Deep RNN Learning for EEG based Functional Brain State Inference

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What is EEG(Electro Encephalo Graphy)?

- Electro-encephalo-graphy
- Electro-electrode
- Encephalon = brain

- An electroencephalogram (**EEG**) is a physiological method to plot the electrical activity in the brain. An **EEG** can be used to help detect potential problems associated with this activity

- Since the voltage measured at the electrodes are very small, the recorded data is digitized and sent to an amplifier. The amplified data can then be displayed as a sequence of voltage values.

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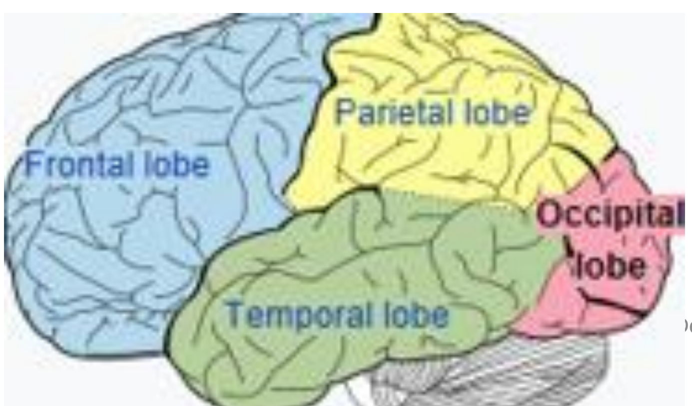
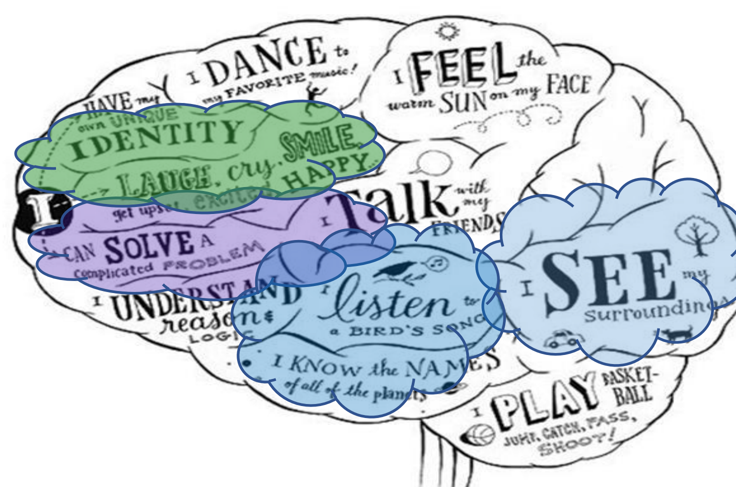
History

- 100 years ago the EEG time course was plot on paper. Current systems display the data as continuous flow of voltages on a screen.
- Applied first to humans in the 1920s by German neurologist Hans Berger (Jung & Berger, 1979), EEG is a non-expensive, non-invasive and completely passive recording technique.
- EEG recordings are done with electrode arrays, comprising various sensor numbers ranging from 10 to 500 electrodes, depending on the scope of the experiment.

How can EEG data be interpreted?

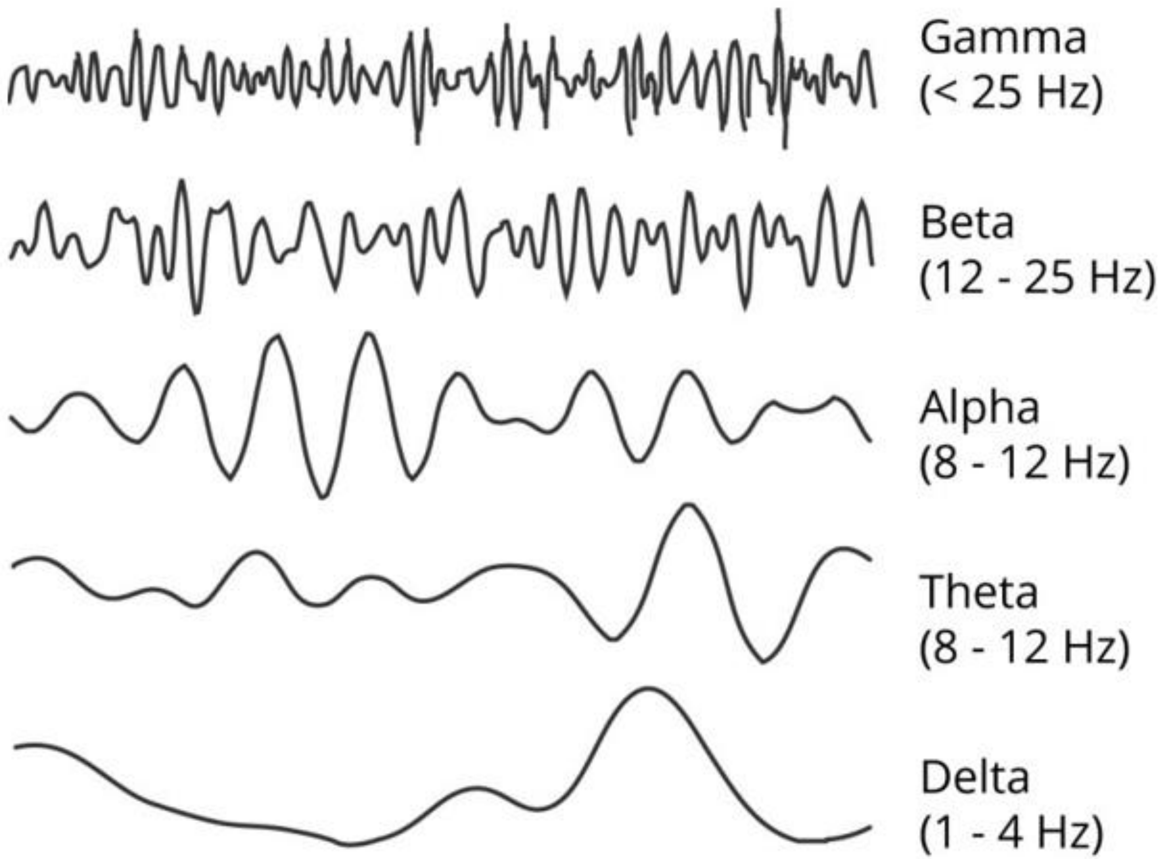
Occipital lobe: is the visual processing center of our brain, including low-level visuo-spatial processing (orientation, spatial frequency), color differentiation and motion perception
Parietal lobe: sensory area:is all about integrating information stemming from external sources as well as internal sensory feedback from skeletal muscles, limbs, head, eyes,
Temporal lobe: is associated with processing sensory input to derived, or higher, meanings using visual memories, language and emotional association.
Frontal lobe: Motor area(associated with rewards, attention, short term memory tasks, planning, motivation)





