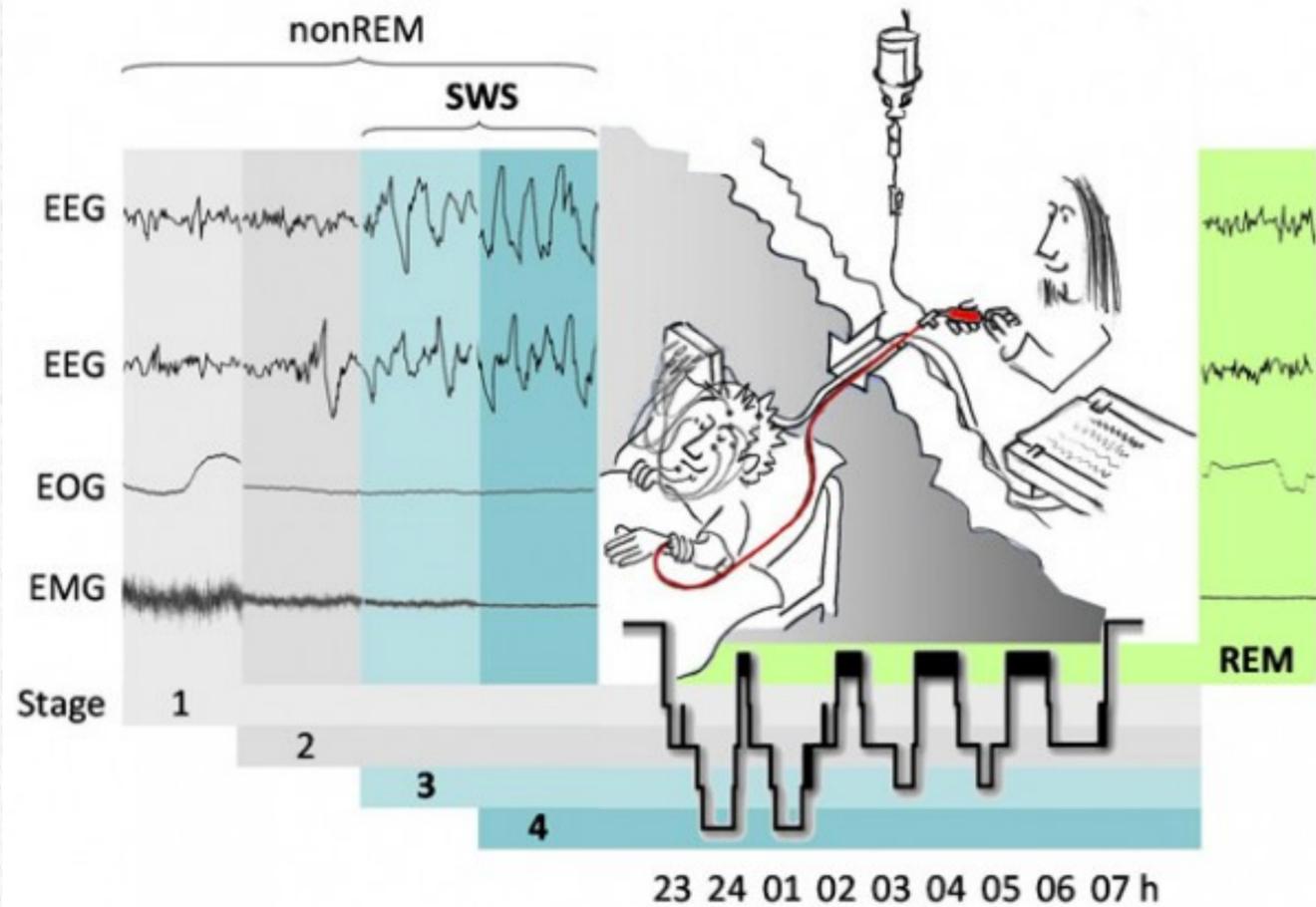


Sleep Analytics and Online Selective Anomaly Detection

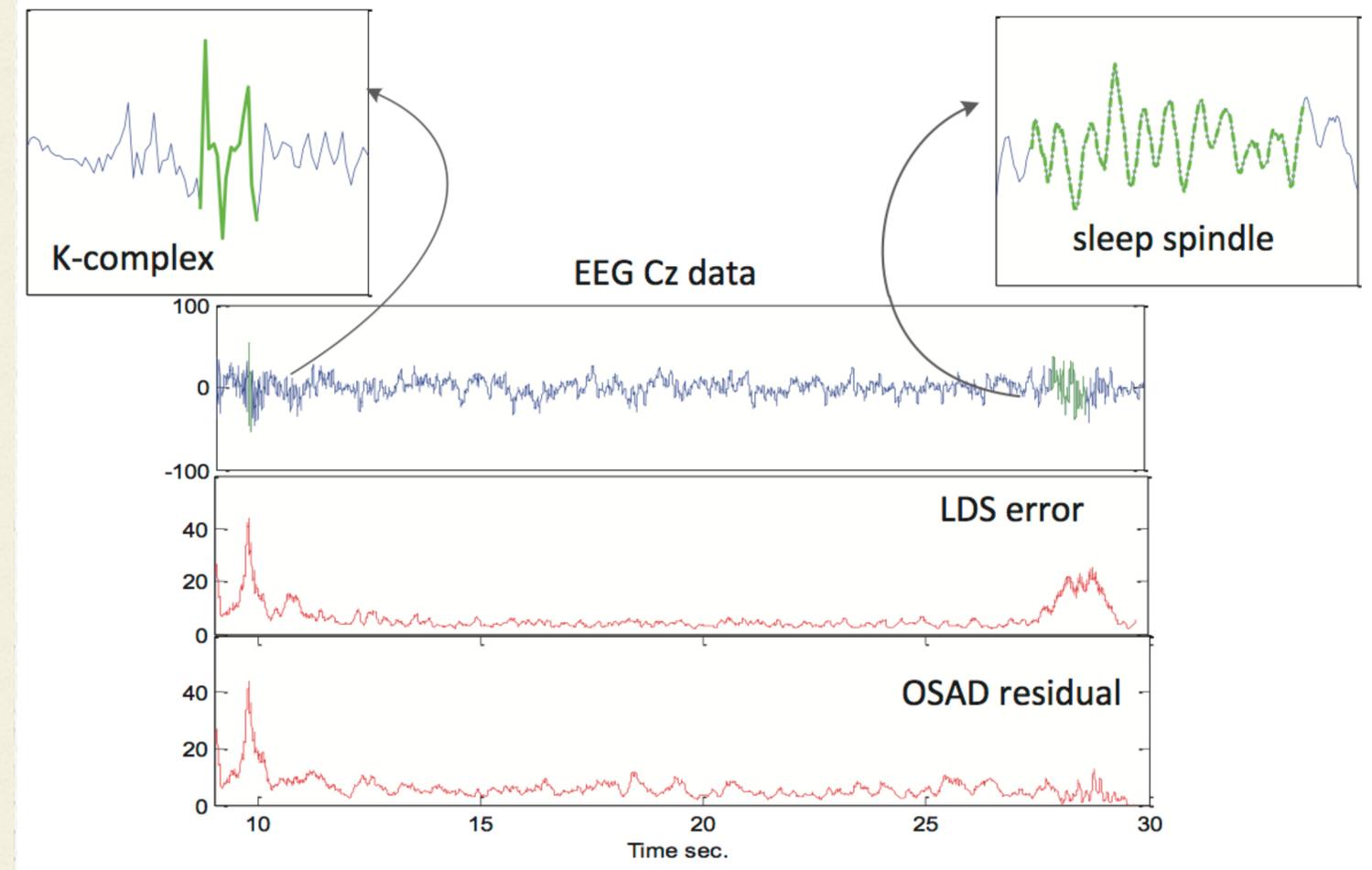
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University of Sydney

Selective Anomaly Detection?



