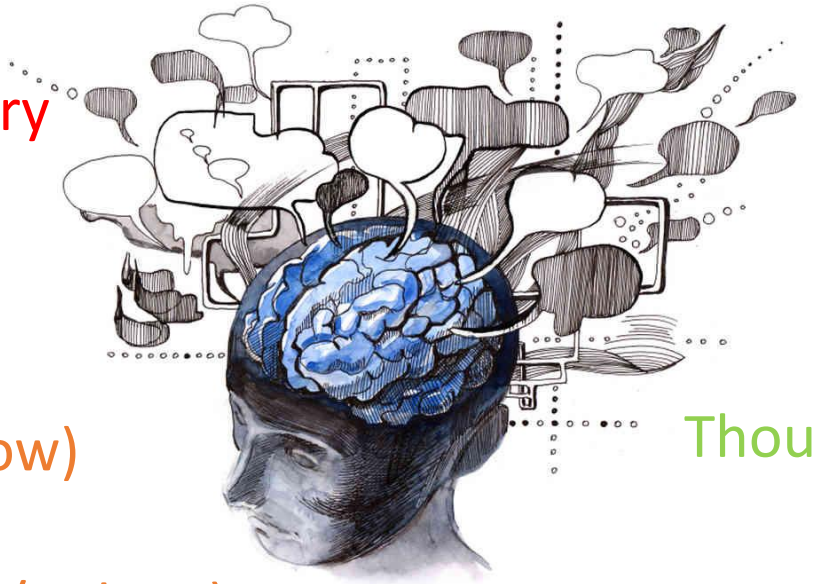
The wandering mind: covert mental state

Spontaneous conscious covert states (Lehmann et al. 1995)

Visual imagery

Concatenated ideas (sudden / coherent)

Acoustic imagery



Free associations

Body percept

Future planning

Arousal (high / low)

Thoughts (goal-oriented?)

Vigilance (high / asleep)

Emotion (positive / negative)

Lehmann et al., Intl. J. Psychophysio., 1995

Why study covert mental states?

- They affects our performance and influence our behaviors.
- They are inevitable in real-world situation

Challenges

- Covert mental states are often (1) ignored by averaging over trials and (2) suppressed in lab experiment design.
- Patterns of brain signals between different states are hard to distinguish.





EEG studies on mental states

Author, Year	Analysis	EEG Features	Mental States
Kaplan et al., 2005	segmentation	rapid transition processes	undefined
Mueller et al., 2008	LDA classifier	alpha power	concentration
Musso et al., 2010	clustering	spatial power distribution	resting
Zhang et al., 2001	segmentation	complexity (entropy)	anesthesia

Our goal

Develop alternative approach and provide different perspective to assess mental states – **a source-level analysis**



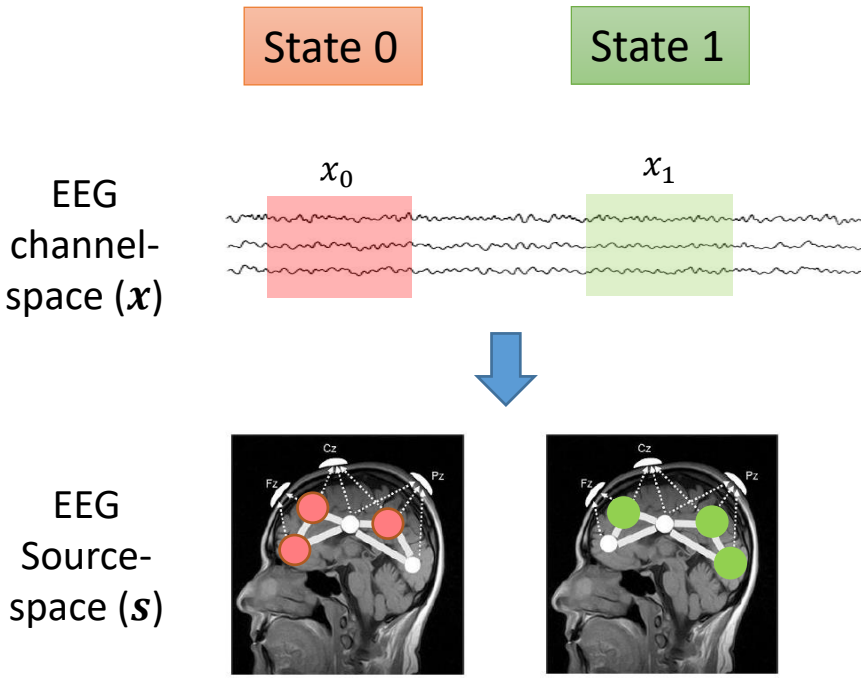


Outline

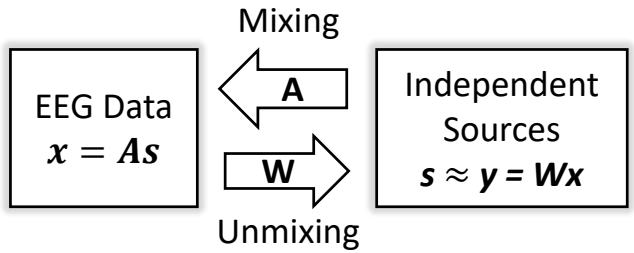
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Hypothesis: different brain states involve distinct active brain sources