Band	Frequency	location		
delta	0.5<4 Hz peak-to-peak amplitude greater than 75µV	frontally in adults, posteriorly in children; high-amplitude waves	adult slow-wave sleep (deep sleep)	
theta	4-7	Found in locations not related to task at hand		
Alpha	**8–15**	**posterior regions of head, both sides, higher in amplitude on dominant side. Central sites (c3-c4) at rest**	**•relaxed/reflecting** **•closing the eyes**	**•Coma**
Beta	16–31	both sides, symmetrical distribution, most evident frontally; low-amplitude waves	•range span: active calm → intense → stressed → mild obsessive •active thinking, focus, high alert, anxious	•benzodiazepines •Dup15q syndrome [50]
Gamma	> 32	Somatosensory cortex		
Mu	8–12	Sensorimotor cortex	•Shows rest-state motor neurons.[53]	

Different Bands:



Typical studies on delta:

- Sleep and sleep disorders. Certain neurological diseases such as Parkinson’s, Dementia or Schizophrenia are often accompanied by sleep disorders.
- Monitoring EEG during sleep can give insights into the depth of sleep and potential risks associated with sleep disorders.
- Alcoholism and sleep. Alcohol has strong side effects on sleep. Heavy drinking decreases slow wave sleep and therefore delta frequencies necessary for memory consolidation – even after long periods of abstinence.

Typical studies on alpha:

- Meditation. As alpha reflects relaxation and sensory inhibition, meditation studies compare alpha levels of experienced and novice meditators (for more details, see Klimecki and colleagues, 2012).
- >> Biofeedback training. Here, alpha band power is monitored to track the relaxation level of a respondent. Increased levels of alpha power are interpreted as deeper relaxation. This is particularly useful in rehabilitation scenarios or for clinical populations, for example children suffering from ADHD.
- >> Attention. Spatial, semantic and social attention are closely related to alpha power. Often, researchers present objects, words or more complex social stimuli on screen and monitor alpha power during the encoding phase. Poor performers and distracted respondents generally show higher amounts of alpha power (for more details, see Rana & Vaina, 2014).

Emotiv EPOC, Emotiv EEG

Number of channels	14 (plus CMS/DRL references)
Channel names (Int. 10-20 locations)	AF3, AF4, F3, F4, F7, F8, FC5, FC6, P3 (CMS), P4 (DRL), P7, P8, T7, T8, O1, O2
Sampling method	Sequential sampling, Single ADC
Sampling rate	~128Hz (2048Hz internal)
Resolution	16 bits (14 bits effective) 1 LSB = 0.51μV
Bandwidth	0.2 - 45Hz, digital notch filters at 50Hz and 60Hz
Dynamic range (input referred)	256mVpp
Coupling mode	AC coupled
Connectivity	Proprietary wireless, 2.4GHz band
Battery type	Li-poly
Battery life (typical)	12 hrs
Impedance measurement	Contact quality using patented system

NeuroSky MindWave EEG

Number of channels	1
Sampling rate	512Hz
Resolution	12 bits ADC
Battery type	Single AAA battery
Battery life (typical)	6 - 8 hrs.
Frequency	2.420 - 2.471 GHz RF
Data rate	250kbit/s RF
UART Baudrate	57,600 Baud
EEG max signal input range	1mV pk-pk
Hardware filter range	3Hz - 100Hz
Resolution	12 Bits ADC

Emotiv epoc+

The award winning EMOTIV EPOC+ is a 14 channel wireless EEG, designed for contextualized research and advanced BCI applications.

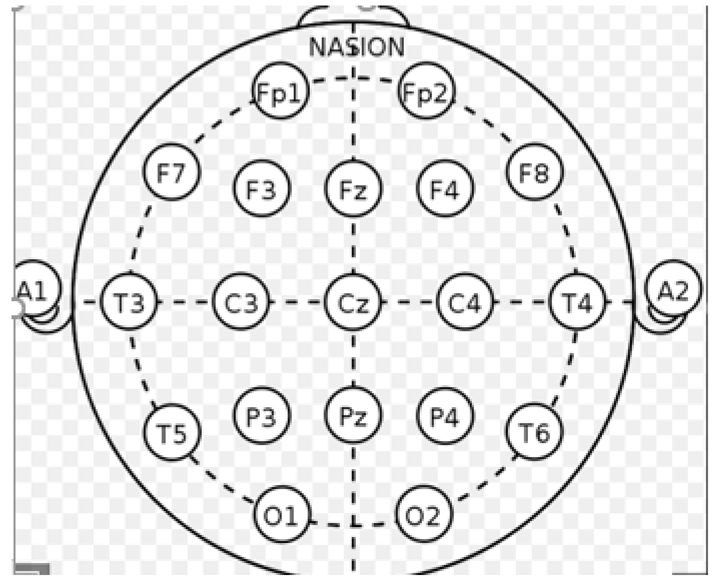
A prosumer 5 channel mobile EEG used by engaged individuals seeking better understanding of their brains and mental states

Electrode arrays and placement

- The most common systems for defining and naming electrode locations/positions along the scalp have been provided by the American Encephalographic Society (1994) as well as Oostenveld & Praamstra (2001).
- Typically, these are referred to as the 10-20 system and 10-5 system, respectively.
- In the 10-20 system, electrodes are placed at 10% and 20% points along lines of longitude and latitude.
- In the 10-20 system, electrode names begin with one or two letters indicating the general brain region or lobes where the electrode is placed (Fp = frontopolar; F = frontal; C = central; P = parietal; O = occipital; T = temporal).