SWS – early night: Systems consolidation, recovery functions on cellular and system levels, immune support

REM – late night: Synaptic consolidation, plasticity and brain maturation during development



what we propose:

1. Introduce a new problem: **Online Selective Anomaly Detection** (OSAD) to address the requirement of selectively reporting sleep anomalies based on specifications by domain experts.
2. Combine techniques from **data mining** and **control theory** to **solve OSAD**
3. Evaluate the method on sleep EEG data

Problem: Learning

- 1- Given an observable time series $\{y_i\}_{i=1:N}$
- 2- assuming that the observed y and the latent x are governed by a **linear dynamic system** (LDS),

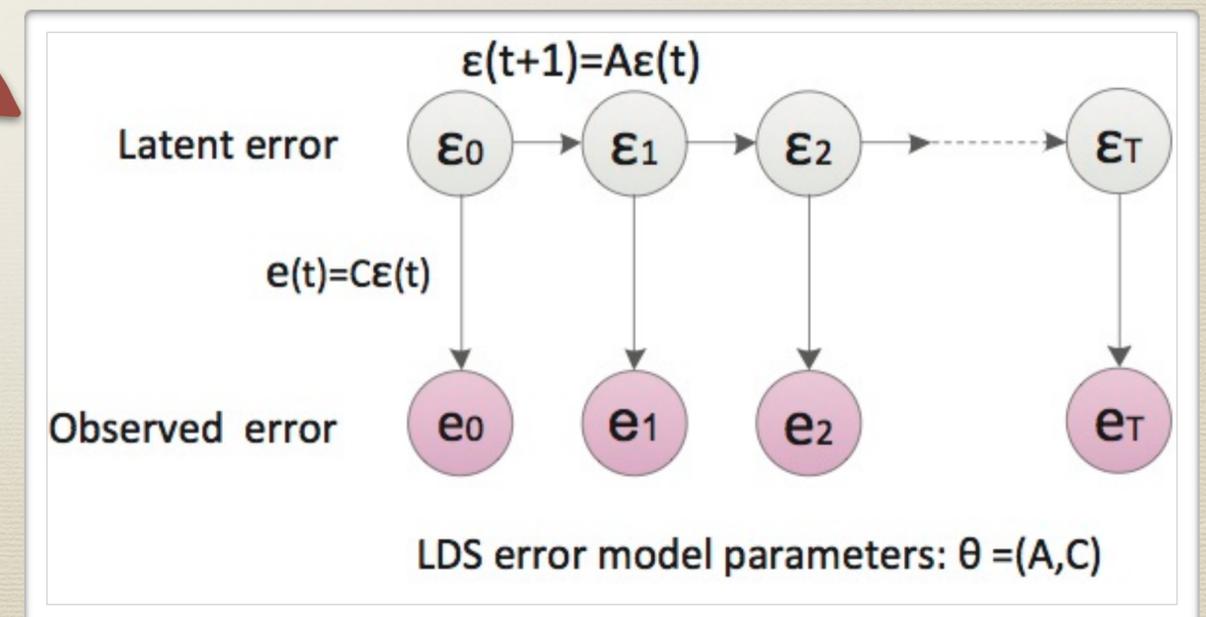
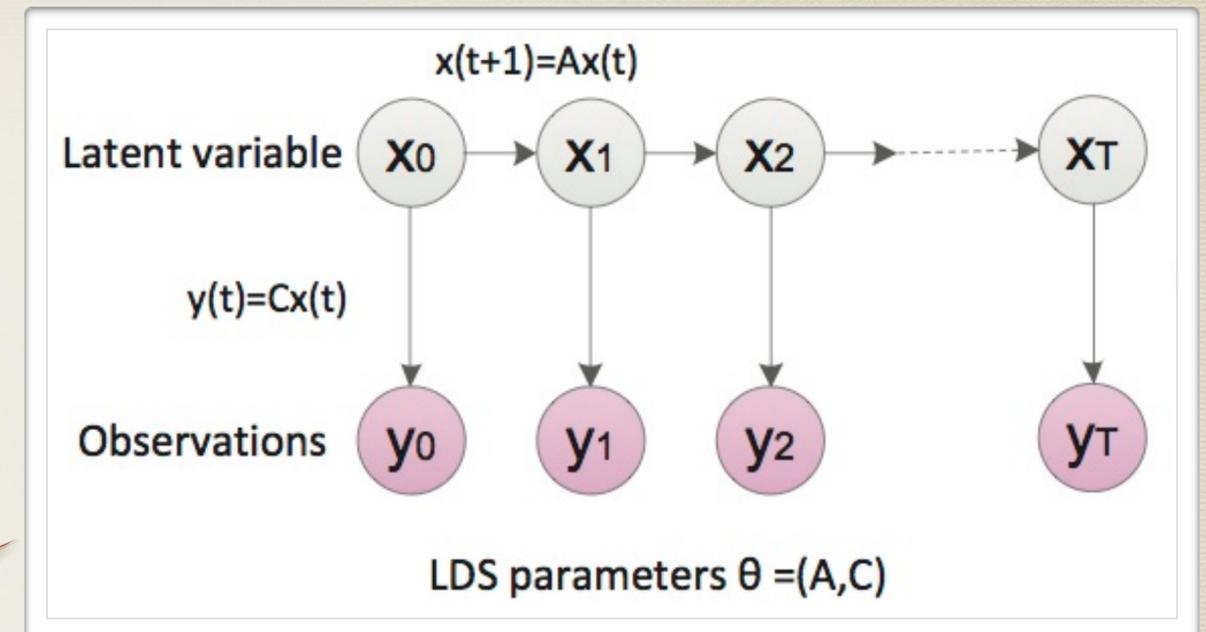
$$x(t+1) = \mathbf{A}x(t)$$

$$y(t) = \mathbf{C}x(t)$$

not_observable $\rightarrow \varepsilon(t) := x(t) - \hat{x}(t)$

observable $\rightarrow e(t) := y(t) - \hat{y}(t)$

linearity



- Shumway 1982 : **EM algorithm** as the classic solution
- Overschee 1996, Ljung 2001 : **subspace method** as a revolution
- Boots 2010 : re-introduced to ML community as **spectral learning**

Problem: Design

A **pattern P** is a user-defined matrix which operates in the latent space.