Independent Component Analysis (ICA)



$$x(t) = A_k \cdot s_k(t)$$

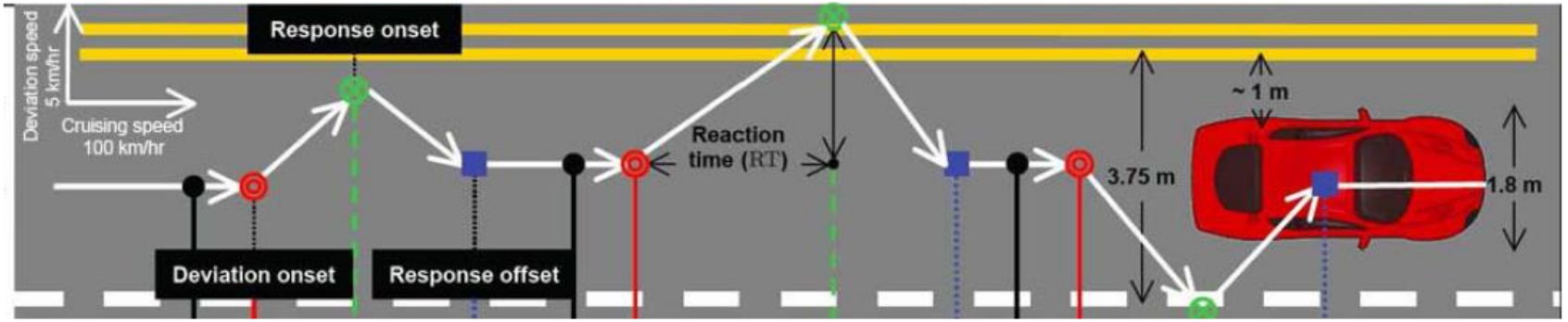
Spatial source structure

Temporal source activities

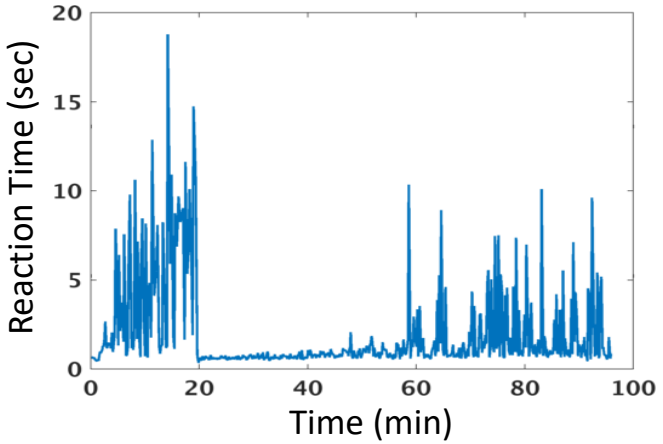
Sustained-attention task for studying alertness fluctuation





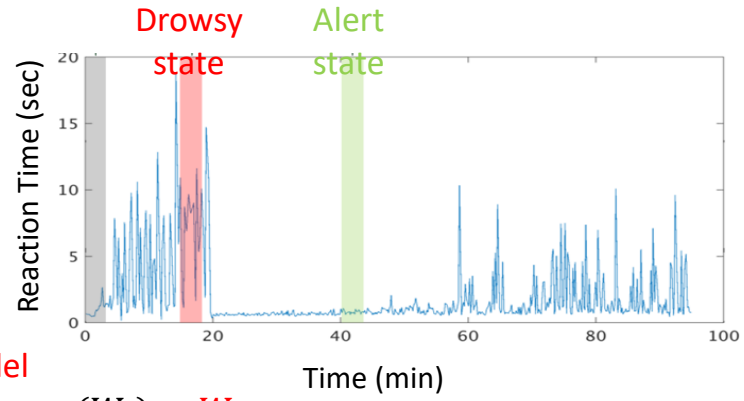


Reaction Time (RT)



Adapted from Chuang et al., *IEEE TNSRE*, 2014

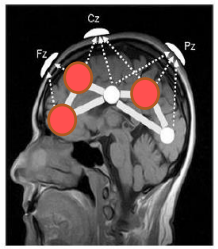
Test the hypothesis by quantifying the model fitting error of ICA models

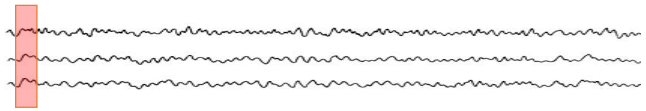


Drowsiness ICA Model

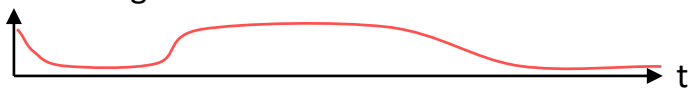
$y_0 = W_0 x_0$

$y(W_0) = W_0 x_{test}$





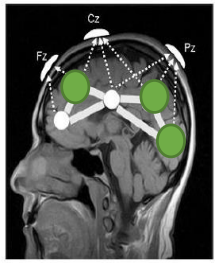
Model fitting error

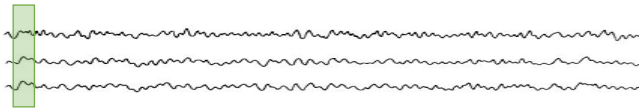


Alertness ICA Model

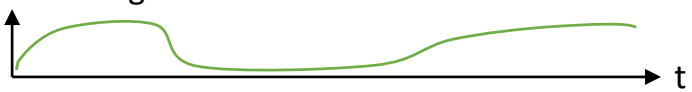
$y_1 = W_1 x_1$

$y(W_1) = W_1 x_{test}$





Model fitting error



Infomax ICA [Lee et al. 1999]:

