ICA visualization, Topic 2

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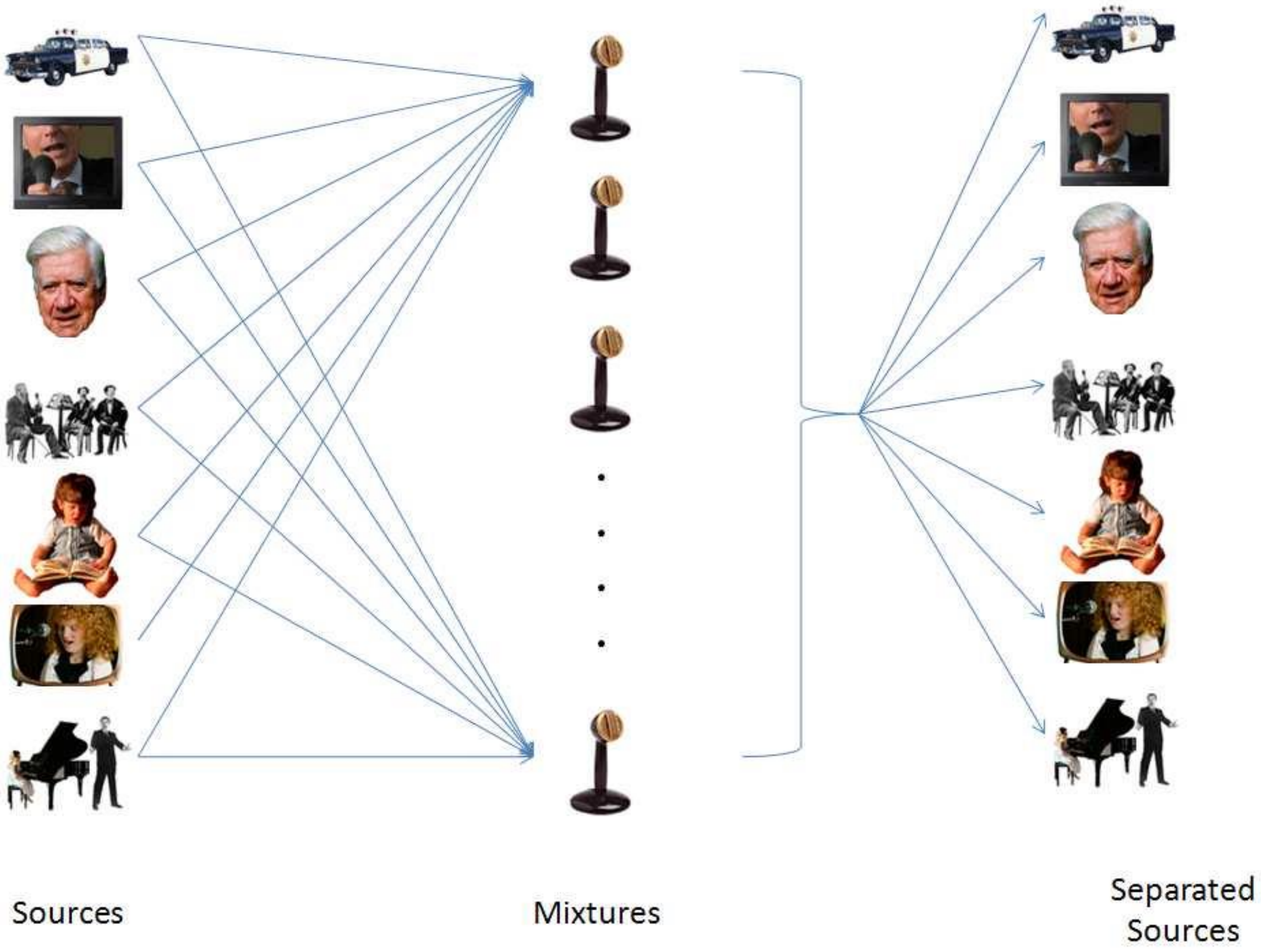
Overview

