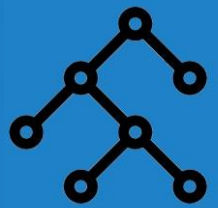
Temporospatial patterns in neural signals at different stages of alertness

Computer vision and machine learning for the analysis of neuroimaging data

Michael Gerstenberger 2020



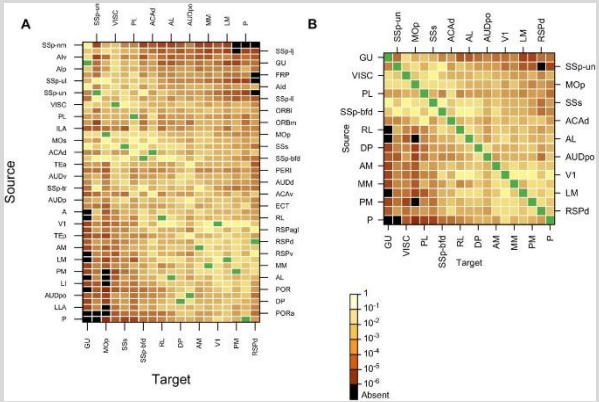
Motivation

Functional division of brain vs. Highly recurrent nature (Regions interact)

→ Spatial patterns of neural information integration?

Correlation strength of neural activity reveals default mode network

→ Temporal dynamic of information integration beyond correlation?



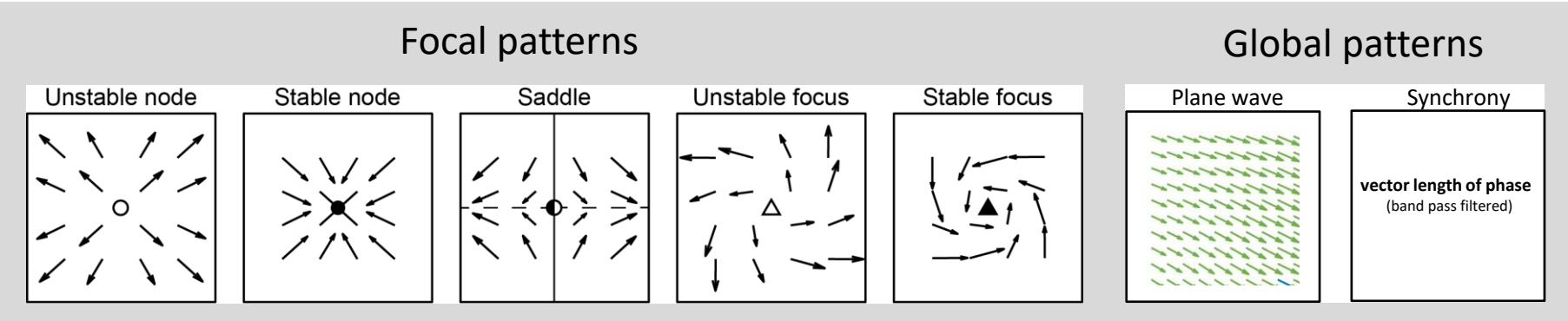
Weighted connectivity matrix (Gămănuţ et al. 2017)

- Modes of local information integration? State transitions (e.g. at slow wave sleep; local or temporal)?

To understand how brain regions interact we need to analyze temporospatial patterns

How to quantify temporospatial dynamics?

The spatial patterns Tunsend and Gong (2017) suggest measuring specific patterns in dense optical flow



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- The suggested definiton allows for the detection of patterns irrespective of their orientation

Patterns in vector fields can be arbitrarily defiend and measured accordingly

How to quantify temporospatial dynamics?

			feature engineering				
data / classification		**Raw data (/little preprocessing)**	**Focus: Most substantial effect**		**Focus: Details**		
			Optical flow	Contrast enhanced	Optical flow	Cluster tracking	Contrast enhanced
Detect predefined patterns (Tunsend & Gong)		x	✓	?	✓	?	(✓)
Data driven: Autoencoder	**Regional**	✓	✓	✓	✓	✓	✓
	Global	✓	✓	✓	✓	✓	✓

Data driven approaches are more flexible; There are many options

Interest of research

(1) How can temporospatial patterns in neural recordings be retrieved?
(2) Are there specific patterns that correlate with stages of alertness? What do temporospatial patterns reveal about the dynamics of information processing at different levels of anesthesia?