10-20 system

- The "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front–back or right–left distance of the skull.
- Each site has a letter to identify the lobe and a number to identify the hemisphere location. The letters F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively.
- Even numbers (2,4,6,8) refer to electrode positions on the right hemisphere, whereas odd numbers (1,3,5,7) refer to those on the left hemisphere.

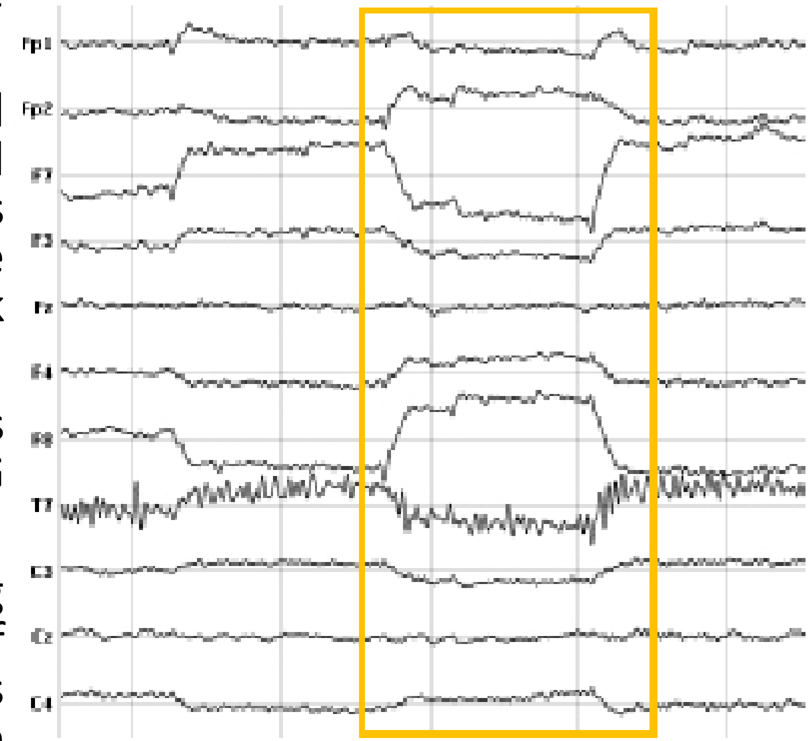


Challenges in EEG analysis

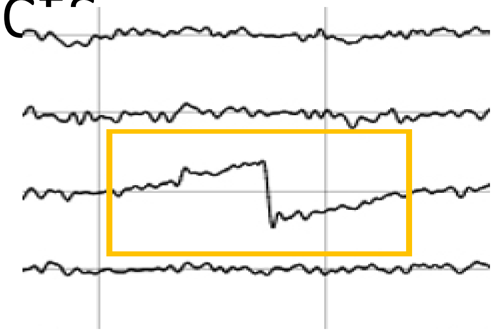
- Noise in EEG signal
- Volume of Data
- **Biological artifacts include:**
  - Eye-induced artifacts (includes eye blinks, eye movements and extra-ocular muscle activity)
  - ECG (cardiac) artifacts
  - EMG (muscle activation)-induced artifacts
  - Eye blinking
- Event Related Potential(ERP) has poor amplitude(μ-volts) resolution.(ERS-ERD)

Noise in EEG data

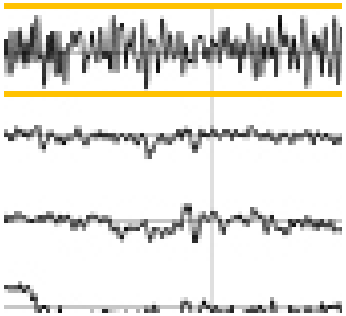
- Muscle activity: Particularly the activity of facial muscles (forehead, cheek, mouth), neck muscles and jaw musculature has severe effects on EEG recordings.
- Eye movements: Eye movements (horizontal and vertical) affect the electrical fields picked up by the electrodes. Vertical eye movements (up-down) look more sinusoidal, while horizontal eye movements (right-left) look more box-shaped
- It's recommended to record eye movements using eye trackers or by placing additional EEG electrodes surrounding the eyes.
- Blinks. Similar to eye movements, blinking interferes with brain signals quite a bit. If respondents blink while a certain stimulus is shown on screen, the EEG might not reflect the cortical processes of seeing the stimulus



External sources of artifacts



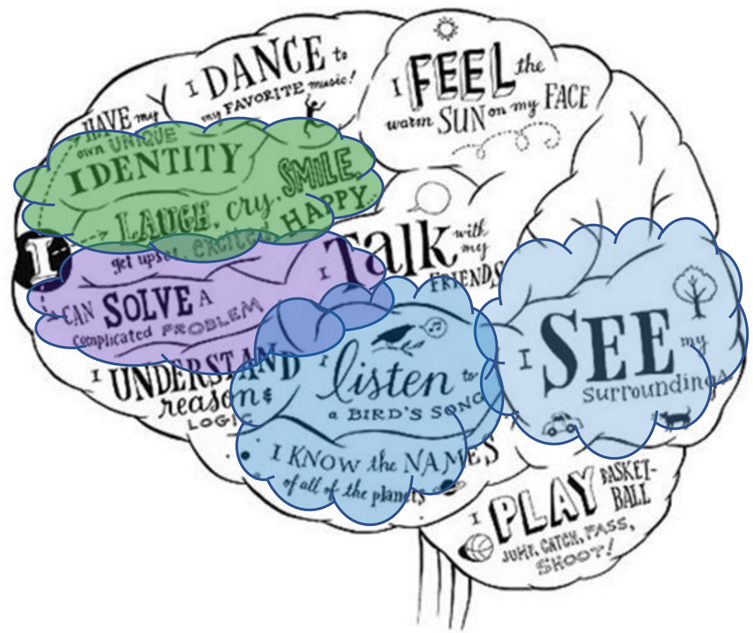
- Movement of an electrode or headset movements can cause severe artifacts that are visible in the affected channel or in all channels.



