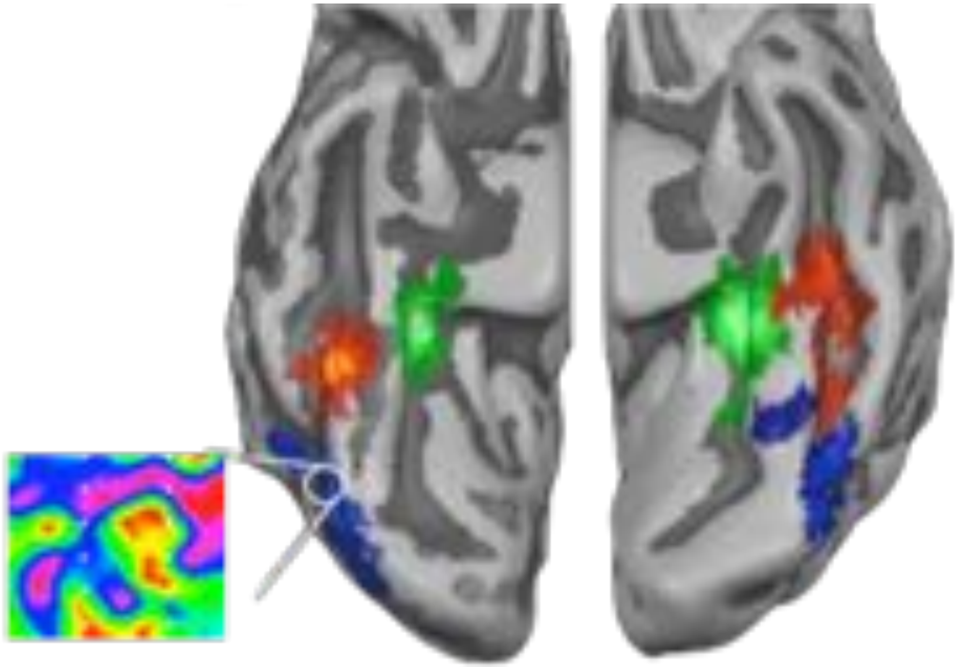
Multi-Scale Functional Brain Imaging:

New Insights for Biological Models of Cognitive Functions

7T



Rainer Goebel

Maastricht Brain Imaging Center (M-BIC), Dept. of Cognitive Neuroscience, Maastricht University & National Institute of Neuroscience (NIN) of the Royal Netherlands Academy of Arts and Sciences, Amsterdam, The Netherlands & CEO Brain Innovation, The Netherlands

Several International Brain Research Projects Launched

"As humans, we can identify galaxies light years away, we can study particles smaller than an atom. But we still haven't unlocked the mystery of the three pounds of matter that sits between our ears."

- President Obama, April 2, 2013 at the launch of the US Brain Initiative

It is expected that better brain measurement technologies (focus of US Brain Initiative) and detailed large-scale brain simulations (focus of EU Human Brain Project, HBP) will substantially improve our knowledge how the brain functions. This should also lead to better treatments of brain disorders.

HP Human Brain Project

The BRAIN Initiative®

Complex Vision Includes Physical Scene Understanding

From Brain Areas to Cortical Columns and Layers

What is the appropriate level of brain organization to explain human perception, action and cogntion?

> "*To explain the mind, we have to show how minds are built from mindless stuff, from parts that are much smaller and simpler than anything we'd consider smart.*"
>
> ***Marvin Minsky, 1985***