$$\boldsymbol{W} \leftarrow \boldsymbol{W} + \eta[\boldsymbol{I} - \boldsymbol{f}(\boldsymbol{y}) \cdot \boldsymbol{y}^{\boldsymbol{T}}]\boldsymbol{W}$$

Gradient

Source activity: $\boldsymbol{y} = \boldsymbol{W}\boldsymbol{x}$

Non-linear function: $\boldsymbol{f}(\boldsymbol{y}) = tanh(\boldsymbol{y}) + y$

Model Deviation Index (MDI)

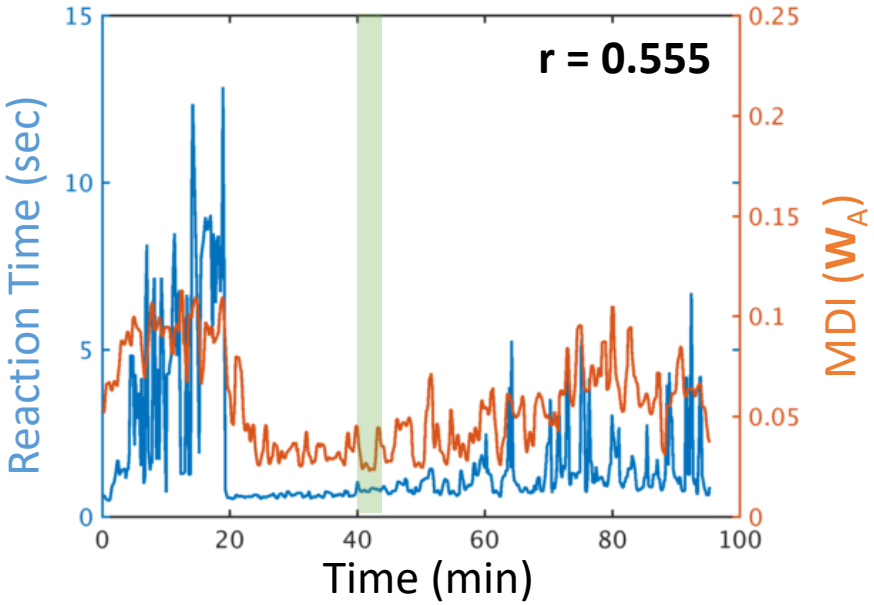
Cross-talks errors

$$MDI\ (\boldsymbol{W}_0) = \frac{\left\| \langle \boldsymbol{f}_i \cdot \boldsymbol{y}_j^T \rangle_{i \neq j} \right\|_F}{\left\| \langle \boldsymbol{y} \cdot \boldsymbol{y}^T \rangle \right\|_F}$$