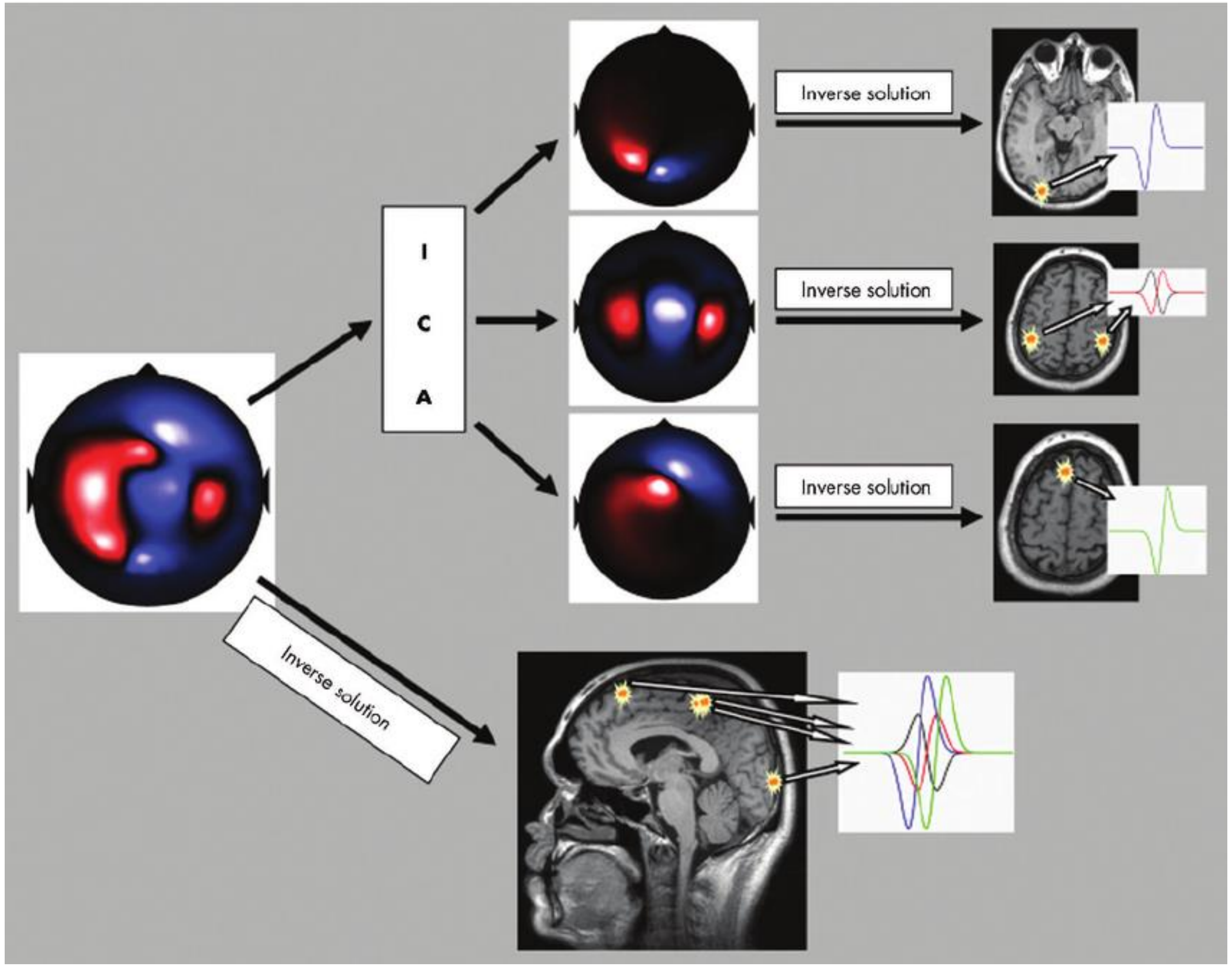
- What can be visualized (Chinmay)
  - Components and spectra
  - Images
  - Audio (time signals)
- Uses & Interpretation (Aria / Anette)
  - Artifact removal
  - Anomaly detection
  - Scalp maps (EEG)
- Code example 1(image) - Cameron
- Code example 2 (EEG) – (Preston)
- Challenges and limitations / (Johan / Saygin)
- Conclusion