$$\mathbf{x}(t + 1) = \mathbf{A}\mathbf{x}(t) + \mathbf{P}\xi(t)$$

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t)$$

Given an LDS, a **pattern P** in the latent space, design/control a residual $\mathbf{r}(t)$ such that

$$r(t) = \begin{cases} 0 & \text{if } \varepsilon(t) = \mathbf{P}\xi(t) \\ \mathbf{S}\varepsilon(t) & \text{otherwise} \end{cases}$$

Where S is a linear transformation matrix

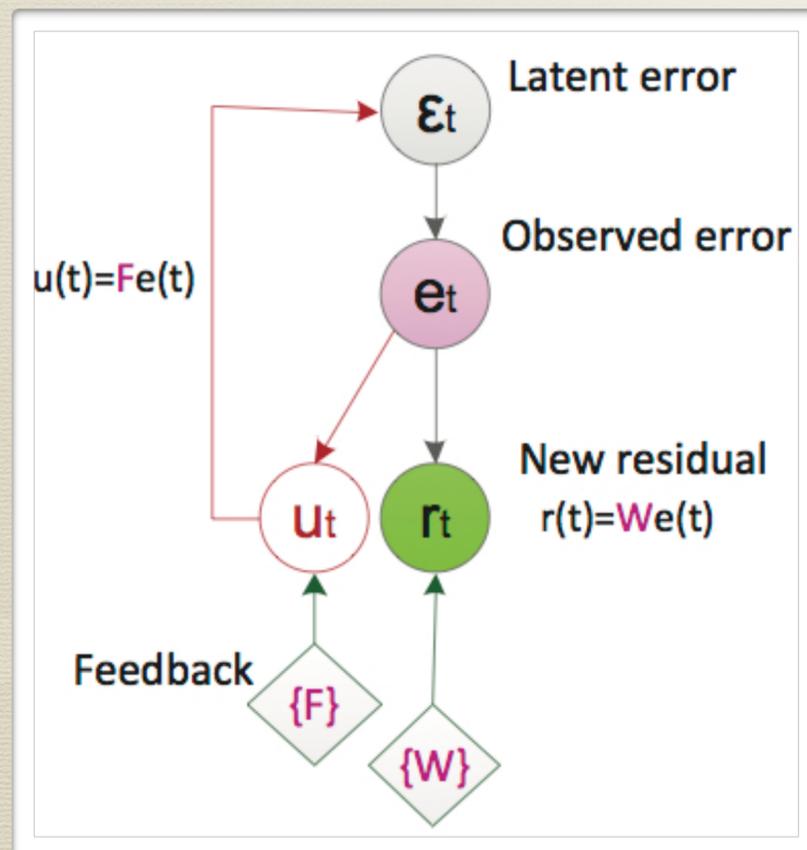
Solution: *Dynamic Residue Model (DRM)*

$$r(t) := We(t)$$

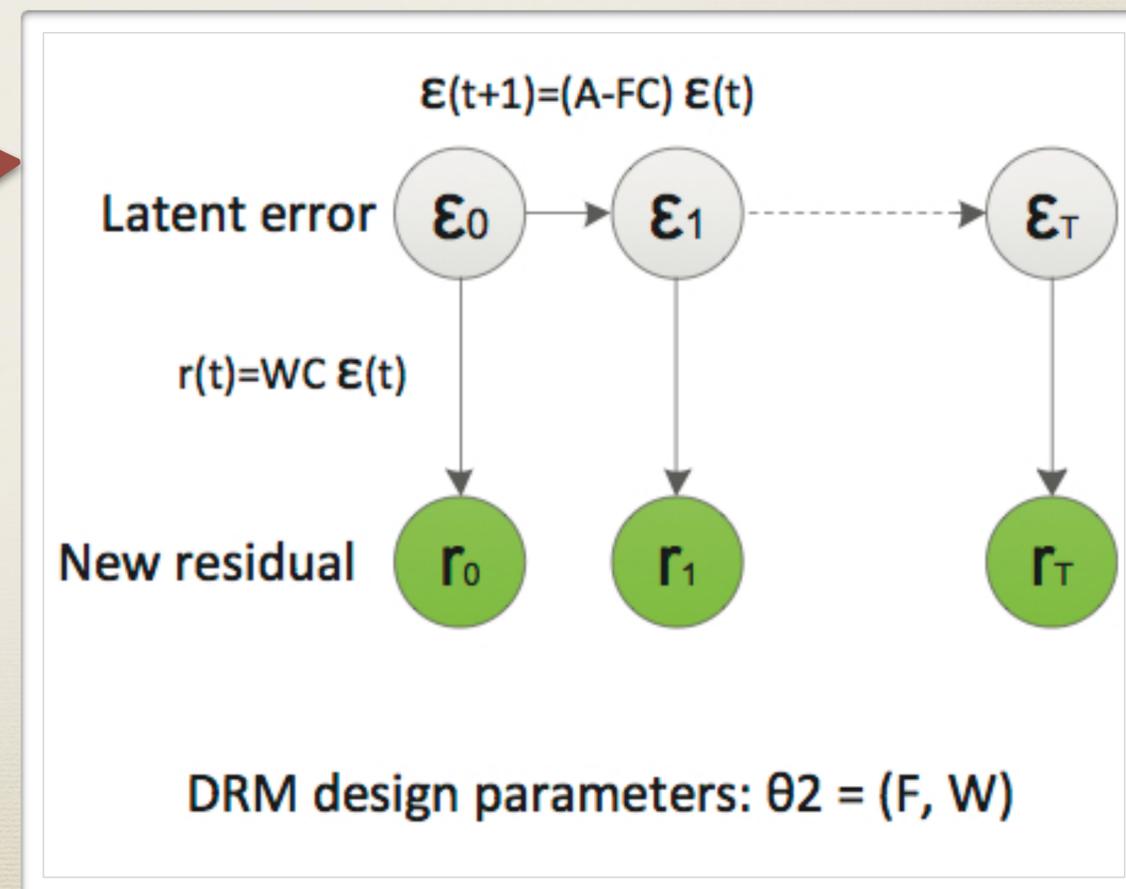
$$u(t) := Fe(t)$$

$$\varepsilon(t + 1) = \mathbf{A}_f \varepsilon(t)$$

$$e(t) = \mathbf{C}_f e(t)$$



DRM



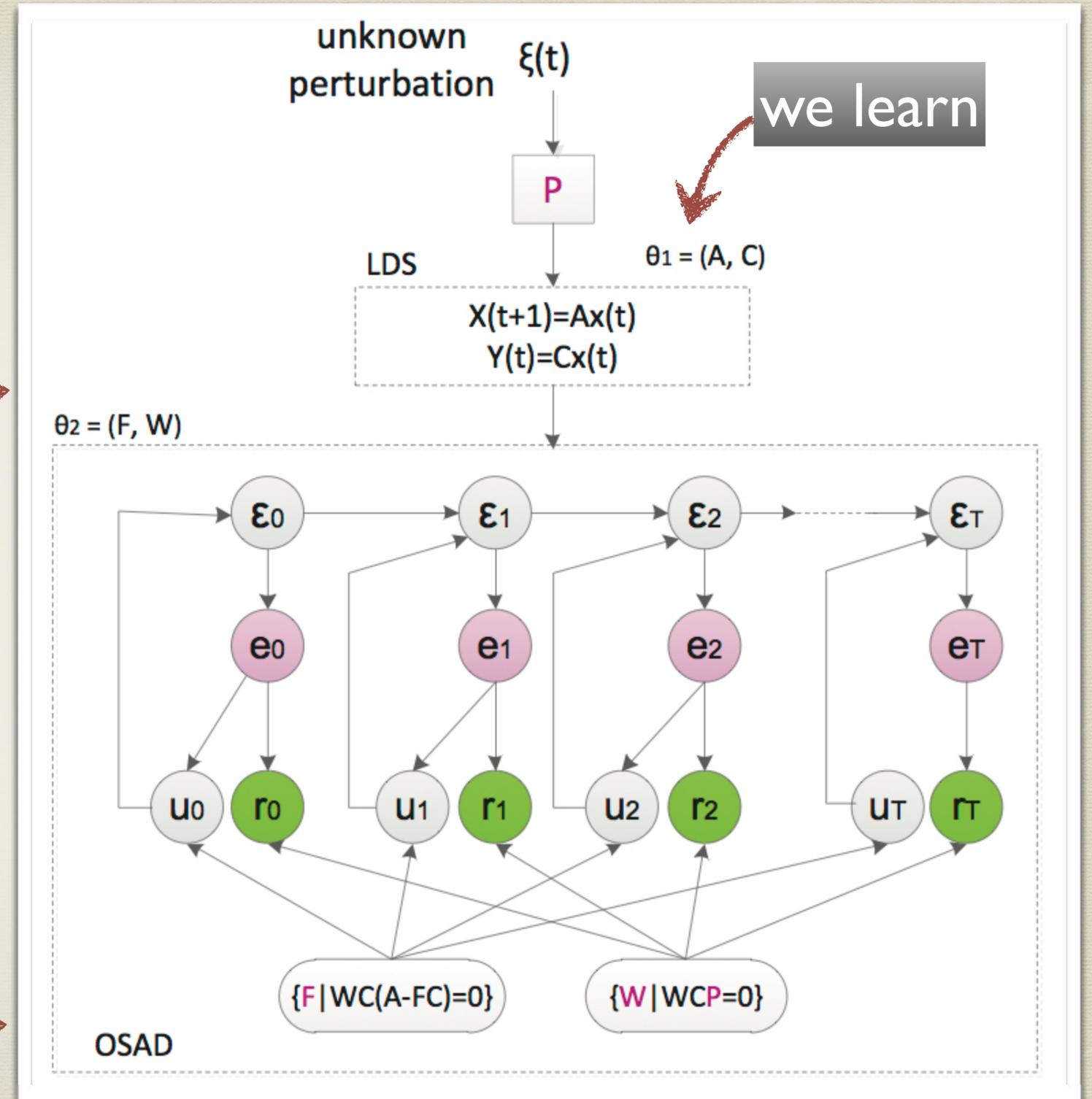
1- Using parameter F a virtual input $u(t)$ is generated to feed the error back to the latent space.

2- The error $e(t)$ is then calibrated by W to generate a new residual space $r(t)$.

we control

$$\begin{aligned} \varepsilon(t+1) &= A_f \varepsilon(t) \\ r(t) &= C_f e(t) \end{aligned}$$

$$r(t) = \begin{cases} 0 & \text{if } \varepsilon(t) = P\xi(t) \\ Se(t) & \text{otherwise} \end{cases}$$



Z-transform as a design approach

$$\varepsilon(t+1) = \mathbf{A}_f \varepsilon(t)$$

$$r(t) = \mathbf{C}_f \varepsilon(t)$$

Z-transform