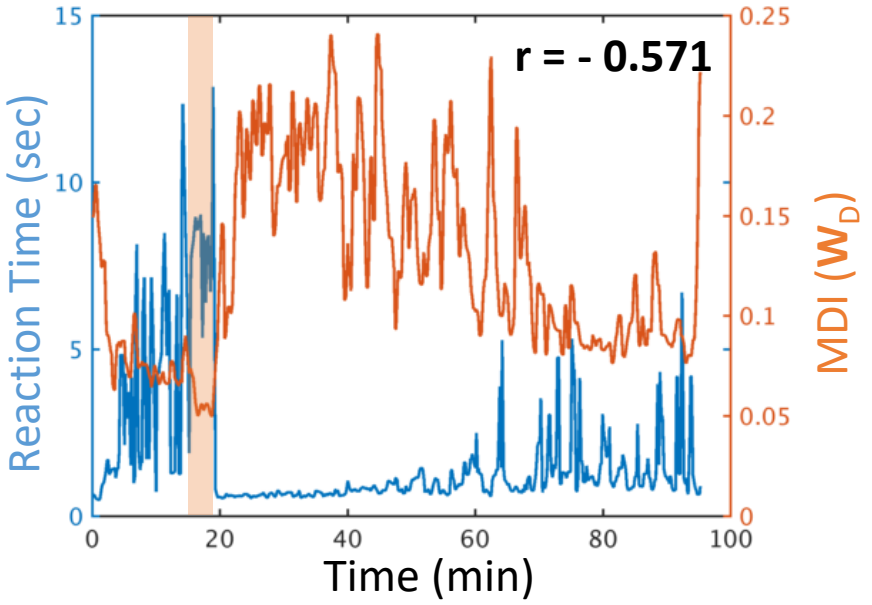
Source Power

Results

Alertness ICA Model

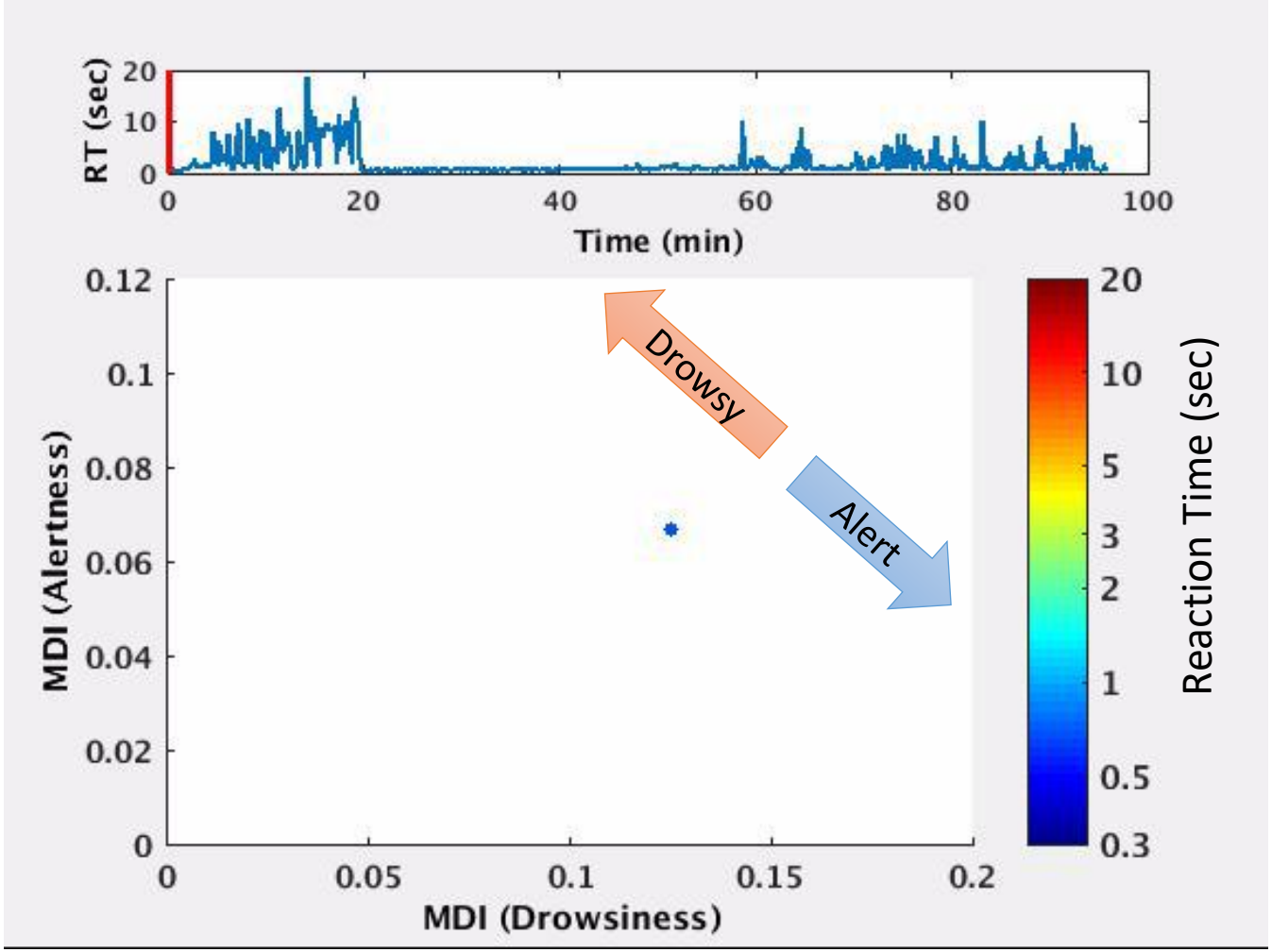


Drowsiness ICA Model



Hsu & Jung, *Lecture Notes in Computer Science*, 2016

MDI feature space for tracking levels of alertness



Hsu & Jung, 2016 (under review)