Temporospatial patterns & optical flow

What are temporospatial patterns?

> “population-level brain activity is often organized into propagating waves that are structured in both space and time” (Townsend & Gong 2018)

In an ideal world we would be able to trace how information flows between numerous neurons
→ Temporospatial patterns can be visualized as vector fields

In reality even with high speed optical imaging and dense optical flow estimation statements can be made only for populations of neurons
→ Temporospatial patterns must not be confused with “velocity fields”(Tunsend & Gong 201)

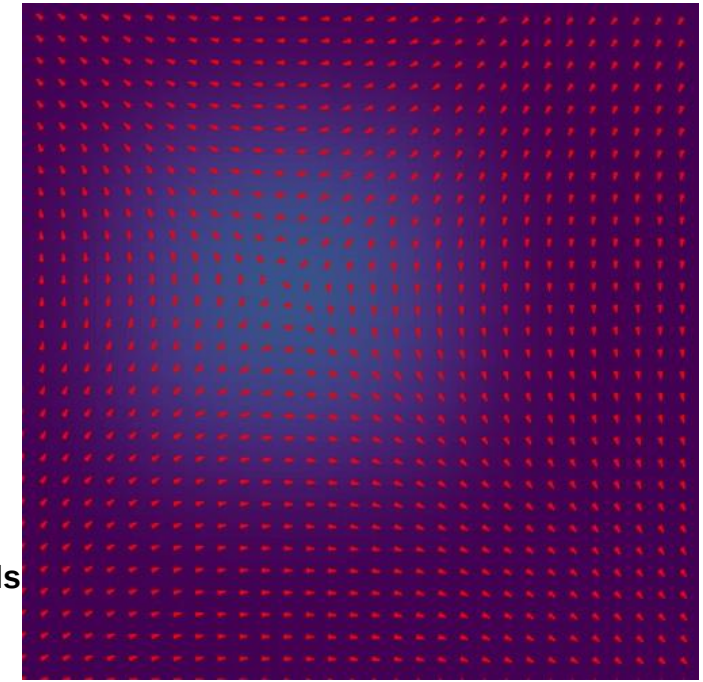
Temporospatial patterns indicate a change in the state of the brain over time

What does dense optical flow (Horn & Schunck) measure?

Minimize Energy functional $E = \iint \left[(I_x u + I_y v + I_t)^2 + \alpha^2 (\|\nabla u\|^2 + \|\nabla v\|^2) \right] \mathrm{d}x\mathrm{d}y$

I_x, I_y and I_t are the derivatives of the image intensity values along the x, y and time dimensions

$\vec{V} = [u(x,y), v(x,y)]^\top$ is the optical flow vector



→Horn & Schunck's method is based on the gradient in time

- Focal patterns like saddles arguably relate to a rising peak (see simulation)
- Spirals might relate to activity that increases at some part of the neighbourhood and decreases at others.

→ **Patterns in dense optical flow do not necessarily capture motion**
→ **Focal patterns do arguably not relate to velocities of travelling signals**

Why optical flow?

- **Optical flow fields indicate temporal dynamics of the brain** (e.g. decrease in V1 increase in V2 stable at M1)
- If there is a transition of peak activation between areas (e.g. frontal and occipital) optical flow may indicate the direction of travelling waves

How does optical flow relate to gradient for data with no motion but growing peaks?

Regional scale vs. global scale?