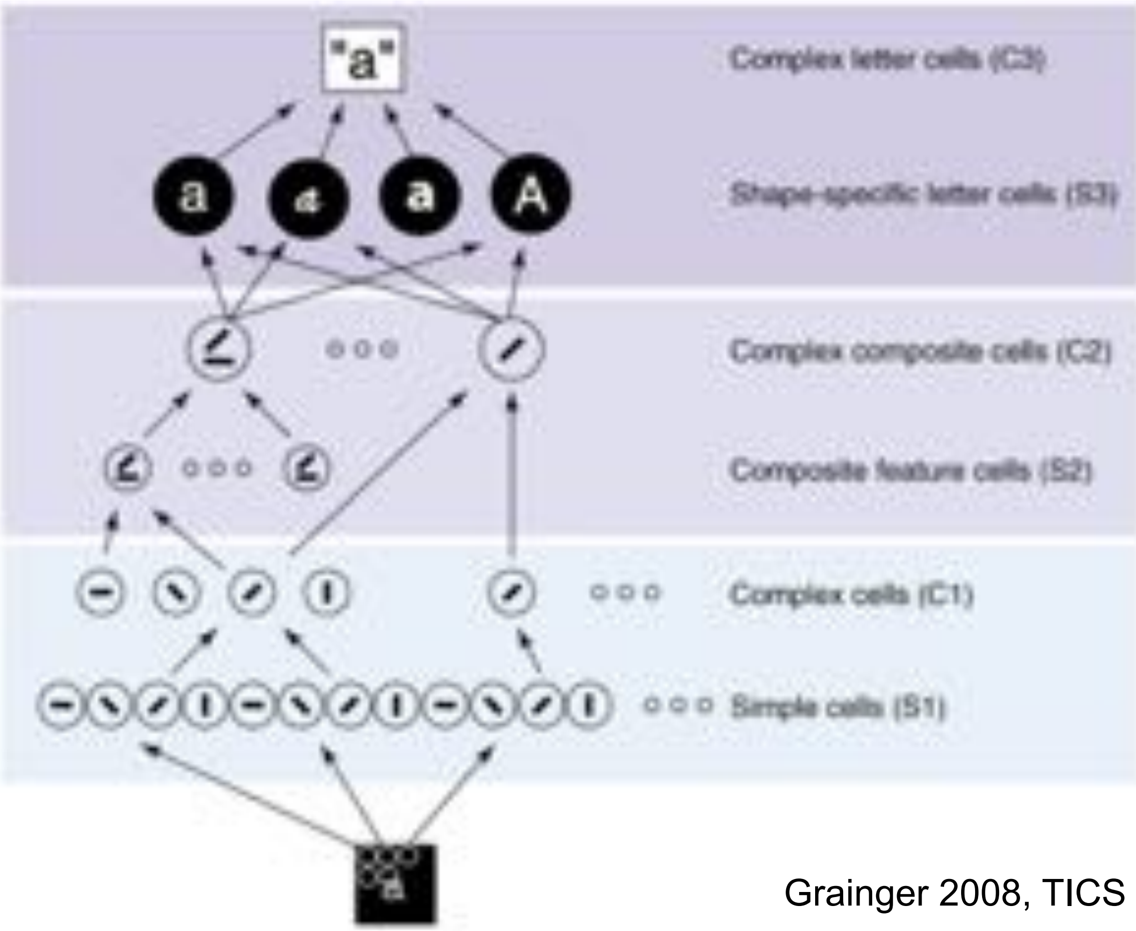
- To understand uniquely human aspects of cognitive processes (perception, language, memory, emotion, thinking), **detailed multi-scale measurements** of the **living human brain** are necessary complementing animal and post-mortem brain research.
- Does functional MRI has the power to measure the right level of brain organization, i.e. the relevant "small and simple parts"?
- Conventional functional human brain imaging reveals brain organization only at the macroscopic level which limits its use in understanding details about how mental content is represented.

How does the Brain “Compute” Cognitive Functions?

Questions such as:

- How is a specific face identified?
- How is reading possible, e.g. how does the brain recognizes letter “a”?

In principle, we ***can*** provide answers to such questions e.g. with deep neural network models ***but*** we do not know the features and connections used by the brain!