- Line noise (60 Hz in the US, 50 Hz in the EU) can have strong artifacts on the electrode recording - this becomes quite obvious in the raw EEG data

EEG Signal Analysis

- Can we use EEG signals to accurately classify whether someone is doing a task involving:
  - Significant amount of logical thinking(math)
  - Perspective visualization(rotation)
  - Recollecting from memory (counting)
  - Linguistic expression(letter)
  - Ideal state of brain(rest)



Research Statement

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  - **Perspective visualization(rotation)**
  - **Recollecting from memory (counting)**
  - **Linguistic expression(letter)**
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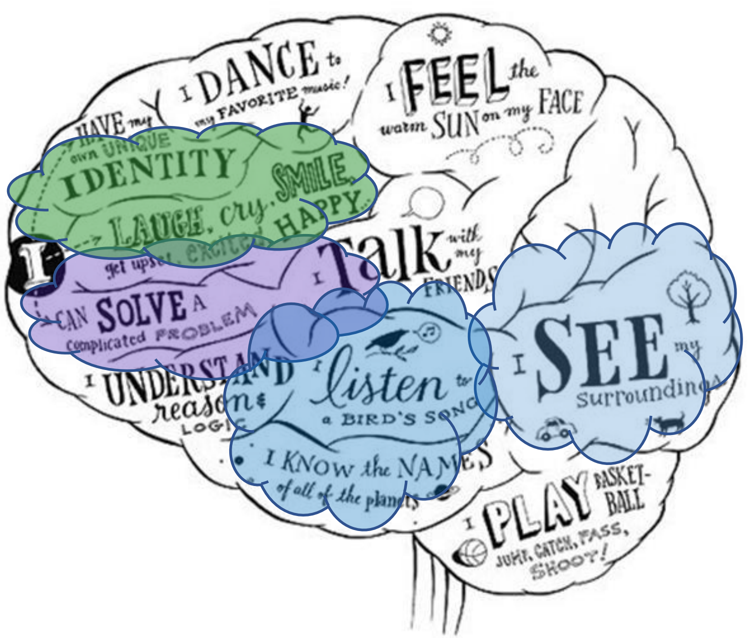
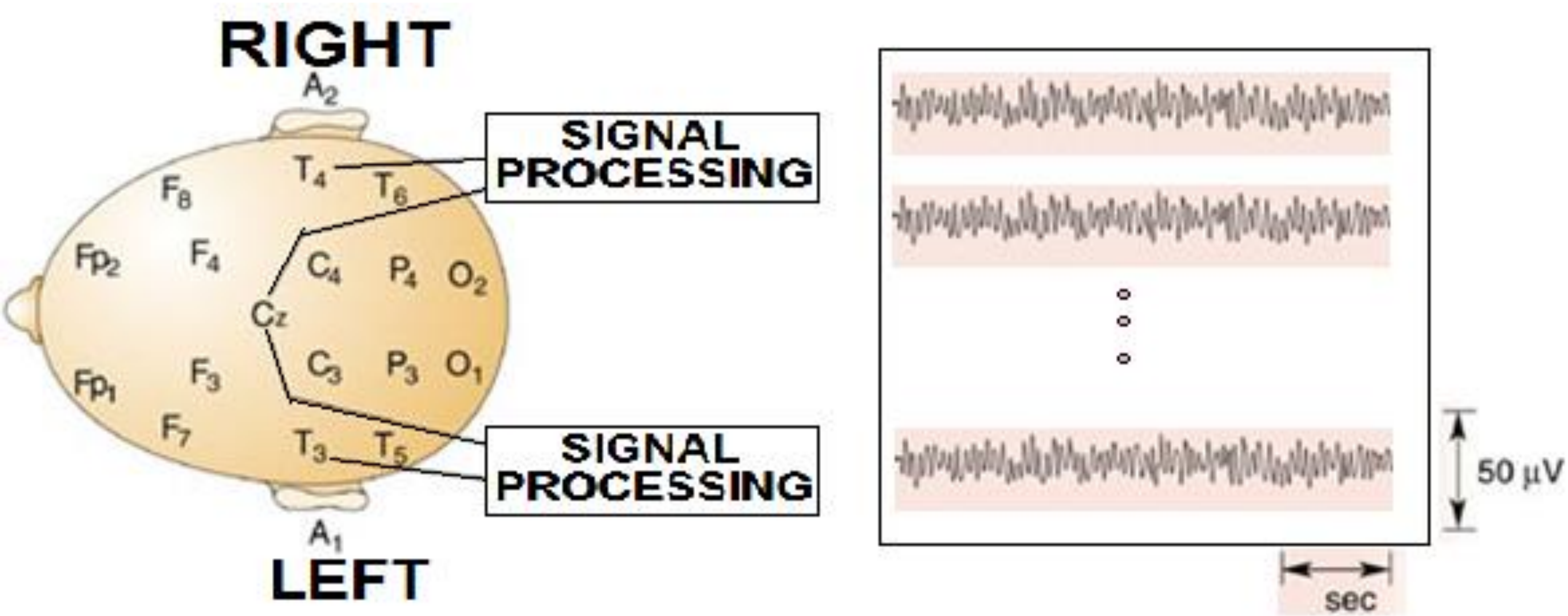


Why EEG….?