Blind source separation



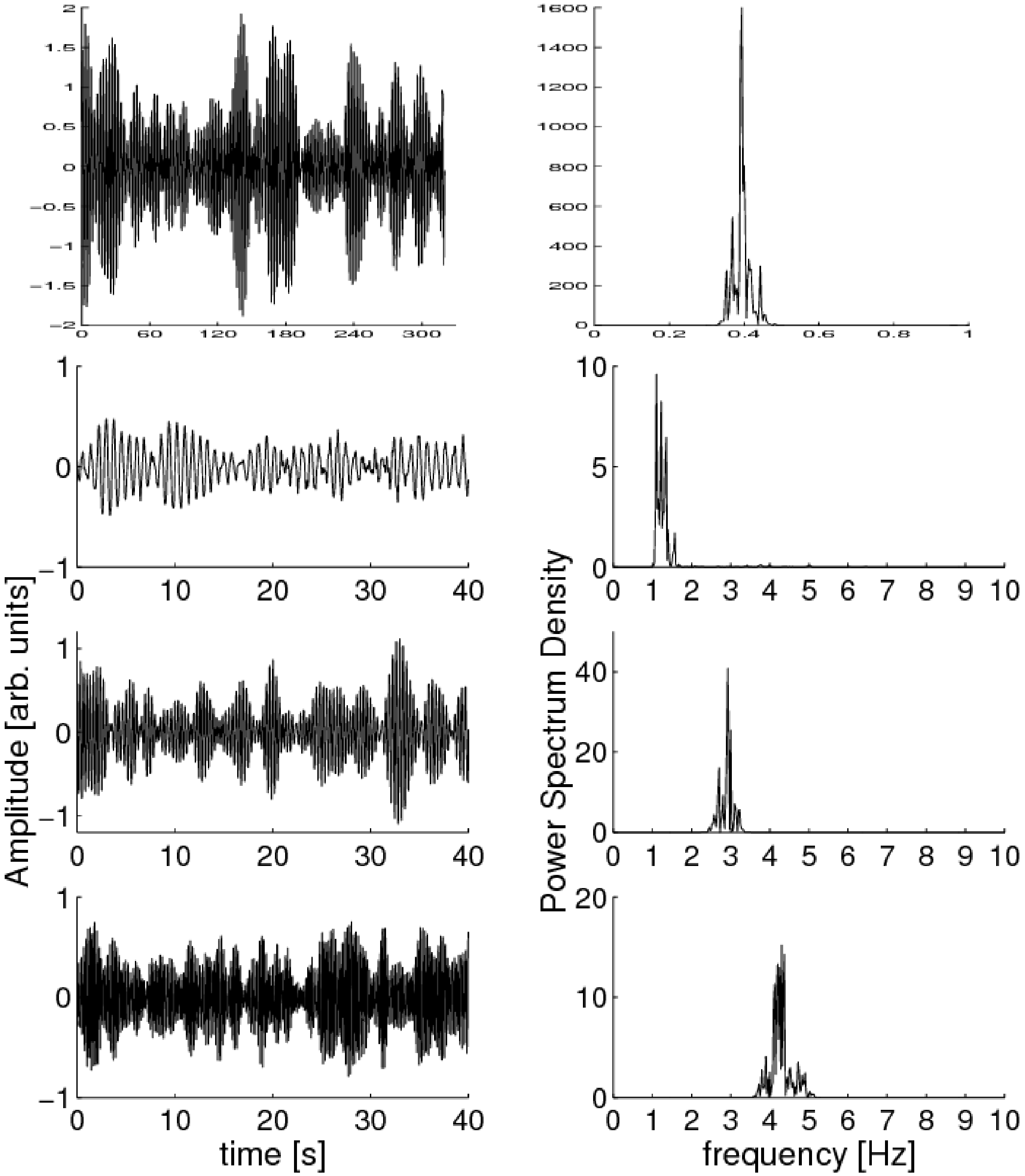
https://onionesquereality.wordpress.com/2010/01/30/blind-source-separation-in-magnetic-resonance-images/

Electroencephalography (EEG) Signal Analysis



Hobson, Anthony & Hillebrand, Arjan. (2006). Independent component analysis of the EEG: Is this the way forward for understanding abnormalities of brain-gut signalling?. Gut. 55. 597-600. 10.1136/gut.2005.081703.

Signal extraction



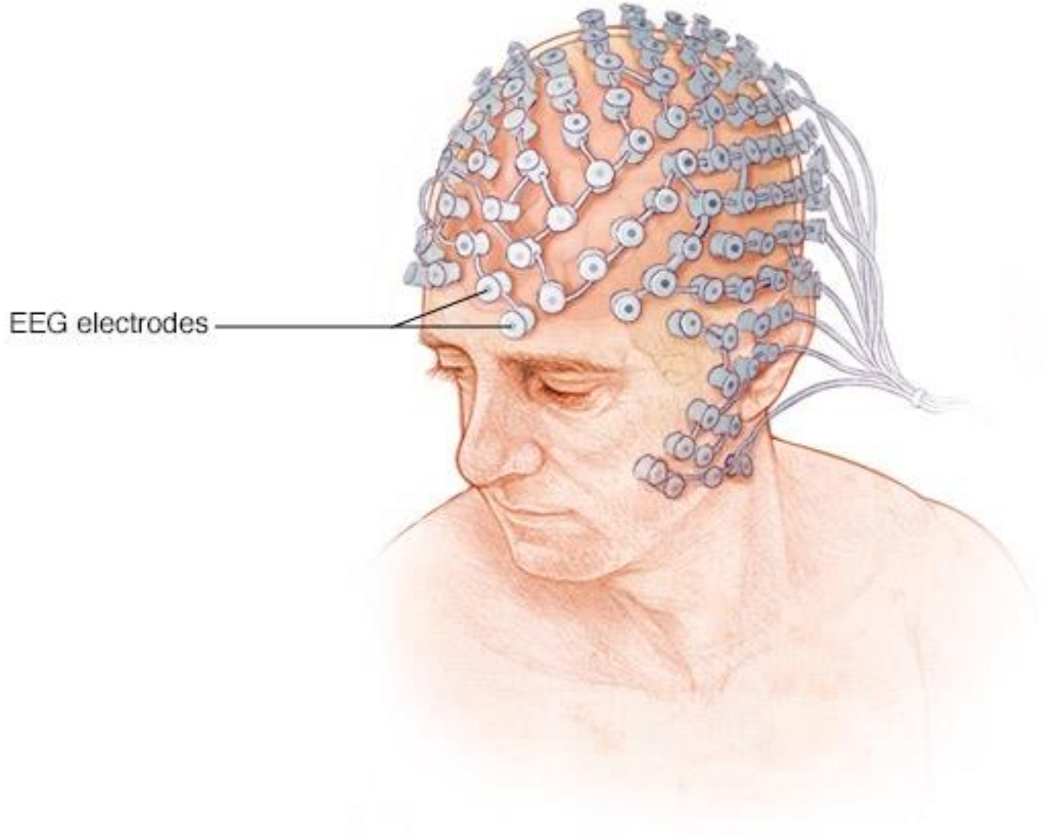
De Lauro, Enza & de martino, Salvatore & Falanga, M. & Palo, Maricel. (2011). Self-sustained vibrations in volcanic areas extracted by Independent Component Analysis: A review and new results. Nonlinear Processes in Geophysics. 18. 925-940. 10.5194/npg-18-925-2011.