$$\begin{cases} z\mathcal{E}(z) = A_f \mathcal{E}(z) + P\xi(z) \\ R(z) = C_f \mathcal{E}(z) \end{cases}$$

soln

$$\begin{cases} \mathcal{E}(z) = (zI - A_f)^{-1} P\xi(z) \\ R(z) = [C_f (zI - A_f)^{-1} P]\xi(z) \end{cases}$$

$$G_\xi(z) \doteq C_f (zI - A_f)^{-1} P$$

$$R(z) = G_\xi(z)\xi(z)$$

Theorem. For a DRM, a sufficient condition for $\mathbf{G}_\xi(z) = 0$ is

$$\mathbf{C}_f \mathbf{P} = 0 \quad \text{and} \quad \{ \mathbf{C}_f \mathbf{A}_f = 0 \quad \text{or} \quad \mathbf{A}_f \mathbf{P} = 0 \}$$

$$\mathbf{C}_f \mathbf{P} = \mathbf{W} \mathbf{C} \mathbf{P} = 0 \Rightarrow \text{find } \mathbf{W} : \mathbf{W} \perp \mathbf{C} \mathbf{P}$$

linear algebraic problem

for $\mathbf{A}_f \mathbf{P} = 0$, it is sufficient to design a matrix \mathbf{A}_f , such that the right eigenvectors corresponding to the zero eigenvalues are the columns of \mathbf{P} . \Rightarrow find $\mathbf{F} : (\mathbf{A} - \mathbf{F} \mathbf{C}) \mathbf{P} = 0$

for $\mathbf{C}_f \mathbf{A}_f = 0$, it is sufficient to design a matrix \mathbf{A}_f such that its left eigenvectors corresponding to the zero eigenvalue are orthogonal to \mathbf{P} . \Rightarrow find $\mathbf{F} : \mathbf{W} \mathbf{C} (\mathbf{A} - \mathbf{F} \mathbf{C}) = 0$