About electroencephalogram EEG

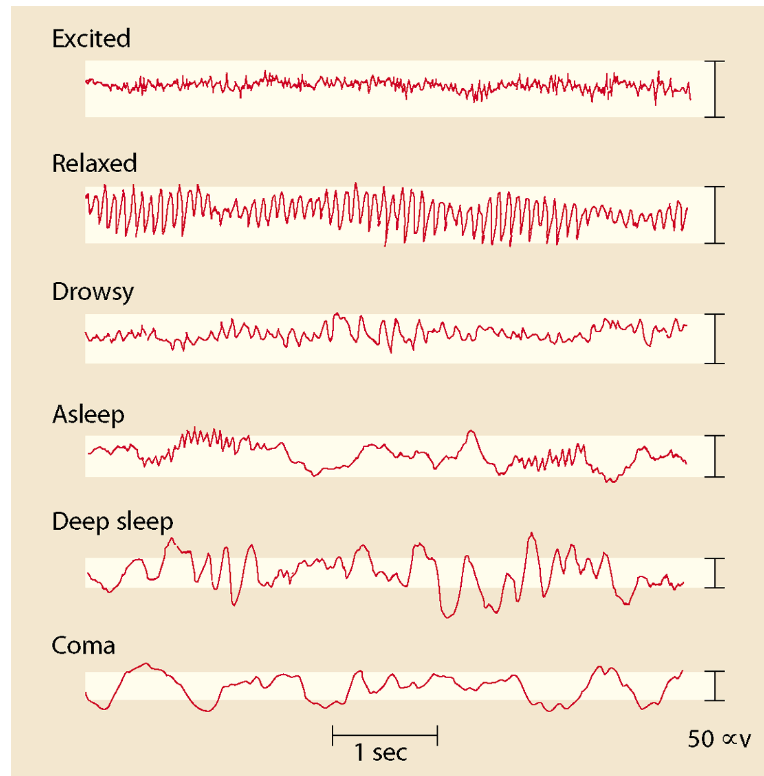
- EEG measures the activity of neurons.
- EEG recordings are noninvasive & painless, do not depend much on subject's ability to move or perceive stimuli.
- EEG having data which is having similarity.



Why EEG....?

Often exhibits rhythmic patterns in distinct frequency bands.

Gamma: 20-60 Hz
(cognitive thinking)
Beta: 14-20 Hz
(excited, tension)
Alpha: 8-14 Hz
(inactive awake ness)
Theta: 4-8 Hz (sleep stages)
Delta: less than 4 Hz
(coma/deep sleep)



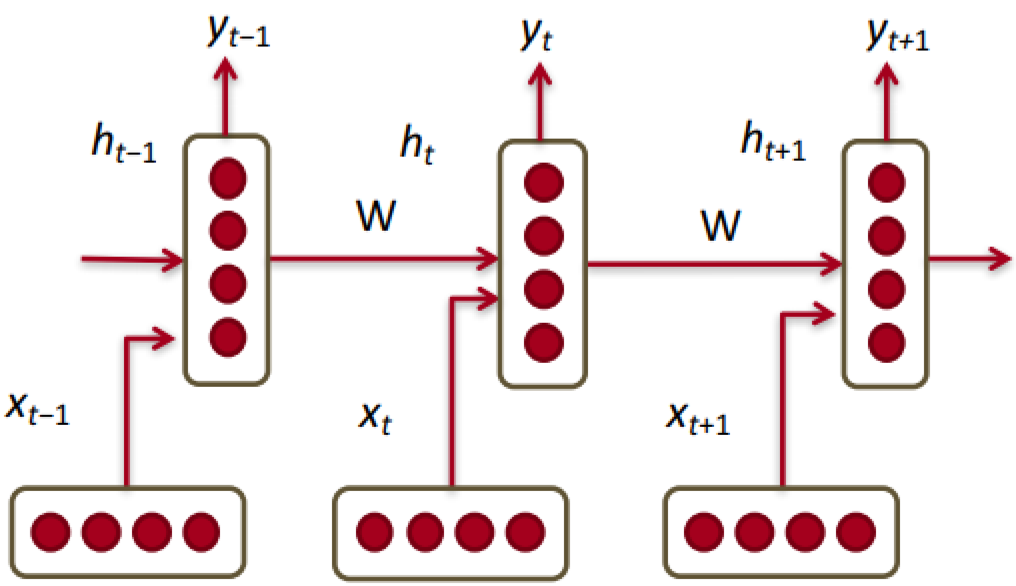
Why EEG….?

Most studied and suits well for interface based embedded system, mainly due to its ease of use and low set-up cost.

- Recently has become portable.
- Posses fine temporal resolution

Recurrent Neural Networks

- RNNs tie the weights at each time step
- Condition the neural network model on all previous frames/responses.
- RAM/ memory requirement only scales with number of frames



Recurrent Neural Network classification model

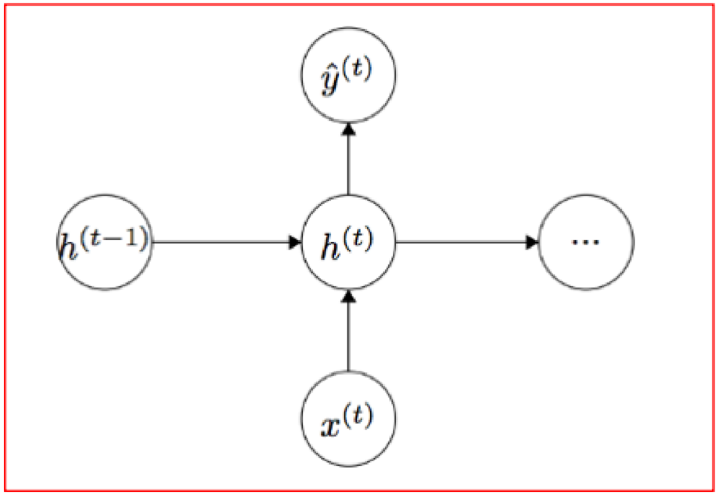
Given list of feature vectors: $x_1, \ldots, x_{t-1}, x_t, x_{t+1}, \ldots, x_T$