Uses and Interpretation

- Artifact removal
  - The subject moves or blinks during an eeg recording.
- Anomaly detection
  - Find signals that lie outside the regular scope
- Scalp maps (EEG)
  - See where the signal originates in the brain.
- Separation of audio signals
  - Cocktail party
- Image processing
  - Image compression, feature extraction
- https://mne.tools/stable/auto_tutorials/preprocessing/40_artifact_correction_ica.html

Electroencephalogram (EEG)

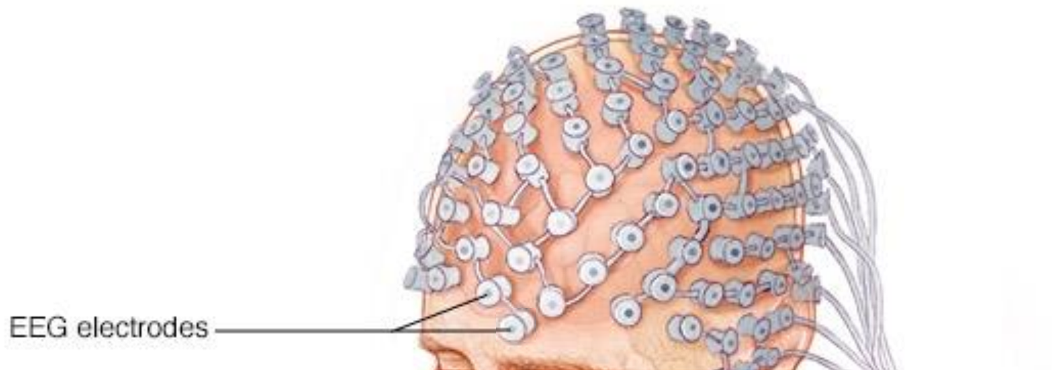
- A test that measures electrical activity in the brain
- Small electrodes are attached to scalp
- Measures electrical impulses of the brain