Outline

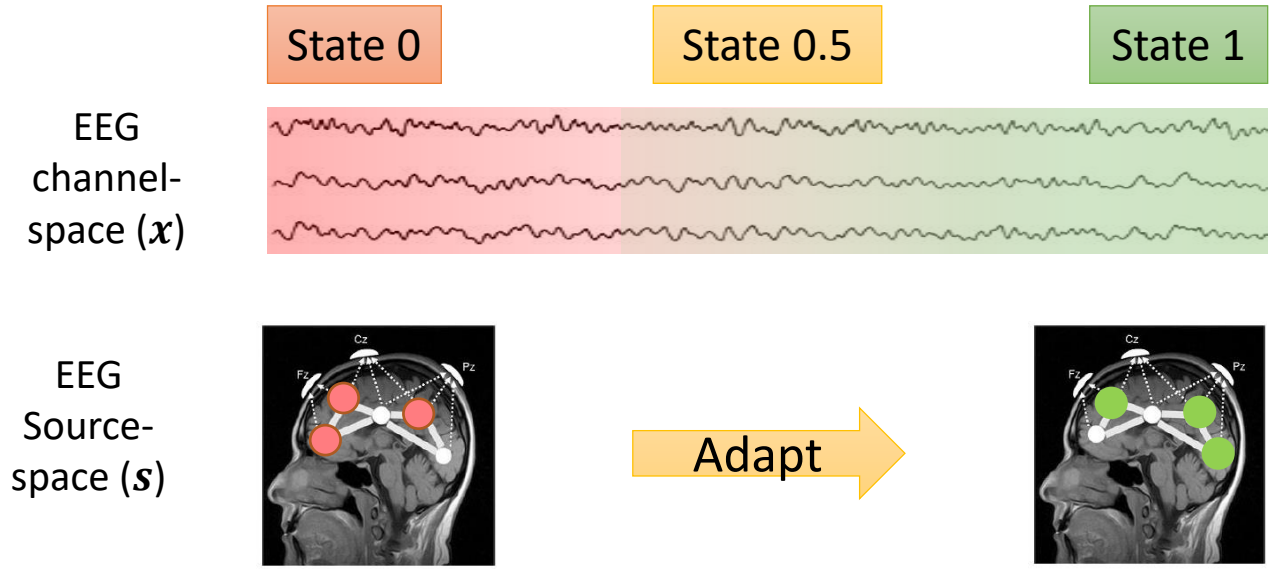
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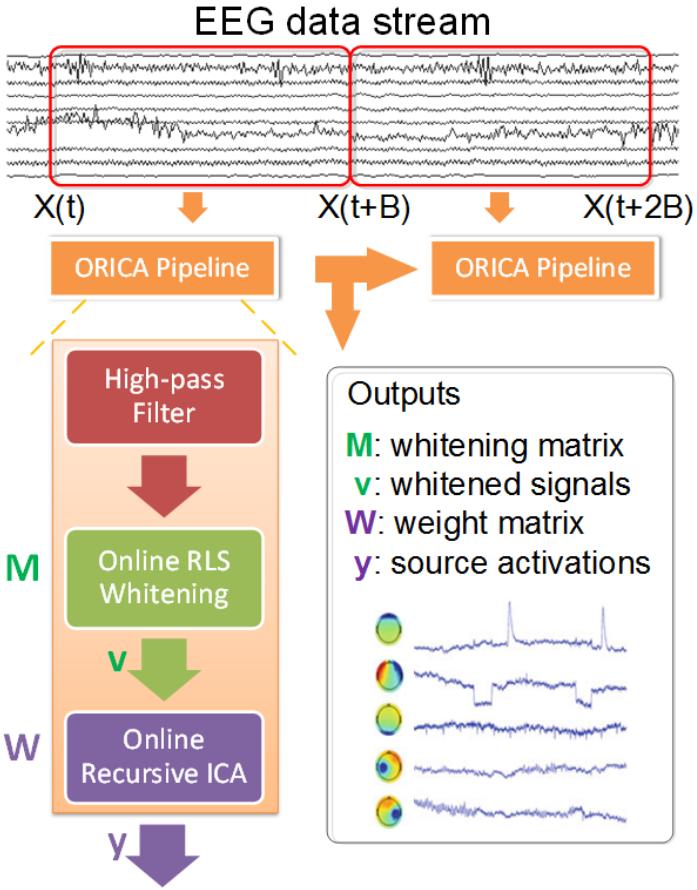


Adaptive source model

	Conventional ICA	Multi-model ICA	Adaptive ICA
ICA model	$x(t) = A \cdot s(t)$	$x(t) = A_k \cdot s_k(t)$	$x(t) = A(t) \cdot s(t)$
Data assumption	(spatially) stationary	quasi-stationary	non-stationary
Brain state hypothesis	single	discrete (predefined state)	continuous
Online capability	offline	offline	online



Online Recursive ICA (ORICA)



Two-step unmixing process: $y = Wv = WMx$

1. Online recursive least squares whitening

$$M_{n+1} = M_n + \frac{\lambda_n}{1-\lambda_n}\left[I - \frac{v_n v_n^T}{1+\lambda_n(v_n v_n^T - 1)}\right]M_n$$

Zhu et al., *Sci. in China Series F: Info. Sci.*, 2004

2. Online recursive ICA (ORICA)

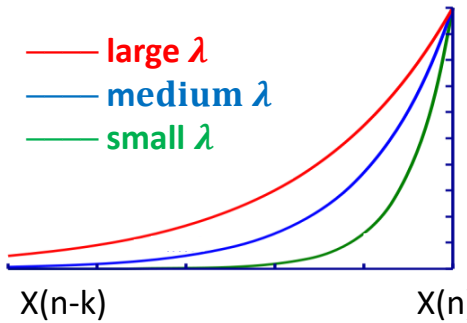
$$W_{n+1} = W_n + \frac{\lambda_n}{1-\lambda_n}\left[I - \frac{y_n \cdot f^T(y_n)}{1+\lambda_n(f^T(y_n)\cdot y_n - 1)}\right]W_n$$