Regional scale: Classification and detection of temporospatial patterns with autoencoders

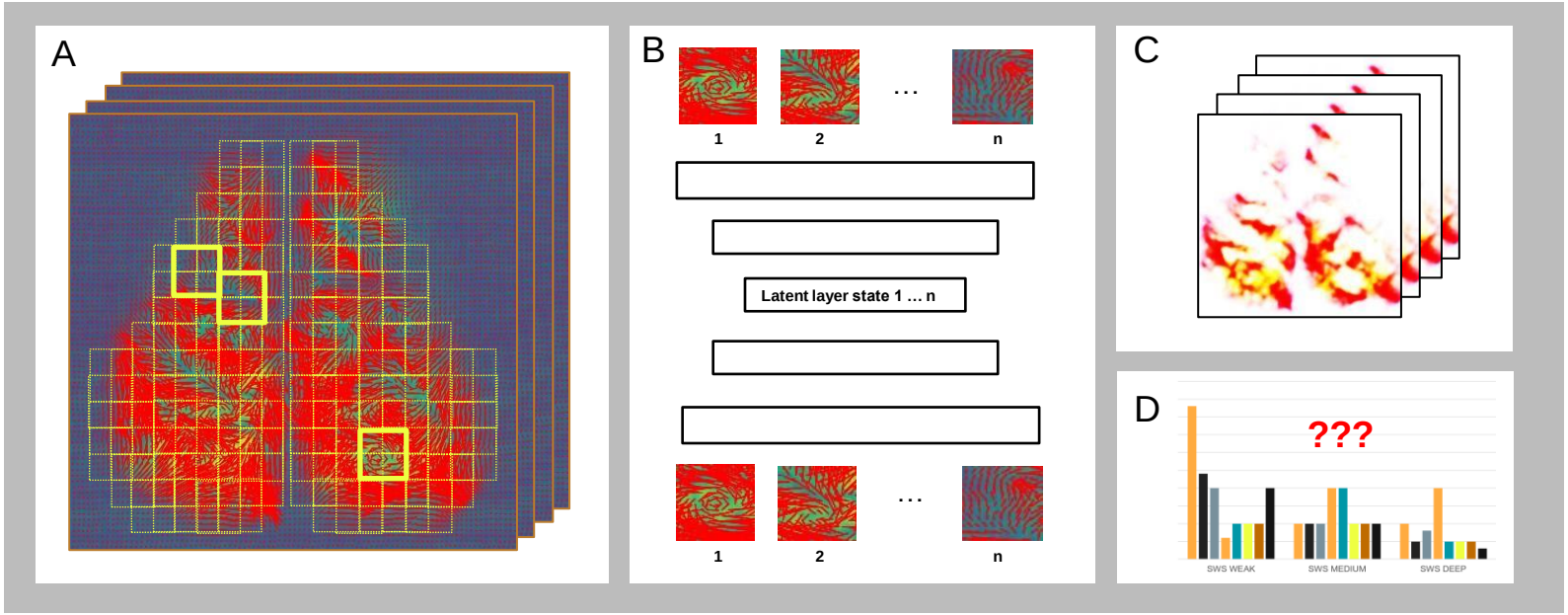


Fig 1: **Schematics for the detection and classification of temporospatial patterns using autoencoders**

A: Sampling of patches in the optical flow (/motion fields)

B: Using a convolutional variational autoencoder for unsupervised pattern classification

C: Density heatmaps for different patterns

D: Probability of the presence of different patterns during different stages of alertness (slow wave)

Global scale: Whole brain autoencoder for visualization of dynamical state transitions