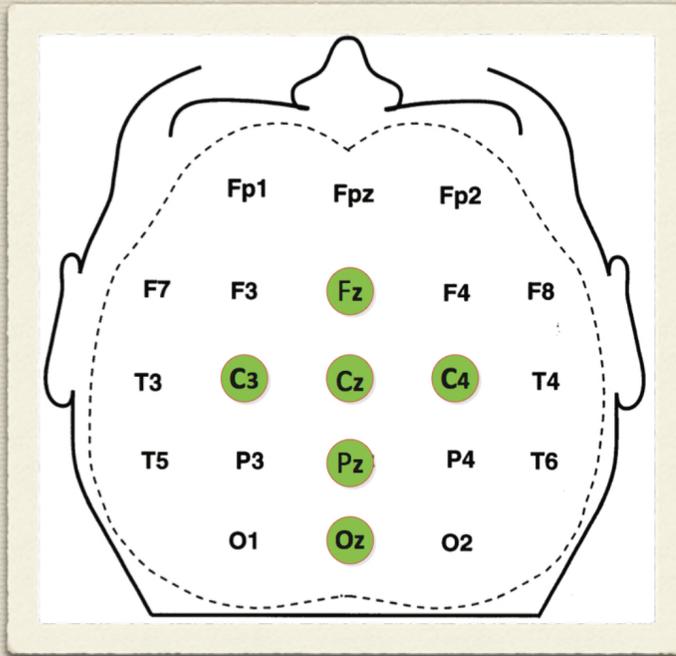
eigen-space assignment problem

Eigen-Structure Assignment (EA) vs SVD

SVD: Given: Matrix X  singular-values λ_i
singular-vectors u_i

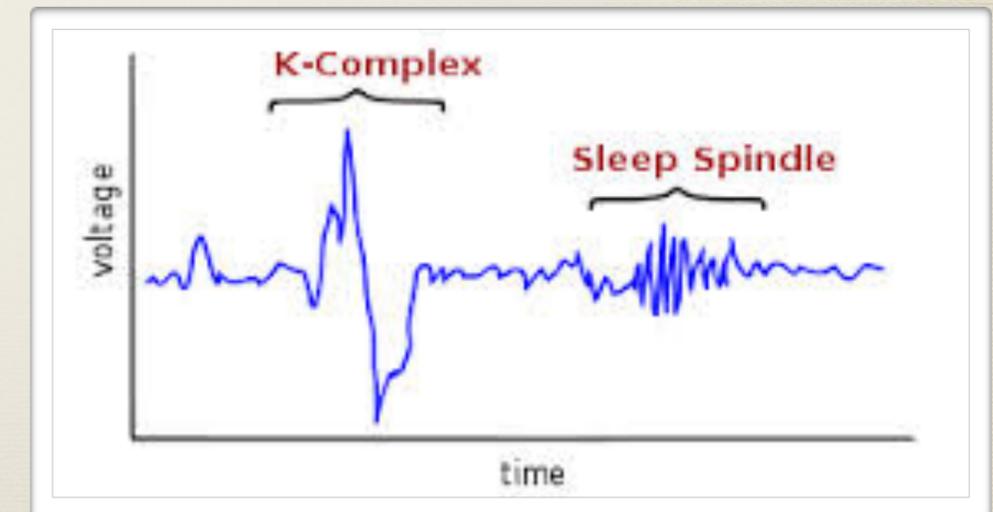
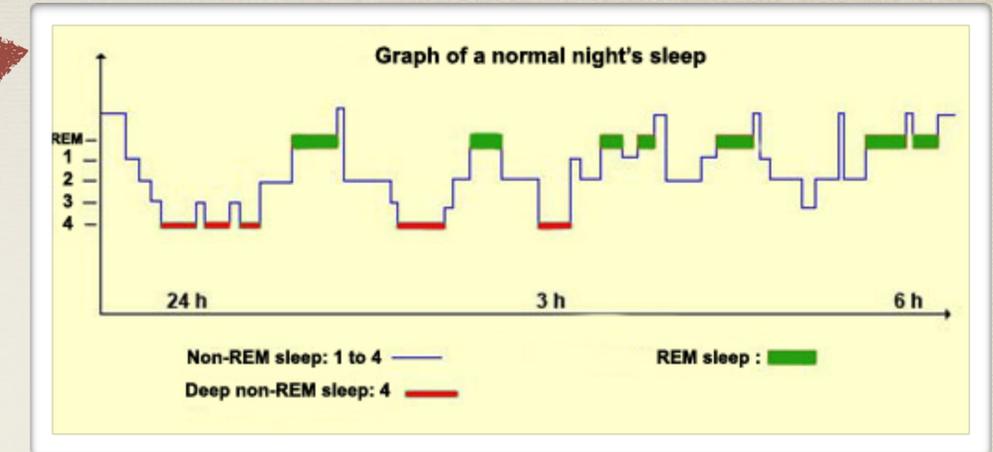
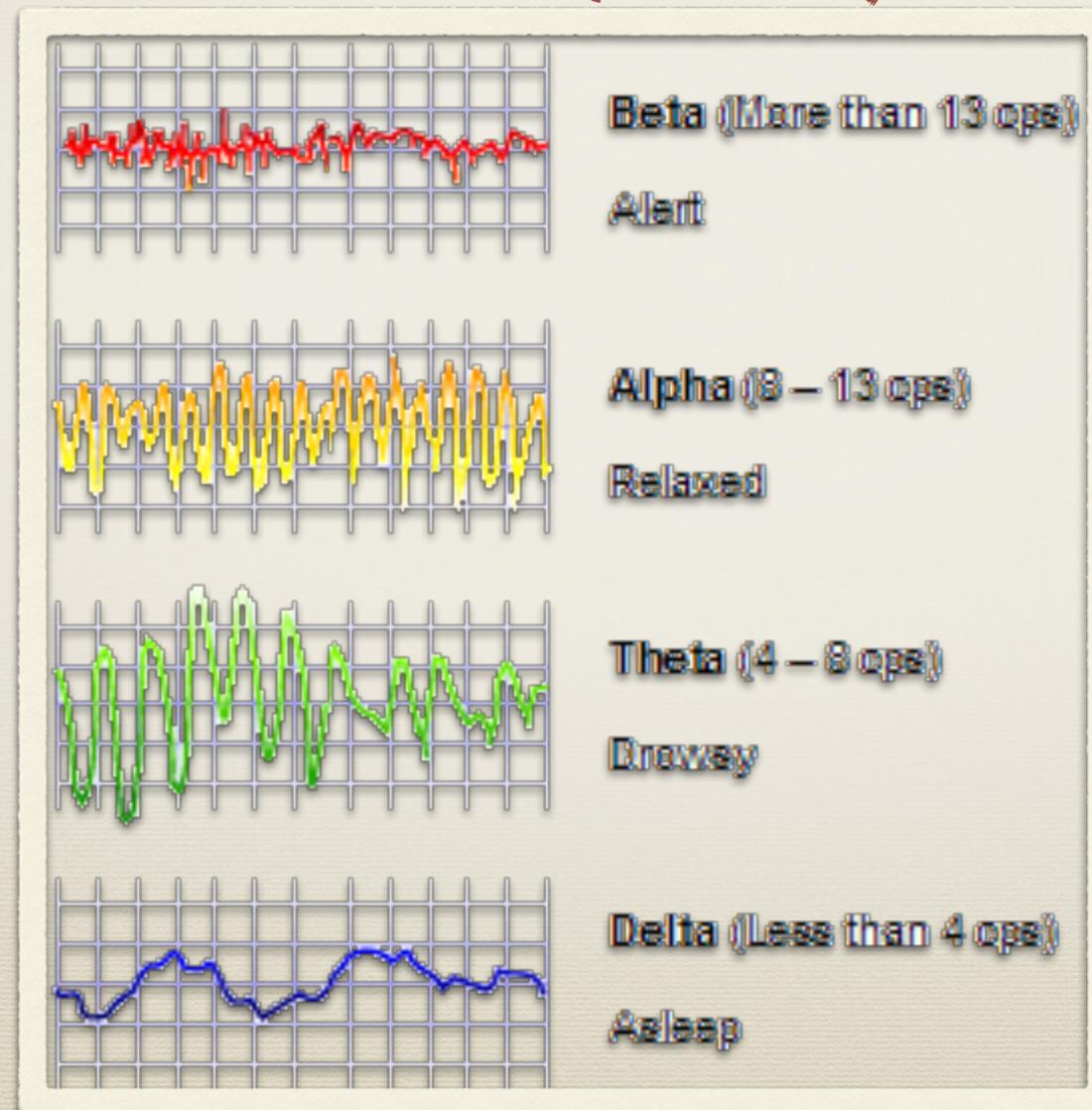
EA: Given: eigen-values λ_j  Matrix X
eigen-vectors u_j

Experiments: Sleep Staging and EEG



data set : EEG time series from four health controls (age 25-36).