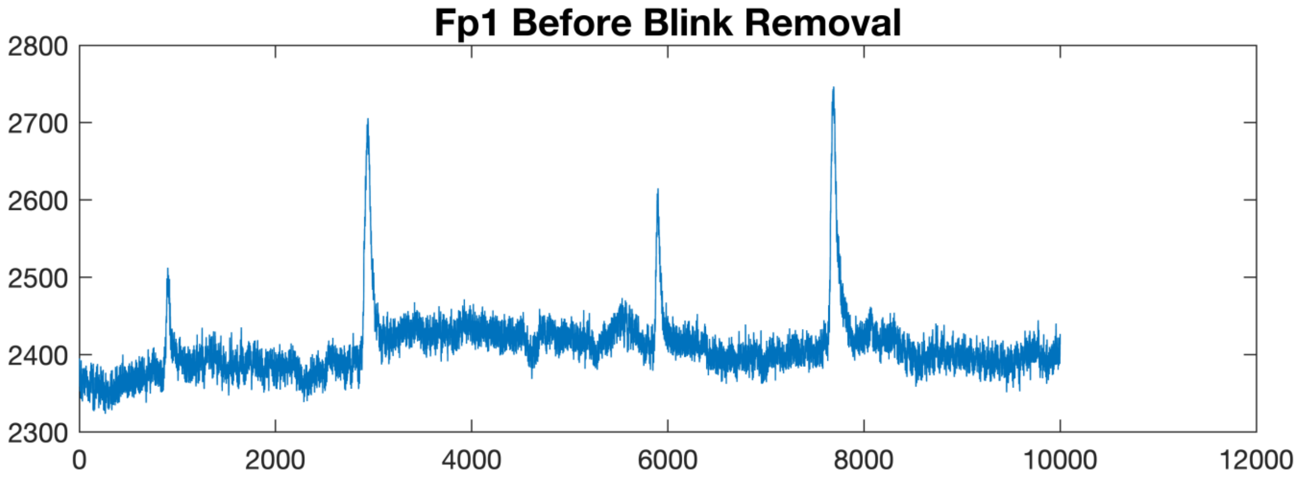


Code source: https://github.com/ShawhinT/YouTube-Blog/tree/main/ica

Artifact Removal

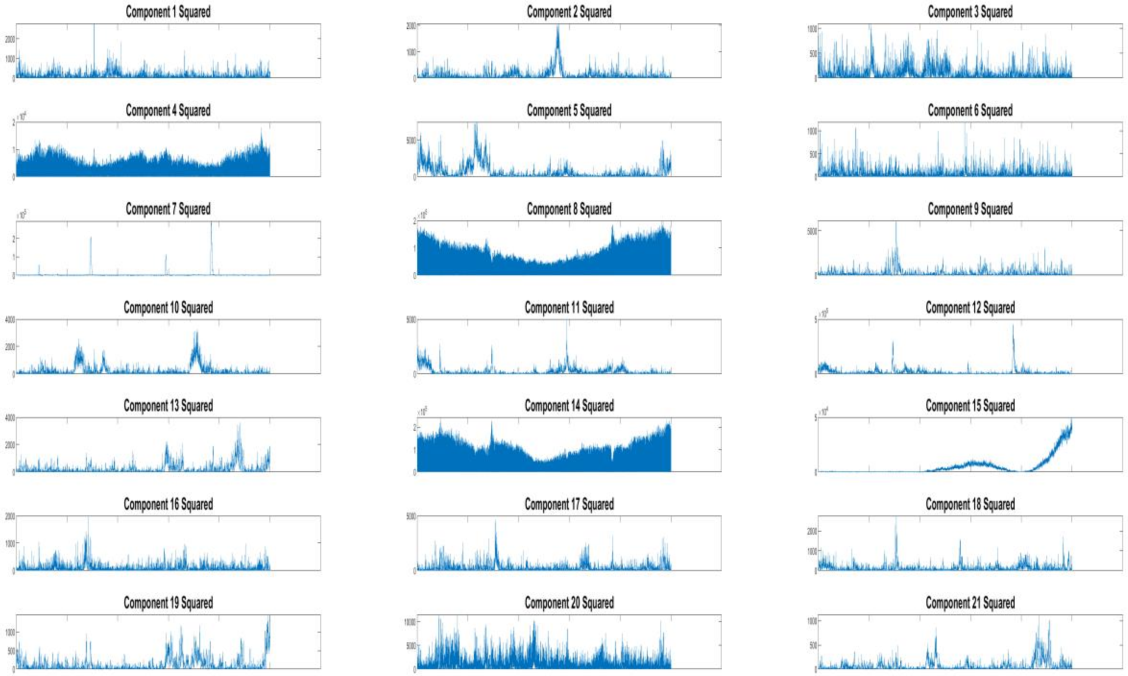
- EEG measures weak electrical signals from the brain
- Muscle movement (blinking) is a much stronger electrical impulse





Using PCA with ICA

- Why do PCA before ICA?
  - Whiten (sphere) the data
  - Removes any correlations
  - Helps ICA converge faster
- Compress the data from the 64 electrodes down to 21 components using PCA



Remove the blinks

```
% use heuristic to pick component corresponding to blink
Components_blink = pickBlinkComponents(Data_ICA);
disp("Blink component(s):")
```

```
Blink component(s):
```