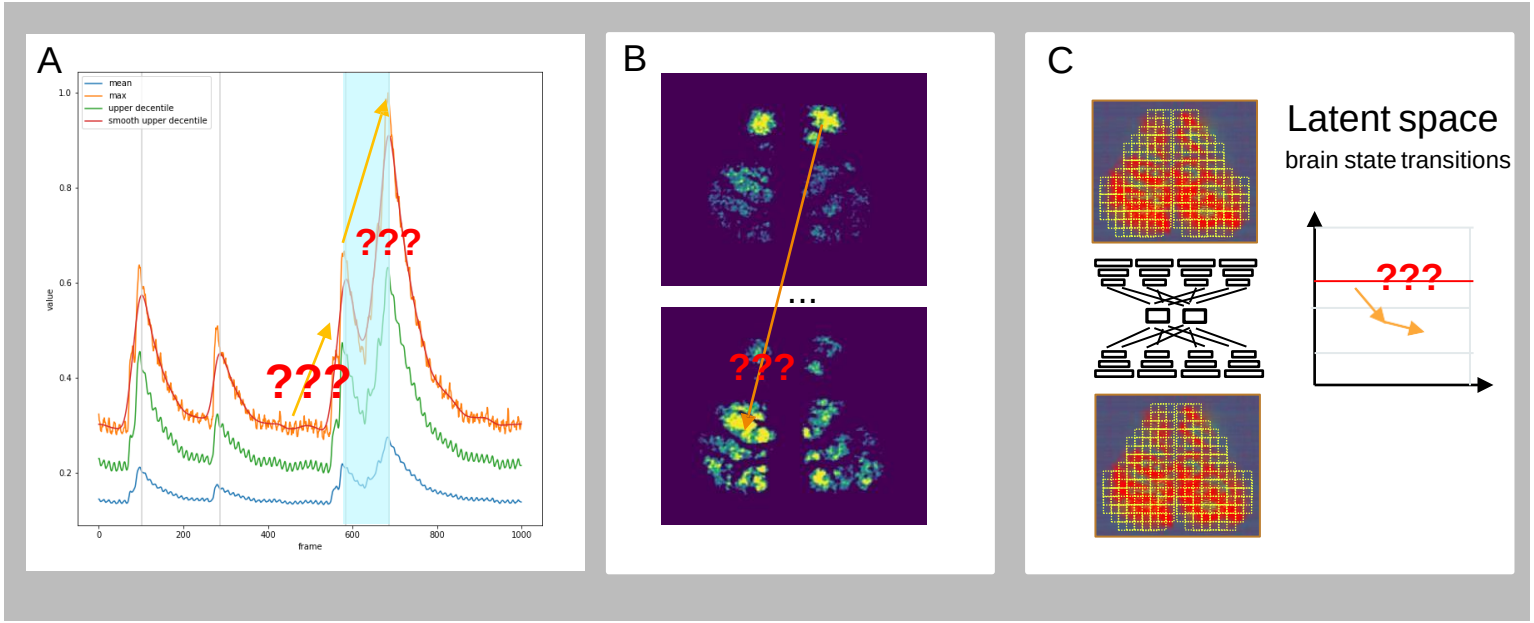


Fig 1: **Autoencoders as a tool for the analysis of state transitions in latent brain state space**

A: Temporal dynamics of slow wave event

B: Spatial dynamics of slow wave event

C: Whole brain autoencoder reveals latent space of brain state transitions

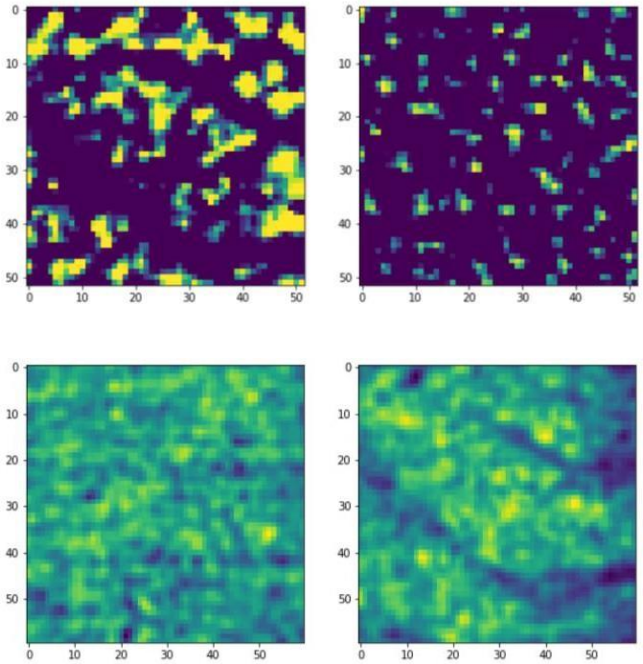
Details
(and cluster tracking)

vs.