Recordings: at the **Woolcock Institute of Medical Research**, at Sydney University, using 6 EEG channels with a sampling rate of 200 Hz.



Detection of Sleep Spindle and K-Complex

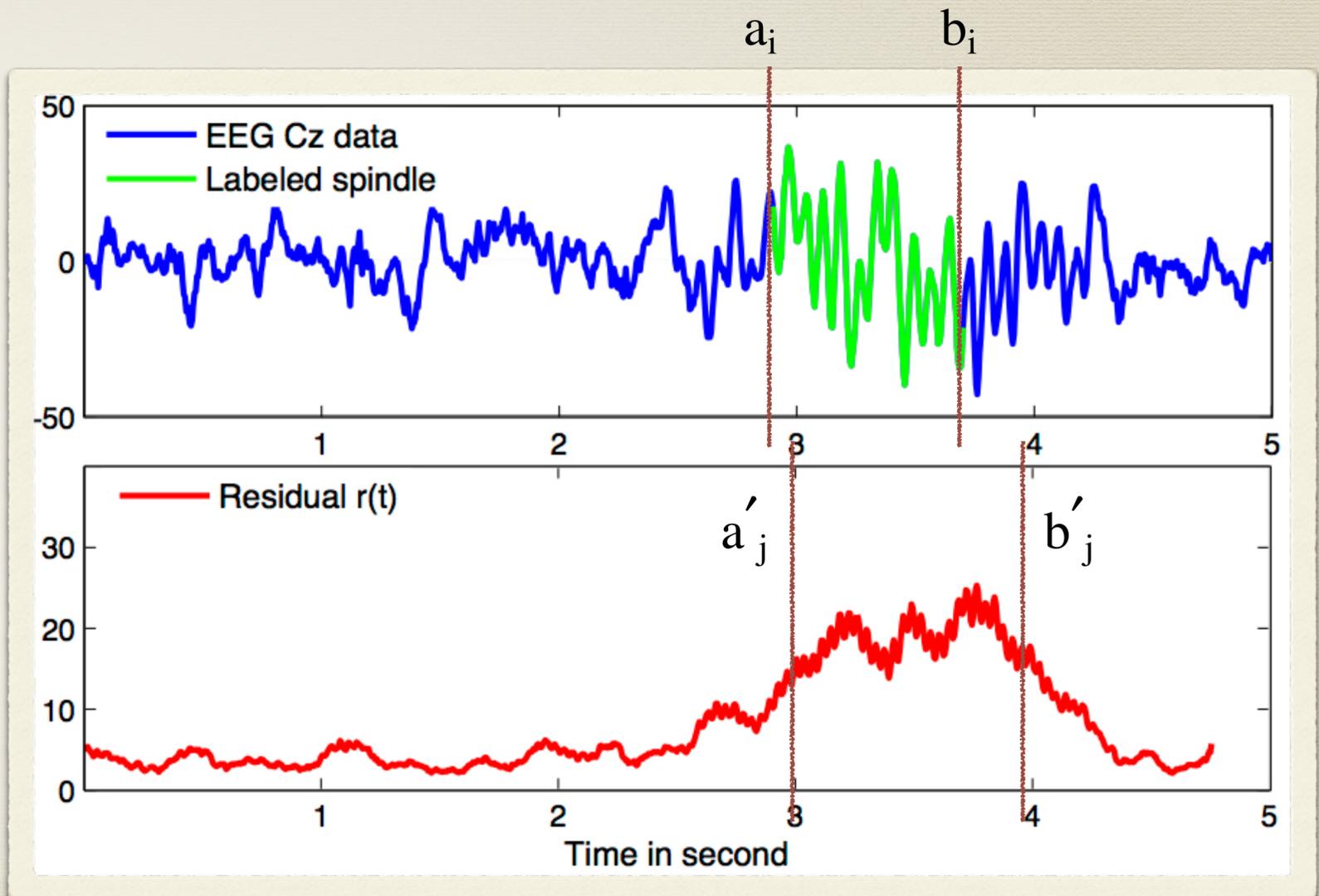
For a given subject,

Let $\{[a_i, b_i]\}_{i=1:n}$: the intervals of the labeled spindles

Let $\{[a'_j, b'_j]\}_{j=1:m}$: the intervals of predicted spindles

$$\text{precision} = \frac{\sum_{i=1}^n \sum_{j=1}^m |[a_i, b_i] \cap [a'_j, b'_j]|}{\sum_{j=1}^m |[a'_j, b'_j]|}$$

$$\text{recall} = \frac{\sum_{i=1}^n \sum_{j=1}^m |[a_i, b_i] \cap [a'_j, b'_j]|}{\sum_{i=1}^n |[a_i, b_i]|}$$



LDS tends to under-predict the number of anomalies

	No. of Labeled Anomalies		No. of Detected Anomalies	
	Spindle	K-Complex	Spindle	K-Complex
subject 1	170	277	164	251
subject 2	6	13	6	11
subject 3	23	38	21	37
subject 4	141	205	132	186

Sleep Spindles: tends to over-predict the length of interval

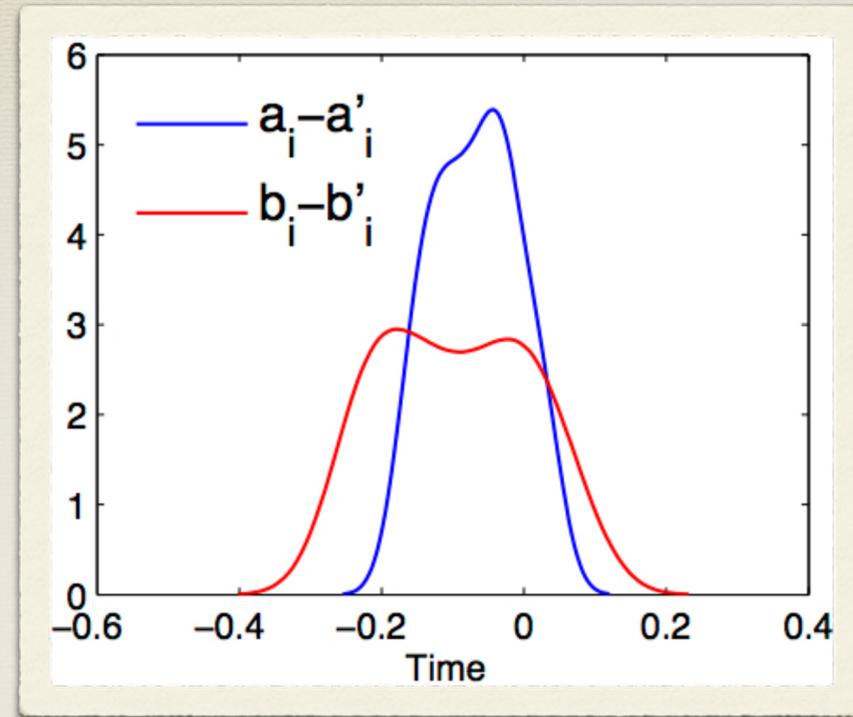
	Total time of K-Complex		Performance	
	Labeled in sec	Detected in sec	Precision	Recall
subject 1	198.23	216.35	90.45%	93.43%
subject 2	11.48	11.25	92.76%	94.12%
subject 3	21.39	24.56	91.01%	92.06%
subject 4	147.68	160.49	91.28%	93.73%