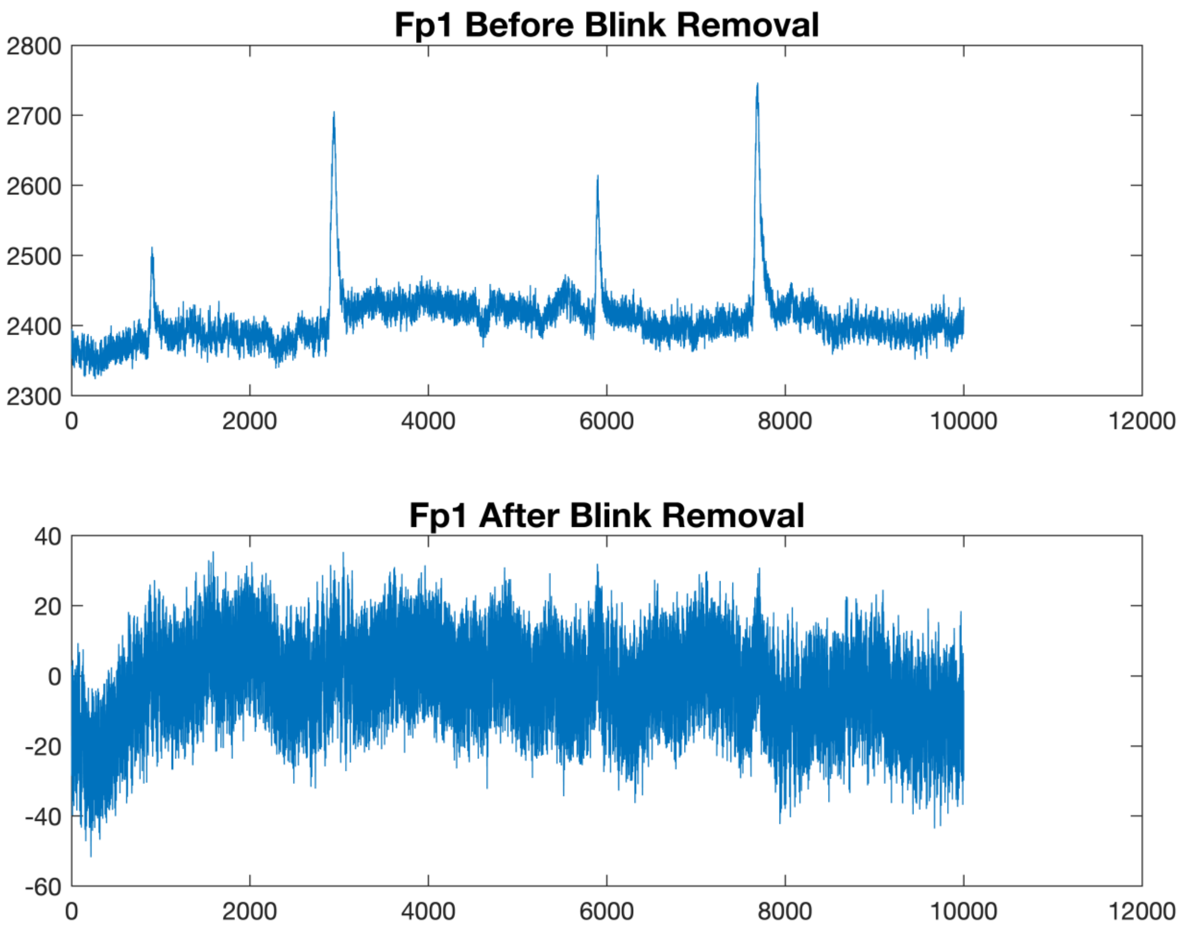
```
disp(Components_blink)
```

```
     7
```

```

% zero all columns corresponsing to blink components
Data_ICA_noBlinks = Data_ICA;
Data_ICA_noBlinks(:,Components_blink) = ...
    zeros(length(Data_ICA), length(Components_blink));
```

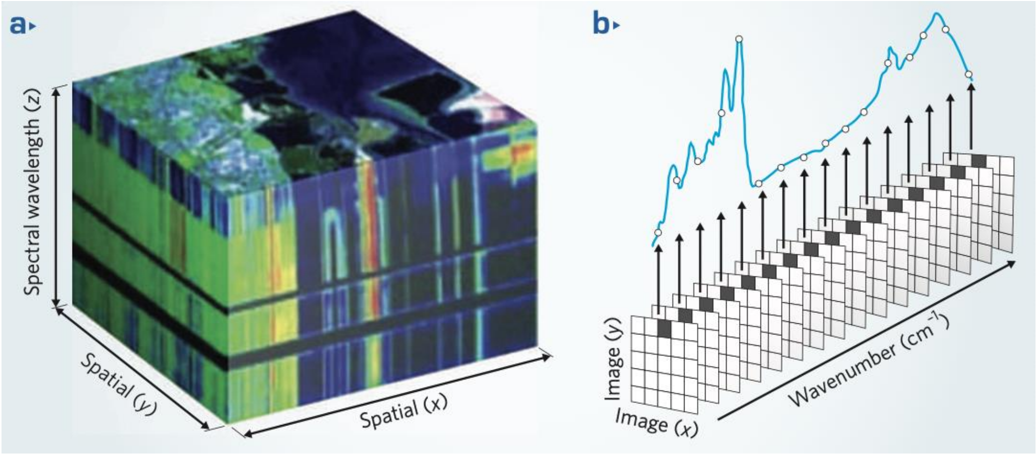
Unwrap your data ICA -> PCA

```
% perform inverse ica transform
Data_PCA_noBlinks = Data_ICA_noBlinks*Mdl.TransformWeights;

% perform inverse pca transform
Data_noBlinks = Data_PCA_noBlinks*coeff';

% plot Fp1 electrode before and after
figure(3)
subplot(2,1,1)
```