Most substantial effect
(and optical flow)

Computing vector fields: Tracking microscopic patterns

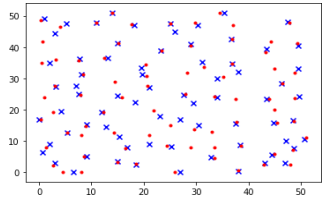
Details vs. Bloodflow (16Hz)

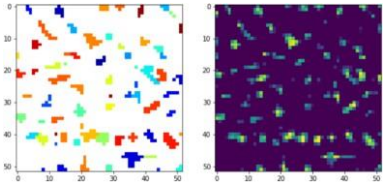


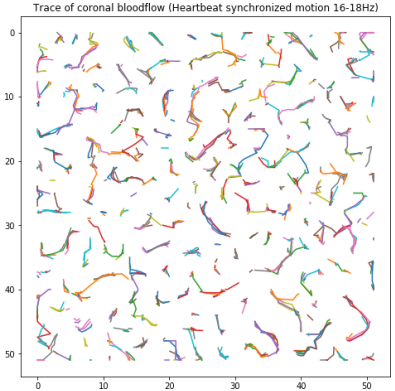
Is it all due to bloodflow? How find out?

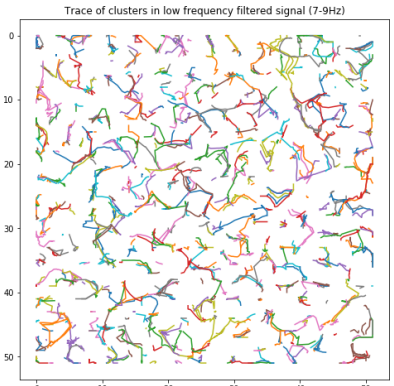
A custom approach allows for clustering and tracking

- Clustering is achieved using a mean shift technique in a density based approach
- Tracking is based on the location of the cluster centres





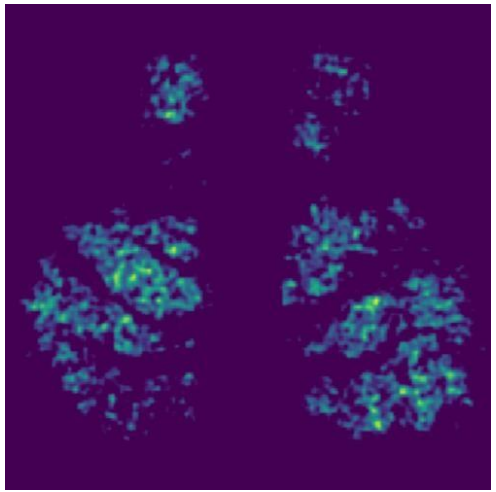




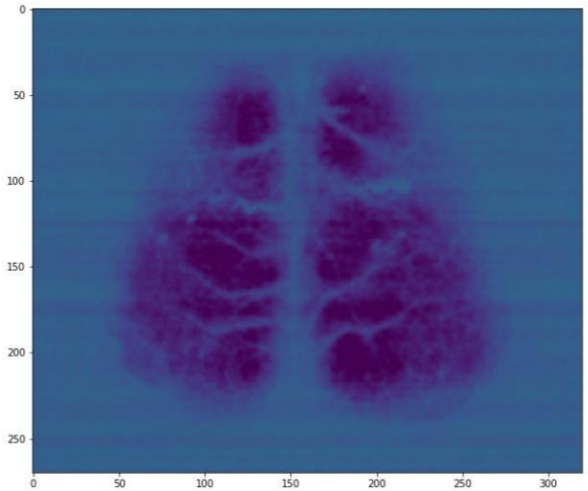
One may retrieve trajectories for different frequencies/ vessels of different size

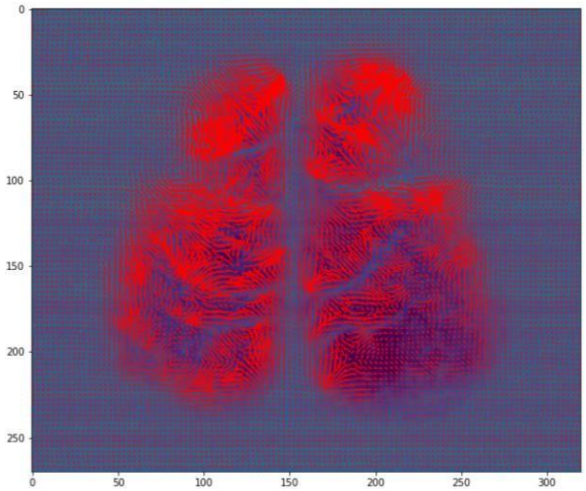
Computing vector fields: Optical flow for macroscopic patterns

Upper decentiles



First PCAs and Horn Schunck





Open questions:
Is Horn Schunck sensitive to anatomical structures? How to deal with that?
Are patterns visible for the other conditions also or only when slow waves occur?