	Total time of spindles		Performance	
	Labeled in sec	Detected in sec	Precision	Recall
subject 1	129.8	168.74	71.24%	95.53%
subject 2	3.45	3.55	97.18%	97.38%
subject 3	15.15	16.23	83.88%	95.66%
subject 4	93.5	103.2	79.15%	95.42%

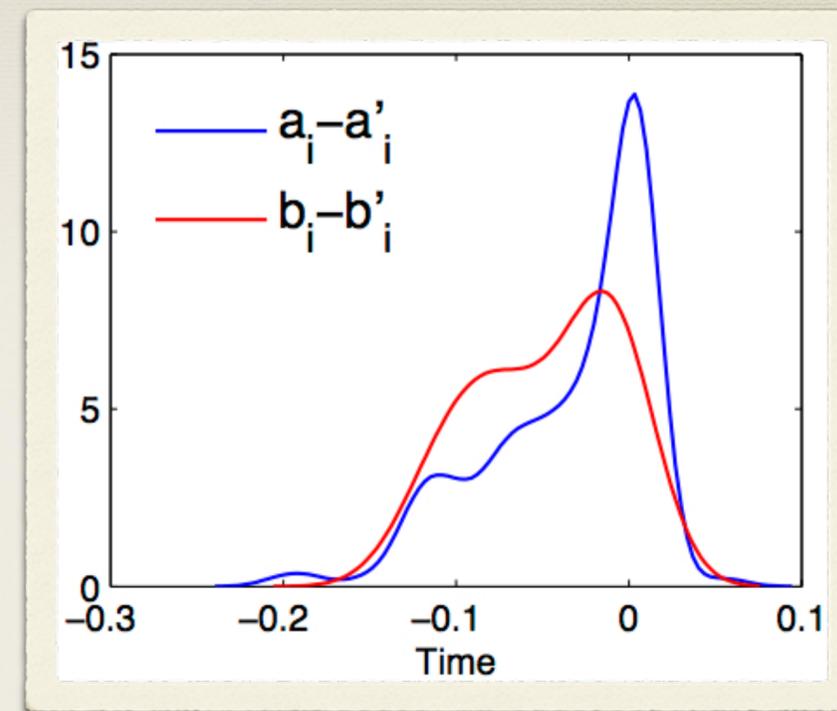
K-Complex: tends to over-predict the length of interval

On-Line Analysis

subject 1

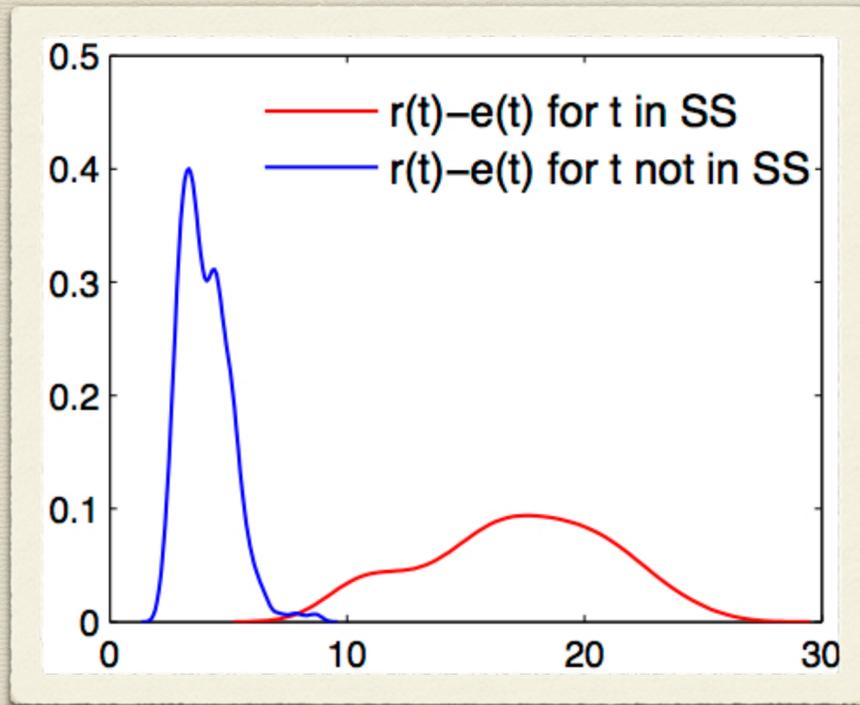


subject 4

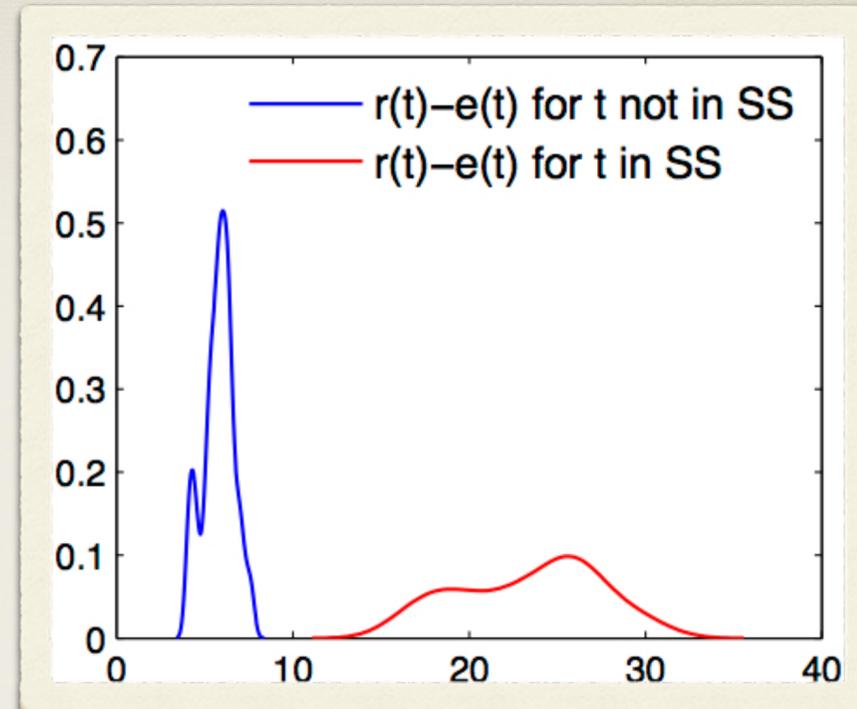


- 1- OSAD provides near real time detection.
- 2- There is a tendency to start early and end early.
- 3- There is subject to subject difference.