Akhtar et al. *ISCAS*, 2012

$$W \leftarrow (WW^T)^{-1/2}W$$

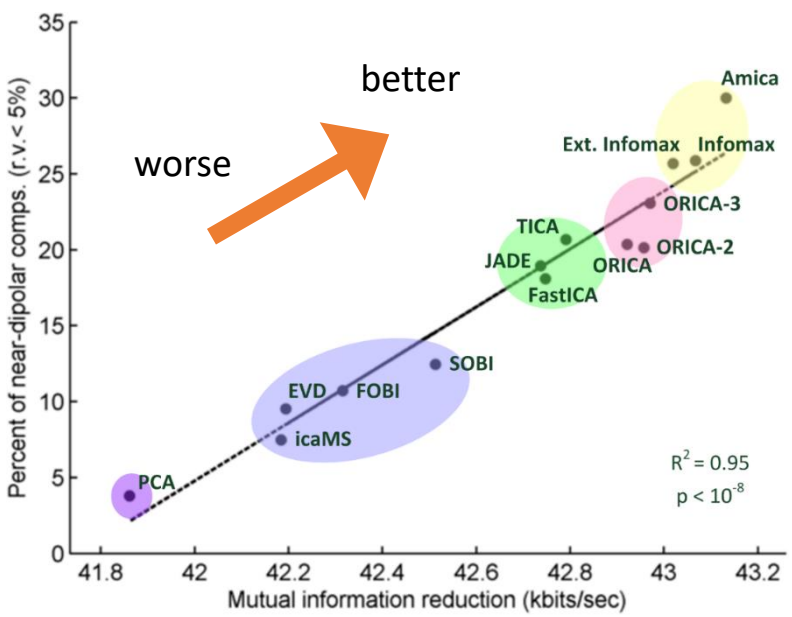
$$f = \begin{cases} -2\tanh(y), & super gaussian \\ \tanh(y) - y, & sub gaussian \end{cases}$$

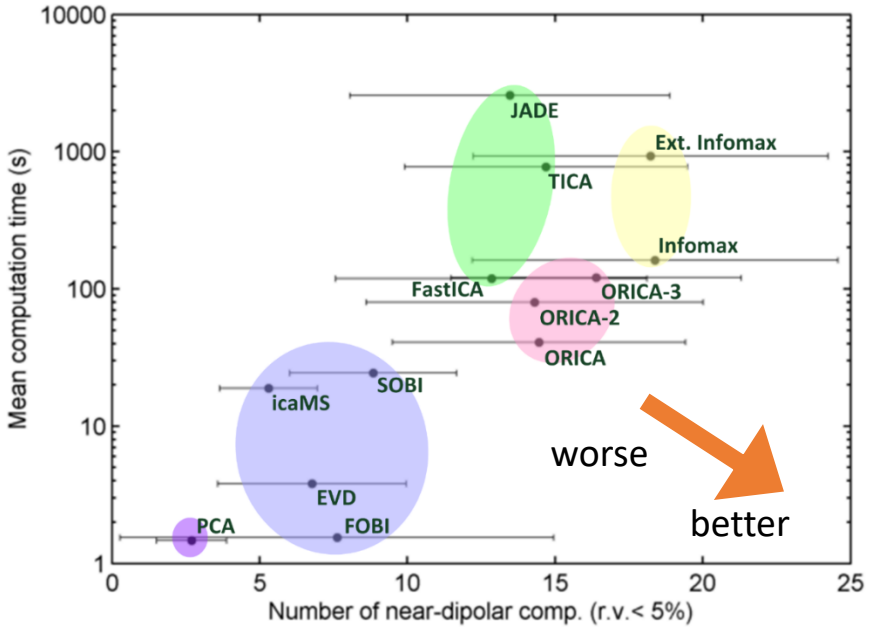
λ: forgetting factor



Hsu et al., *EMBC*, 2014 Hsu et al, *IEEE Trans. Neural System and Rehab. Eng.*, 2016

ORICA approaches performance of Infomax ICA at low computational cost for stationary EEG