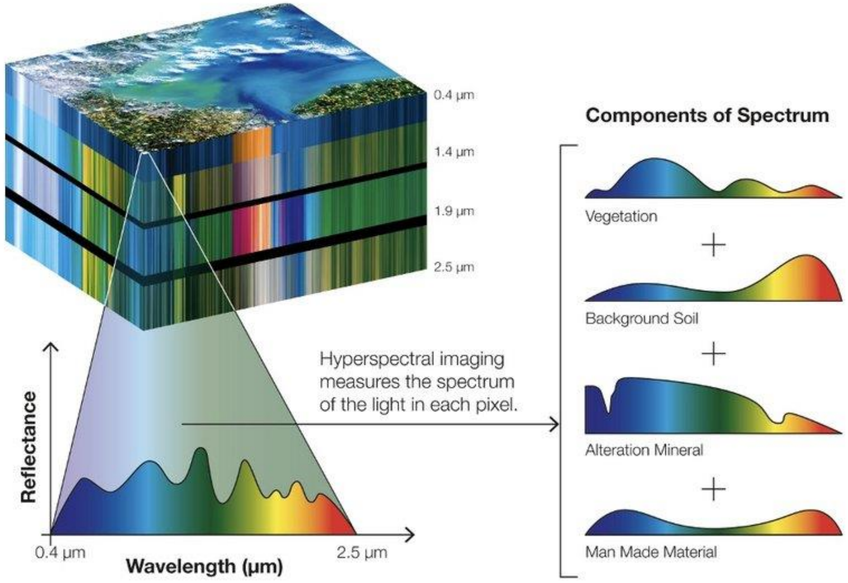


Example – hyperspectral image

- Hyperspectral image: spectral info across a continous spectrum

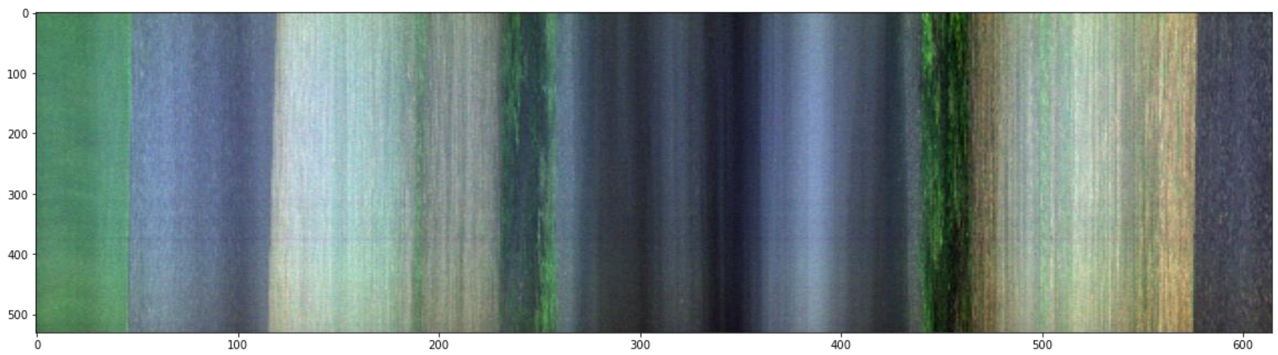


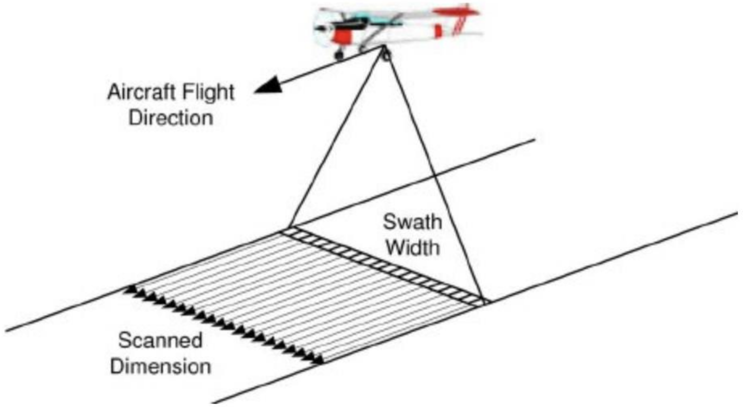
- Spectra in the image are mixtures of spectra from multiple sources or materials