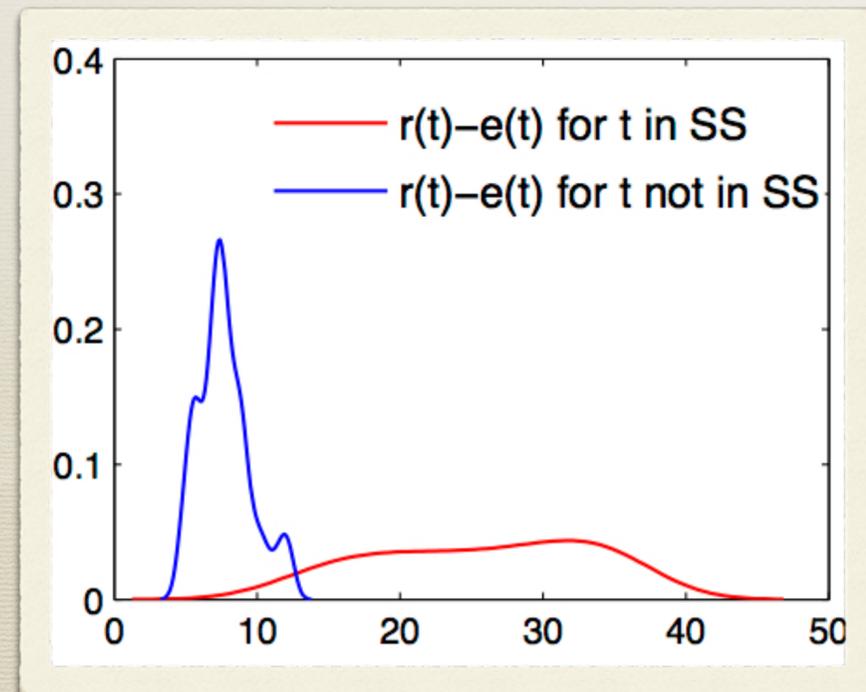
Performance of Designed Residual for Sleep Spindle (SS)



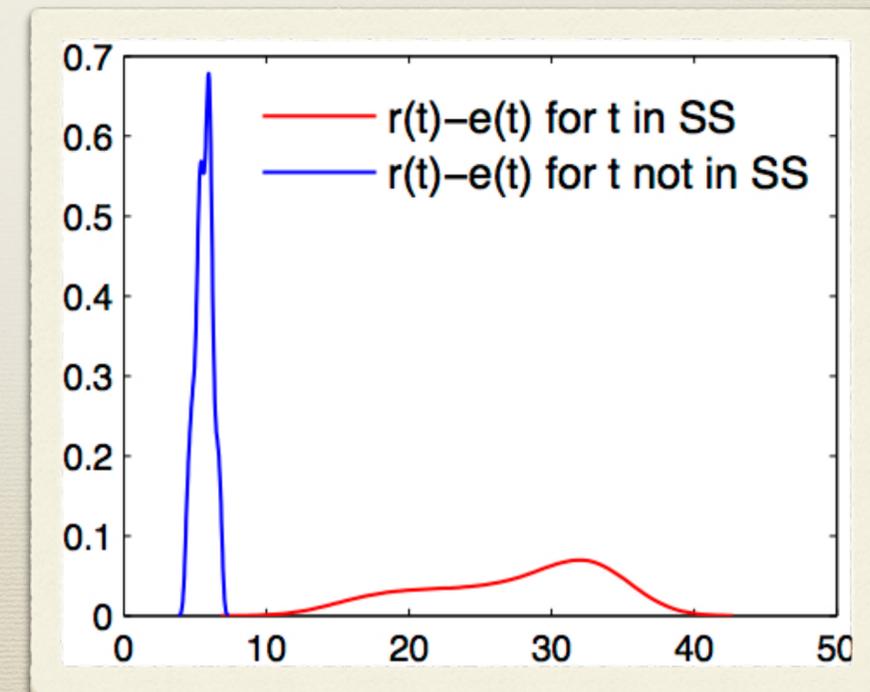
subject 1



subject 3



subject 2



subject 4

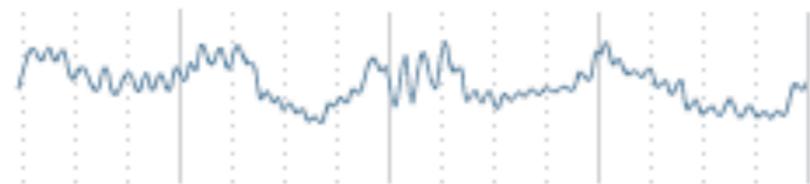
Conclusion

1. Linear Dynamical Systems (LDS) show high accuracy in modelling multidimensional EEG sleep data.
2. The advantage of a model-based approach is the capability to control the system, the residual system in our case.
3. OSAD problem is general and can be applied in many other situations.

Questions?

“Spare Slides”

Four Categories of Brain Wave Patterns



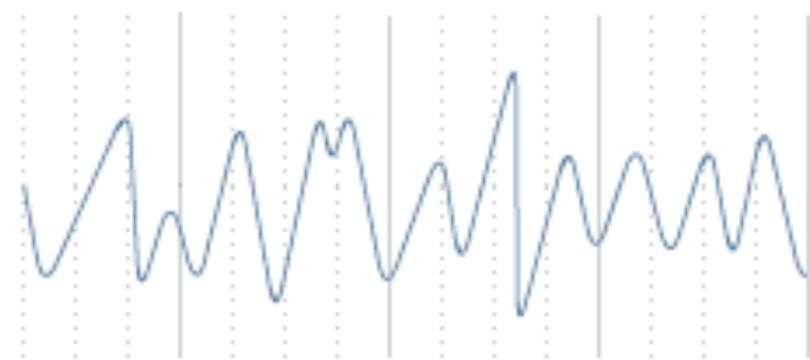
Beta (14-30 Hz)

Concentration, arousal, alertness, cognition
Higher levels associated with anxiety, disease, feelings of separation, fight or flight



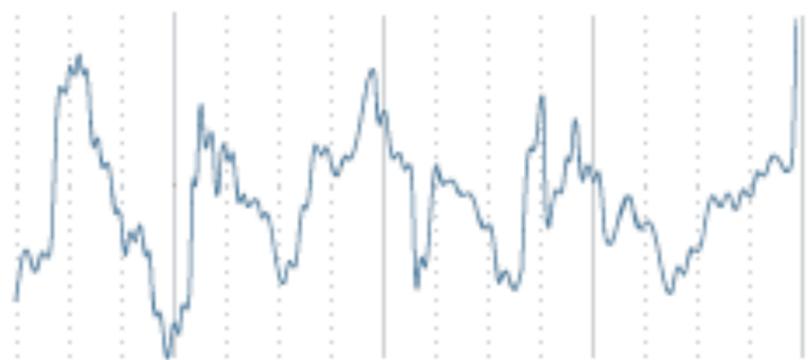
Alpha (8-13.9 Hz)

Relaxation, superlearning, relaxed focus, light trance, increased serotonin production
Pre-sleep, pre-waking drowsiness, meditation, beginning of access to unconscious mind



Theta (4-7.9 Hz)

Dreaming sleep (REM sleep)
Increased production of catecholamines (vital for learning and memory), increased creativity
Integrative, emotional experiences, potential change in behavior, increased retention of learned material
Hypnagogic imagery, trance, deep meditation, access to unconscious mind



Delta (.1-3.9 Hz)

Dreamless sleep
Human growth hormone released
Deep, trance-like, non-physical state, loss of body awareness
Access to unconscious and "collective unconscious" mind, greatest "push" to brain when induced with Holosync®