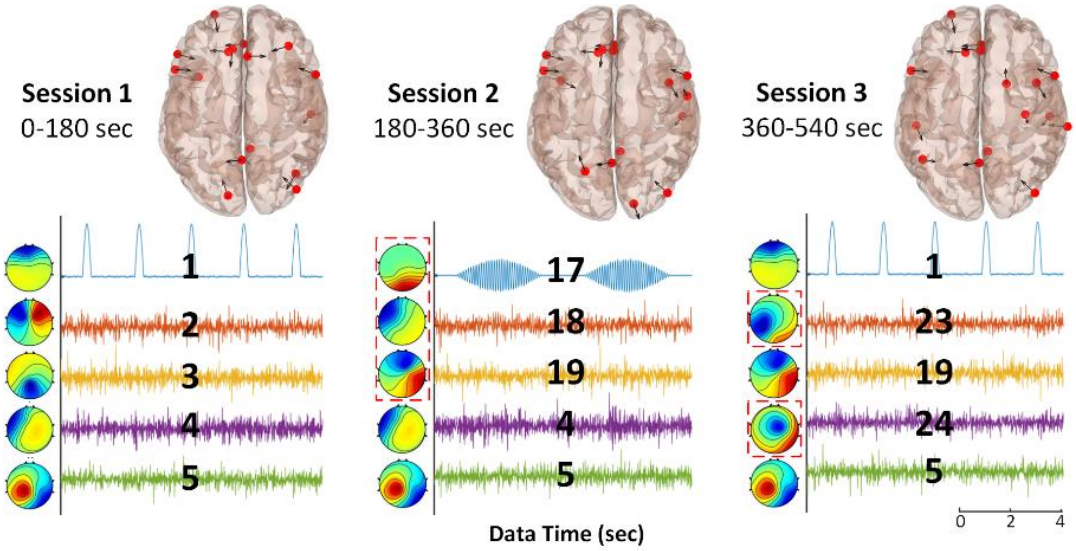
Mutual Information Reduction

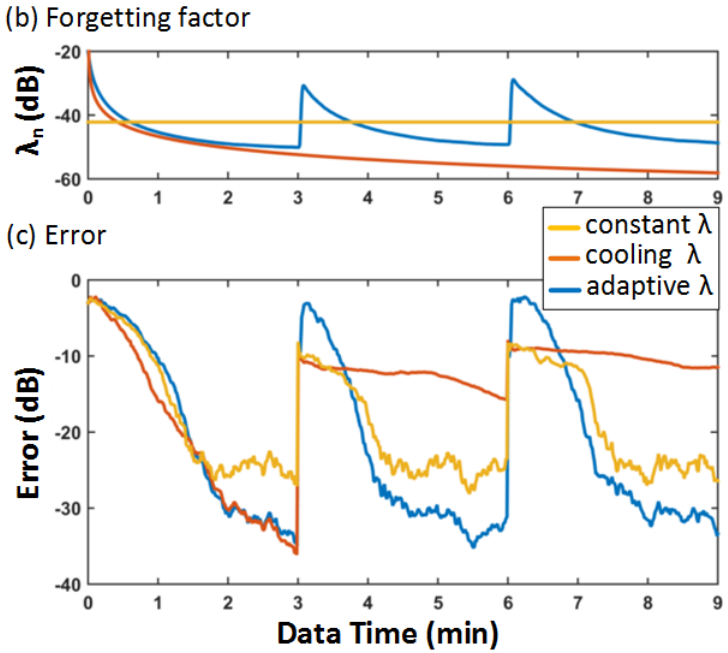
$$MIR = I(x) - I(y) = \log|\det W| + [h(x_1) + \cdots + h(x_N)] - [h(y_1) + \cdots + h(y_N)]$$