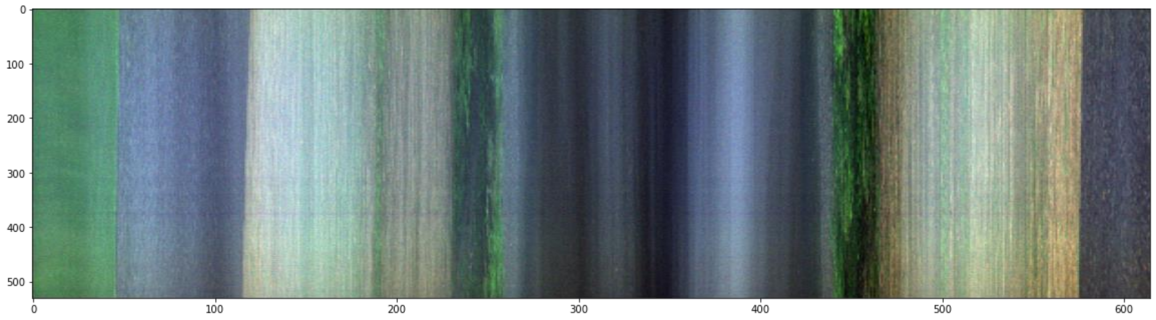
Example – hyperspectral image

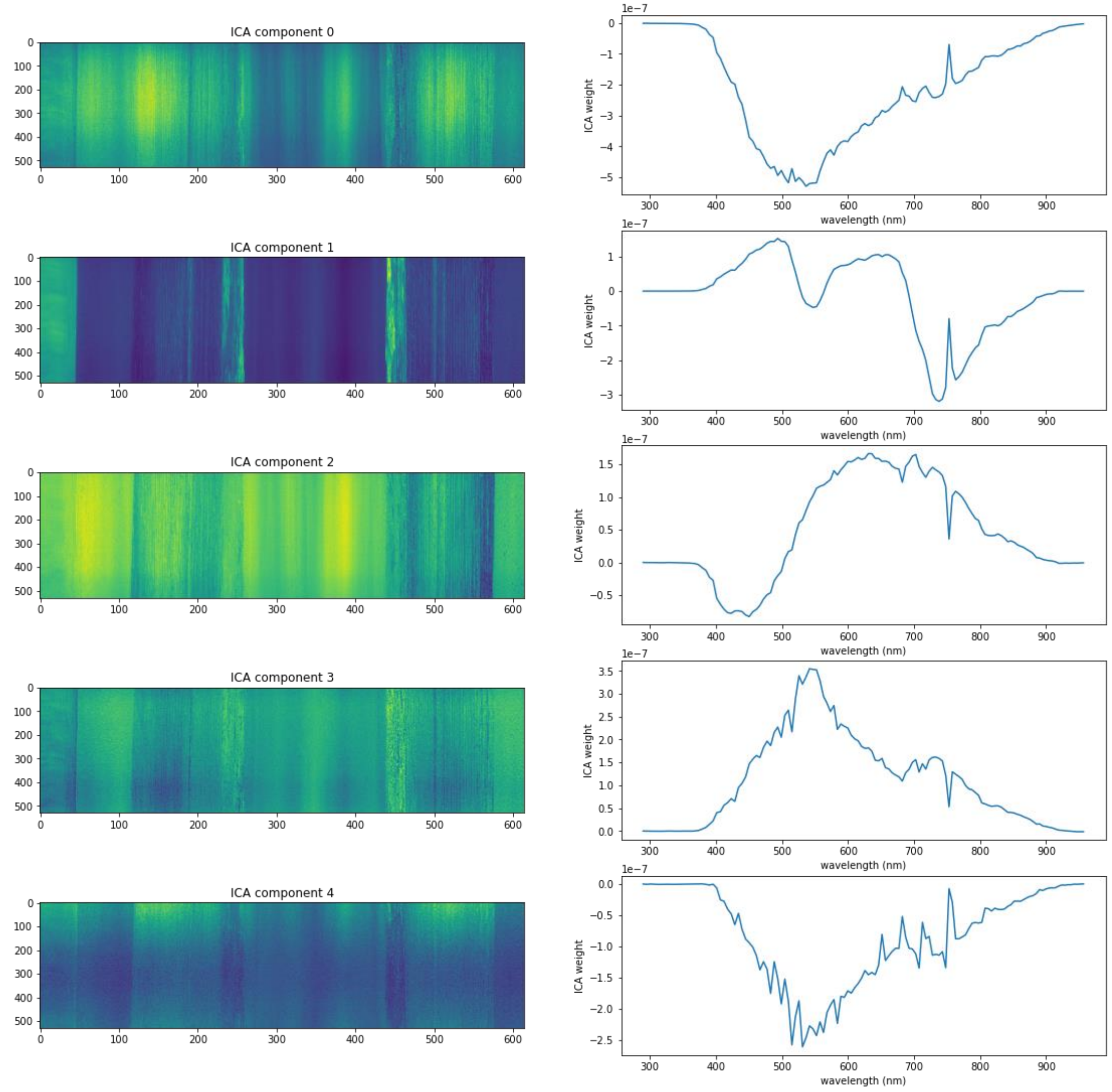
- Image aquired using hyperspectral camera on a drone
- Farm field and river





Example – hyperspectral image





Challenges

- Overfitting: when the number of independent components is too high. We need validation techniques and domain knowledge.
- Nonlinear Mixing: if the actual mixing process is nonlinear, ICA may not perform optimally. Check non-linear ICA variants or other techniques.
- Sensitivity to Initial Conditions: try running the algorithm multiple times with different initializations and selecting the best result.
- Model Assumptions: ICA assumes independence and non-Gaussianity of sources. Deviations from these assumptions can affect the quality of the results.
- Noise Sensitivity: Can extract noise components as independent components leading to complications in analysis

Conclusion

- A useful tool to identify/separate independent sources in a multivariate dataset
- Helps understand better the hidden structure of data
- Used in a variety of fields: signal process, brain imaging, finance..
- Assumes non Gaussianity, independence and linearity of sources in data
- Needs attention for initial conditions and noise in data