A metric for the complexity of brain activity

A metric for the complexity of brain activity

- The Perturbational Complexity Index is computed by compressing the (EEG) response to (TMS) stimulation
- Autoencoders can be considered a compression technique. One can get a sparse representation of the signal using an autoencoder trained on the vector fields. The latent layer activation can e.g. be discretized and compressed using RLE. The entropy of the sparse representation can be computed.
- If one finds a higher compression ratio for deeper levels of anesthesia one may argue that it‘s justified to assume a less complex brain state

One may apply a complexity metric on the sparse representation retrieved by autoencoders

Literature

Gămănuţ, R., Kennedy, H., Toroczkai, Z., Van Essen, D., Knoblauch, K., & Burkhalter, A. (2017). The mouse cortical interareal network reveals well defined connectivity profiles and an ultra dense cortical graph. bioRxiv, 156976.

Notes on open questions / possibilities

. . .

Ehance data (flip & rotate) aiming at detection of rotation invariant patterns?

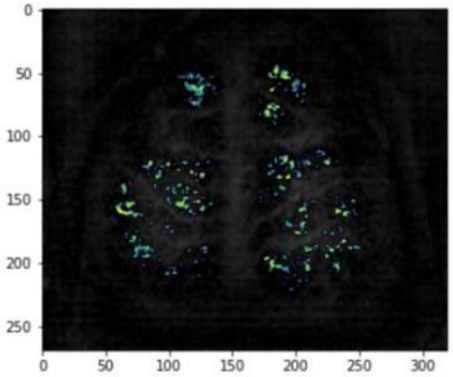
If one wants to detect rotation invariant features? How do that with autoencoders?

Preprocessing & vector field computation

Removing details results in more robust yet rather less complex measures

- How many details should be removed
  (e.g. do anatomical features have an effect on the optical flow)?
- One can try removing vascular blood flow by removing PCA components that correlate with the heartbeat or removing the respective frequencies in from the pixel-vectors using FFT.

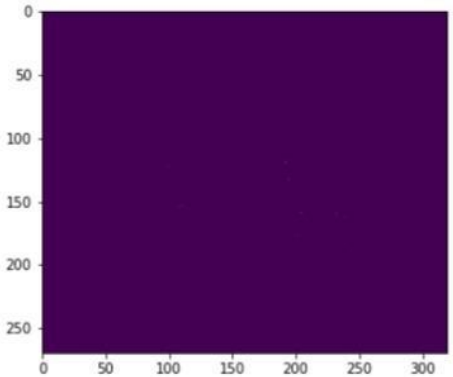
Open question: What is the best way to go here?



Filtering details results in complex patterns.

(+) If it is possible to remove undesired effects one would be able to correlate the overall level of activity (alertness) with patterns of information processing e.g. during up and down-states of slow wave sleep (!!!).

(-) However details are strongly confounded by vascular blood flow **(blood only?)**



Sampling windows at different locations or using the whole brain recordings?

→ **Training on patches; using pretrained autoencoder for whole brain encoeder!**

- Training of autoencoder tied to spacial region
  - Whole brain recordings & Variational autoencoder:
    - (+) Possibility to track transitions between brain states in 2D latent space
      - Investigate for which brain states a second peak occurs
  - Region of interest based analysis
    - (+) Impact of vessels on optical flow is less important
- Training of autoencoder for random samples of motion vectors
  - (-) Impact of vessels on the shape of the optical flow (If one finds differences between conditions it's hard to understand what they relate to)
  - (+)Possibility to perform pattern detection and retrieve heat-maps for different patterns. Then correlate with level of anesthesia (It's clear that there will be more saddles for slow wave sleep because of the growing peaks).
  - •Using single or multiple scale input?