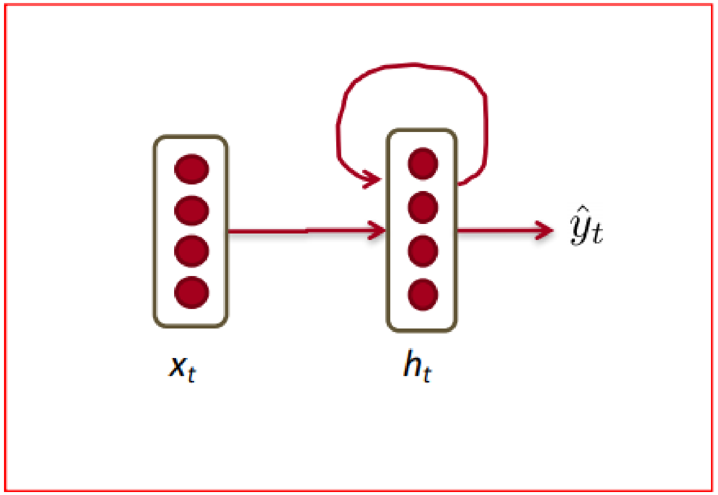
At a single time step:

$$h_t = \sigma\left(W^{(hh)} h_{t-1} + W^{(hx)} x_{[t]}\right)$$

$$\hat{y}_t = \operatorname{softmax}\left(W^{(S)} h_t\right)$$

$$\hat{P}(x_{t+1} = v_j \mid x_t, \ldots, x_1) = \hat{y}_{t,j}$$





Why RNN?

- RNN use for sequential data.
- EEG data is sequential.

About the database used for this study:

http://www.cs.colostate.edu/eeg/main/data/1989_Keirn_and_Aunon

-Experimental data is publicly available.

load_eegdata:

-eegdata_subjects = 's1' 's3' 's4' 's5' 's6'

-eegdata_tasknames = 'rest' 'letter' 'math' 'rotation' 'counting'

-eegdata_trials = 1 2 3 4 5

-eegdata_rows = 'c3' 'c4‘ 'p3‘ 'p4' 'o1‘ 'o2' 'eog‘

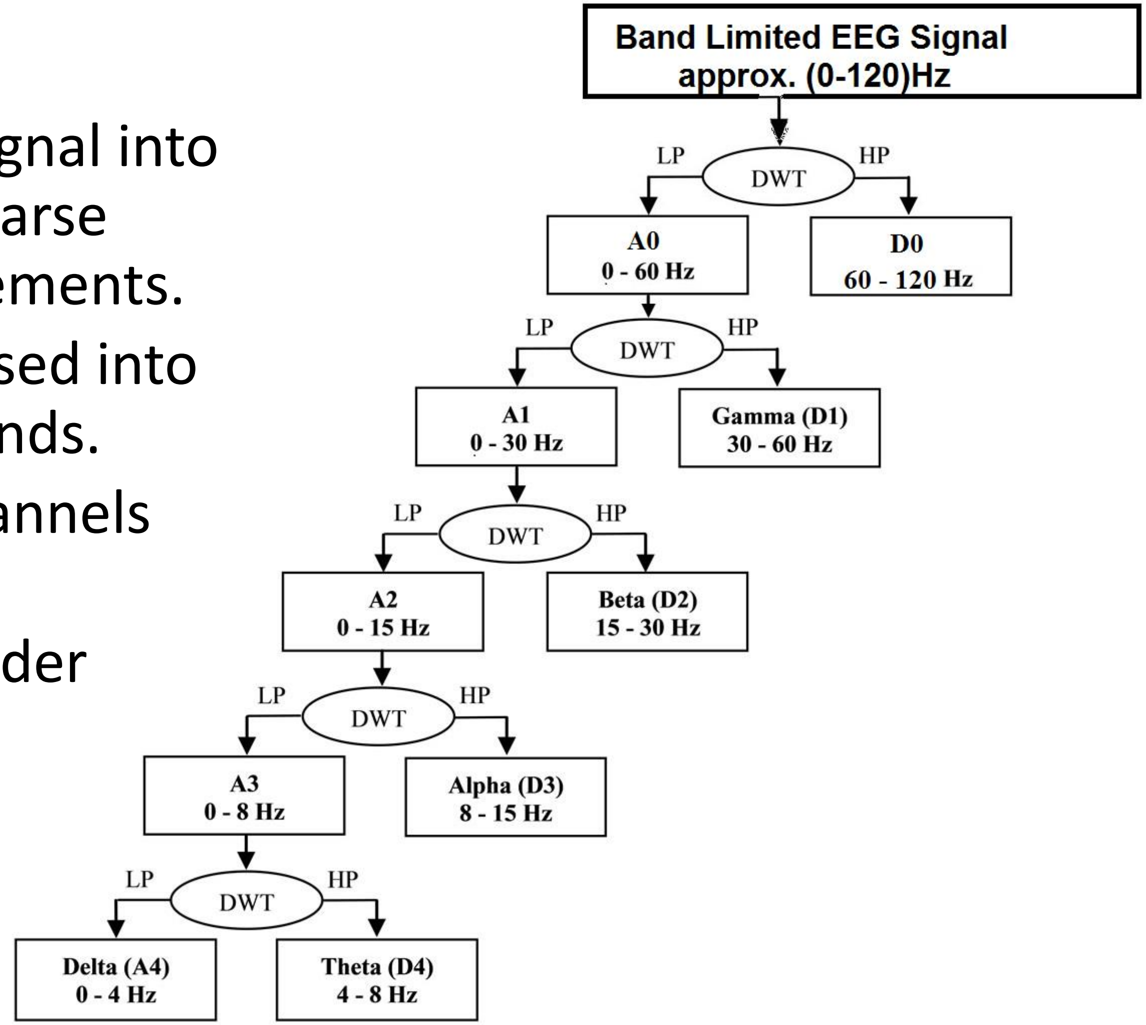
-No of Samples: 2500 (10secs @250Hz sampling rate)

EEG sub-band signals:

- DWT for EEG signal
  - Disintegrates input signal into fine detail (D_i) and coarse approximation(A_i) elements.
  - EEG signals are analysed into various frequency bands.
  - Applied on all the channels except EOG
  - In this work fourth order Daubechies (db4)

  wavelet filters

  have been used

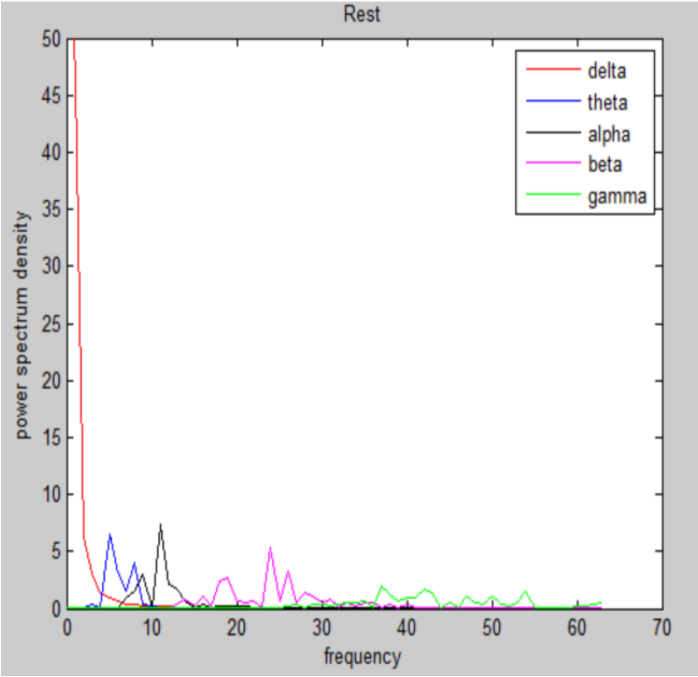


Cross-coherence:

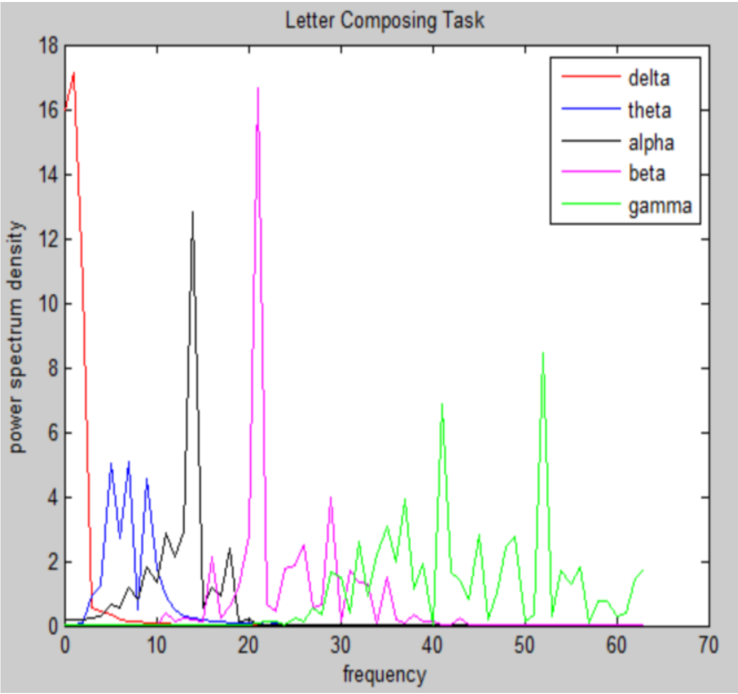
- The coherence of two waves expresses how well correlated the waves are as quantified by the cross-correlation function
- Cross coherence corresponds to coherence between corresponding locations of left and right hemisphere.

EEG Classification based on alpha-band:

- Power Spectral Density plots (P3-electrod)