Hsu et al. *IEEE NER*, 2015

ORICA adapts to spatial and temporal quasi-stationary data

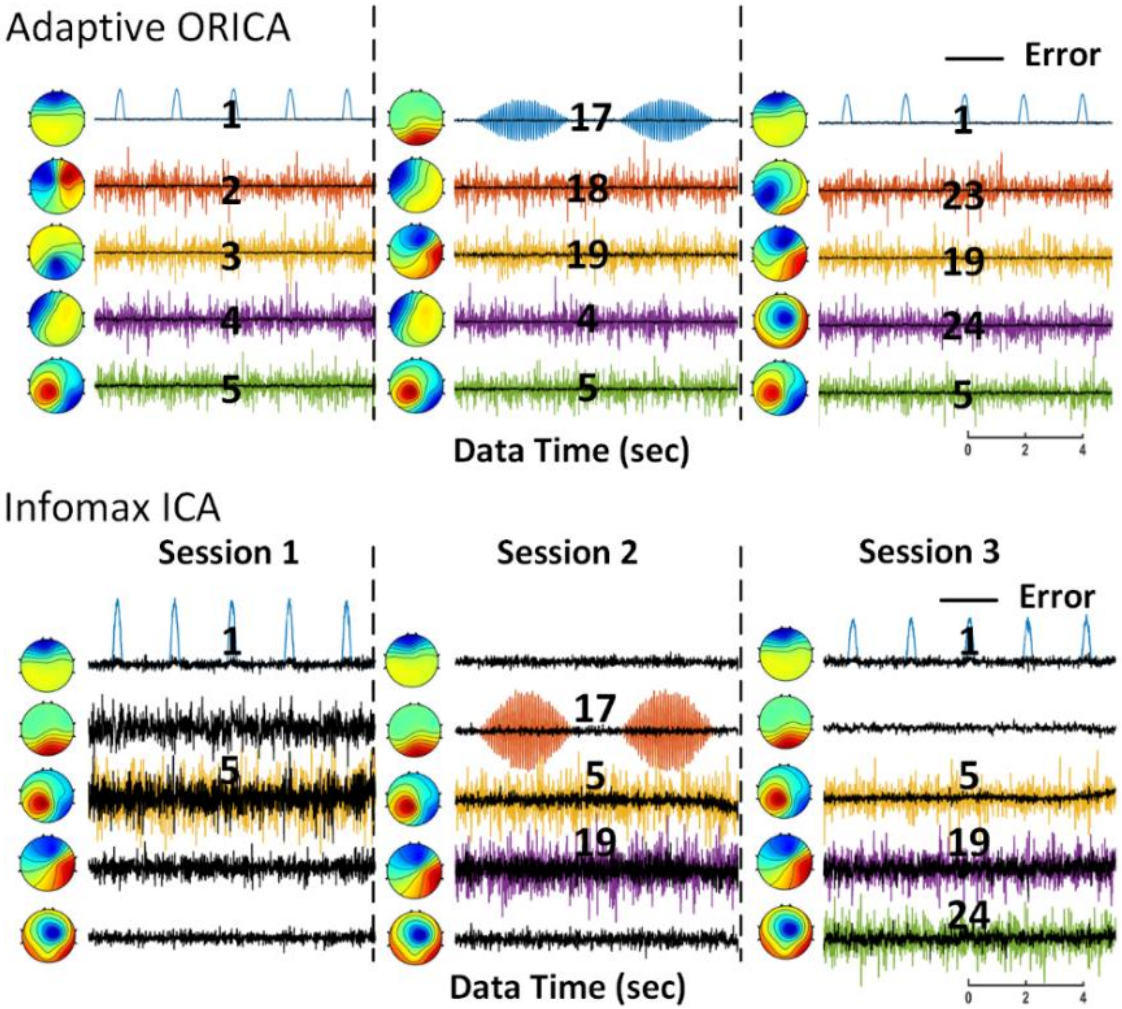
$$x^{(i)} = A_i s_i$$ i: session number





Hsu et al. *IEEE EMBC*, 2015

ORICA finds more active sources than Infomax ICA does when EEG data are quasi-stationary

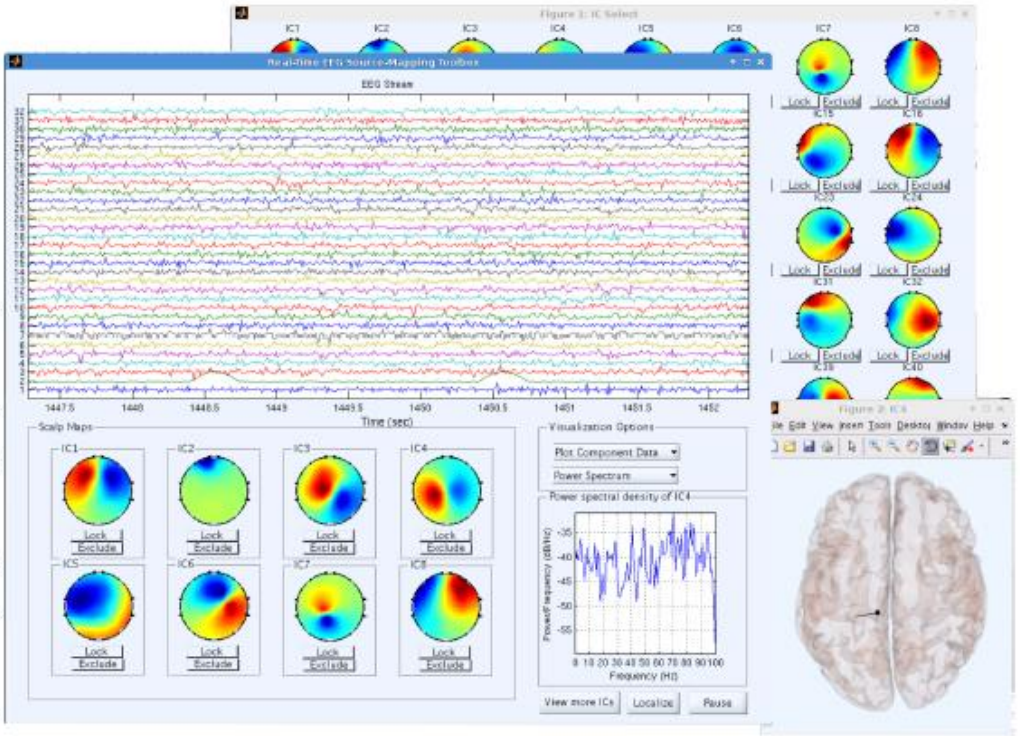


Hsu et al. *IEEE EMBC*, 2015

Visualizing adaptive sources

[Real-time EEG Source-Mapping Toolbox (REST)]

[Online ICA-based EEG ocular artifact removal]



Pion-Tonachini & Hsu, *IEEE EMBC*, 2015

Conclusion

- (Covert) Mental state is inevitable yet often ignored.
- The hypothesis is that mental states can be characterized by distinct sets of active sources and modeled by ICA.
- Multi-model ICA approach found distinct source models of alert and drowsy states and can quantitatively assess levels of alertness.
- Adaptive ICA approach can track non-stationary sources and opens up online applications such as online artifact removal and mental states monitoring.



References

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- S.-H. Hsu, T. Mullen, T.-P. Jung, and G. Cauwenberghs, “Validating Online Recursive Independent Component Analysis on EEG Data,” 7th International IEEE EMBS Neural Engineering Conference (NER), 2015.
- S.-H. Hsu, T. Mullen, T.-P. Jung, and G. Cauwenberghs, “Online recursive independent component analysis for real-time source separation of high-density EEG," *IEEE EMBC*, 2014.

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Q&A