Rest Condition

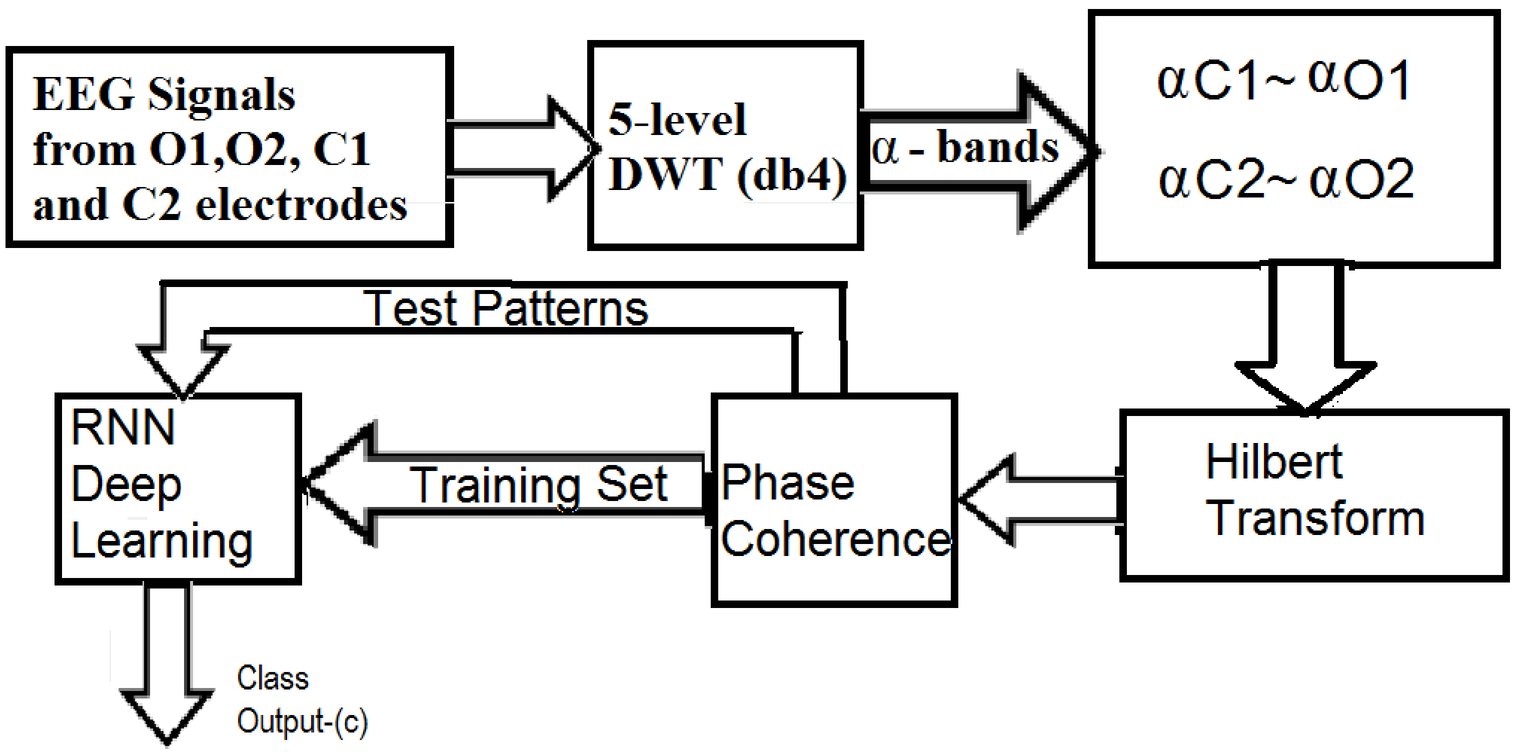


Letter Composition Task

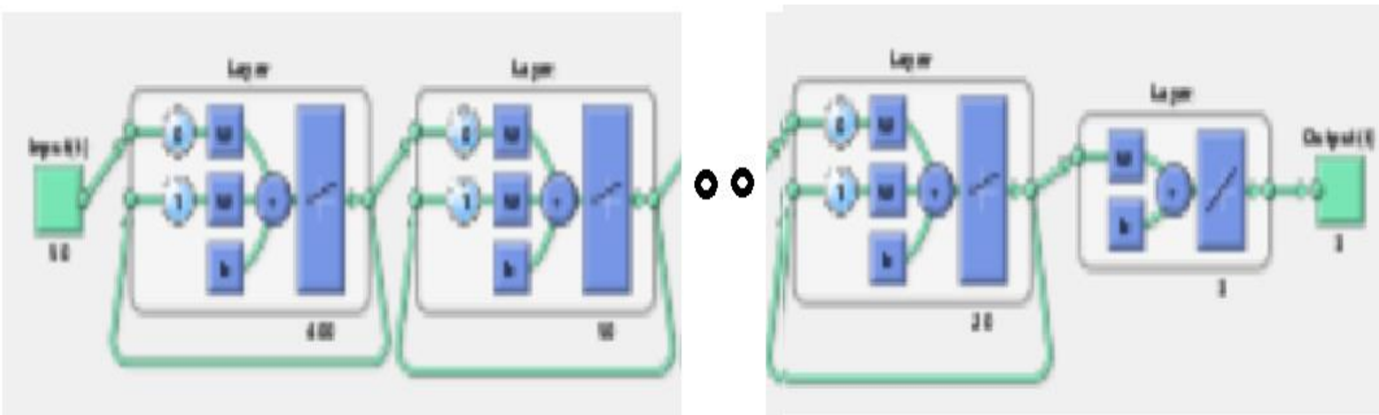
α-band exhibits:

- Energy compaction
- Intra class variation

Proposed EEG Classification Model:



Bottleneck Architecture of RNN:



- A bottleneck layer is a layer that contains fewer nodes compared to the previous layers.

- Bottleneck architectures are generally used for image compression and encoding applications.

- It is commonly used to obtain a representation of the input with reduced dimensionality.

- Conceptually bottleneck layer neurons are expected to convert the large dimensional features into lower variance and less overlapped clusters of sub-space features.

Proposed EEG Classification Steps:

- Proposed feature analysis method is based on coherence between alpha subbands coefficients extracted using DWT from central and occipital electrodes of left and right hemispheres.
- A 5-layer network with 53-400-50-200-20-T neurons is trained to classify the tasks, where 'T' corresponds to the number of tasks.

- RNN is trained to classify considering two, three or four different tasks at a time with 100 epochs.

- The database considered for this study has 65 instances for four activities. 25 instances are deliberated for testing and remaining 40 are considered for training.

- Output layer neurons compete with each other and only the neuron with the highest activation stays active while all other neurons are marked neutral. Decision is taken in favour of the class with maximum output.

$$Class(c) = \arg\max_{i} \{net_i\}$$

Confusion Matrix (2-tasks)

	Name of the tasks	
	MATH	***LETTER***
MATH	23	2
LETTER	3	22
ACCURACY=90%		

	Name of the tasks	
	ROTATION	***LETTER***
ROTATION	22	3
LETTER	3	22
ACCURACY=90%		

	Name of the tasks	
	COUNTING	***LETTER***
COUNTING	23	2
LETTER	3	22
ACCURACY=90%		

Confusion Matrix (3-tasks)

	Name of the tasks		
	LETTER	***MATH***	***ROTATION***
LETTER	19	4	2
MATH	2	21	2
ROTATION	2	1	22
ACCURACY=82%			

	Name of the tasks		
	ROTATION	***COUNTING***	***MATH***
ROTATION	21	2	2
COUNTING	3	21	1
MATH	3	3	19
ACCURACY=81%			

Confusion Matrix (4-tasks)

	Name of the tasks			
	LETTER	***MATH***	***ROTATION***	***COUNTING***
LETTER	20	4	0	1
MATH	2	20	1	2
ROTATION	3	3	18	1
COUNTING	2	2	2	19
ACCURACY=77%				

$$accuracy = \frac{TN + TP}{TN + TP + FP + FN}$$

Conclusion and future scope

- Here, RNN model is trained to identify the phase coherence patterns of EEG alpha-bands.

- Difference between EEG signals from central and occipital (C1-O1 & C2-O2) locations is considered to compute phase coherence patterns for various activities.

- Average accuracy attained is around 90% for two tasks, 82% for three tasks and 77% for all the four tasks.

- In future studies, we intend to improve RNN architecture and deal with other database and EEG classification problems.