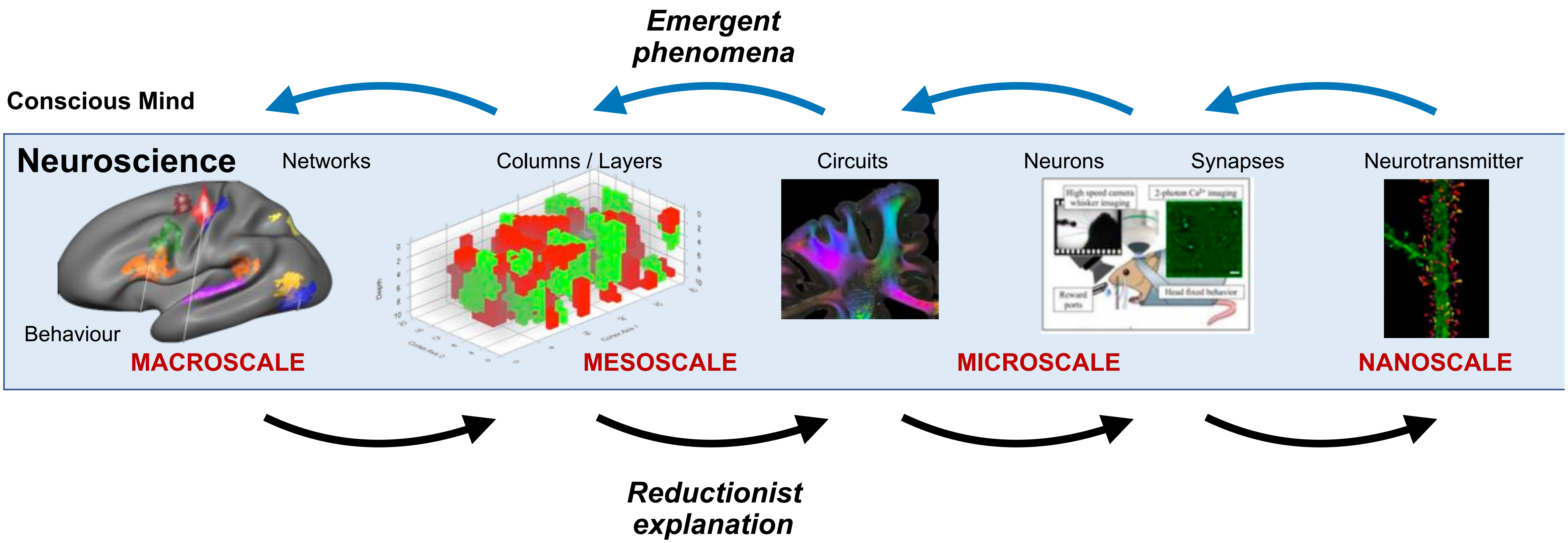


Grainger 2008, TICS

This leads to the following ***challenging goals for brain research***:

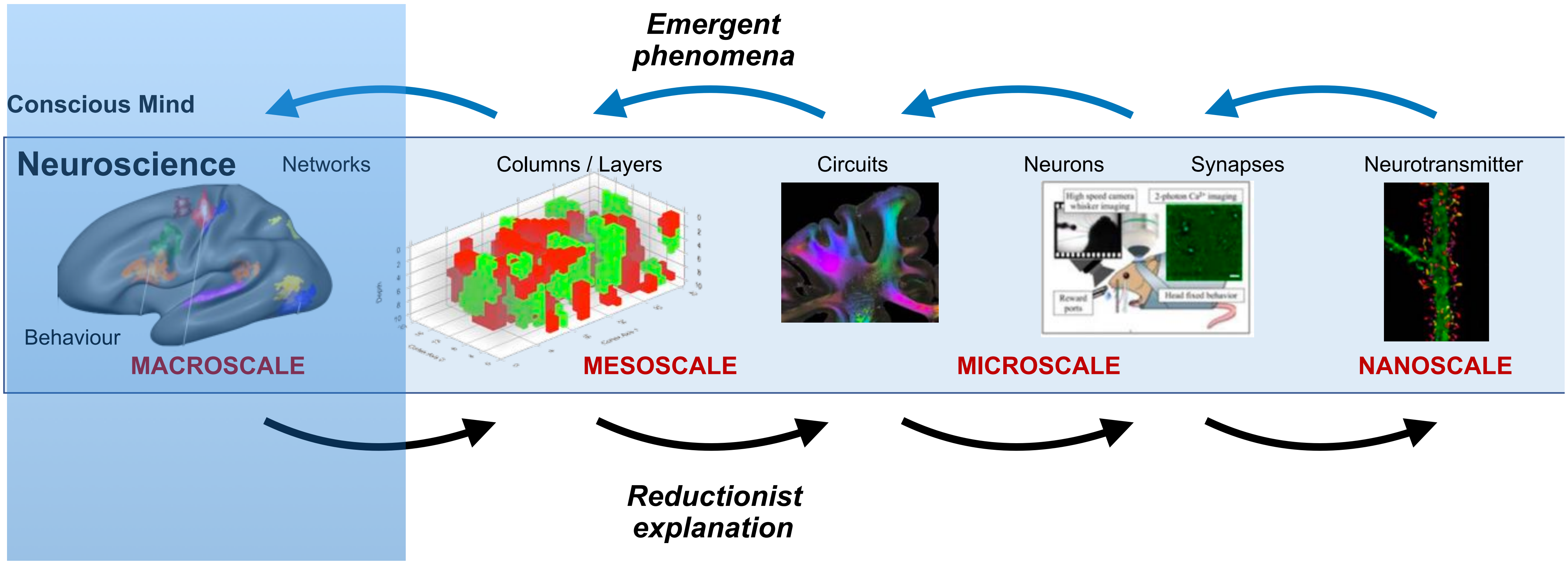
- Reveal what features are coded within specialized brain areas!
- Reveal how features are connected within and across areas!

Relating Anatomy and Function Across Brain Scales



Using neuroscience and computer simulations, a causal understanding will emerge of how events at lower levels determine events at higher levels - up to the level of the conscious mind.

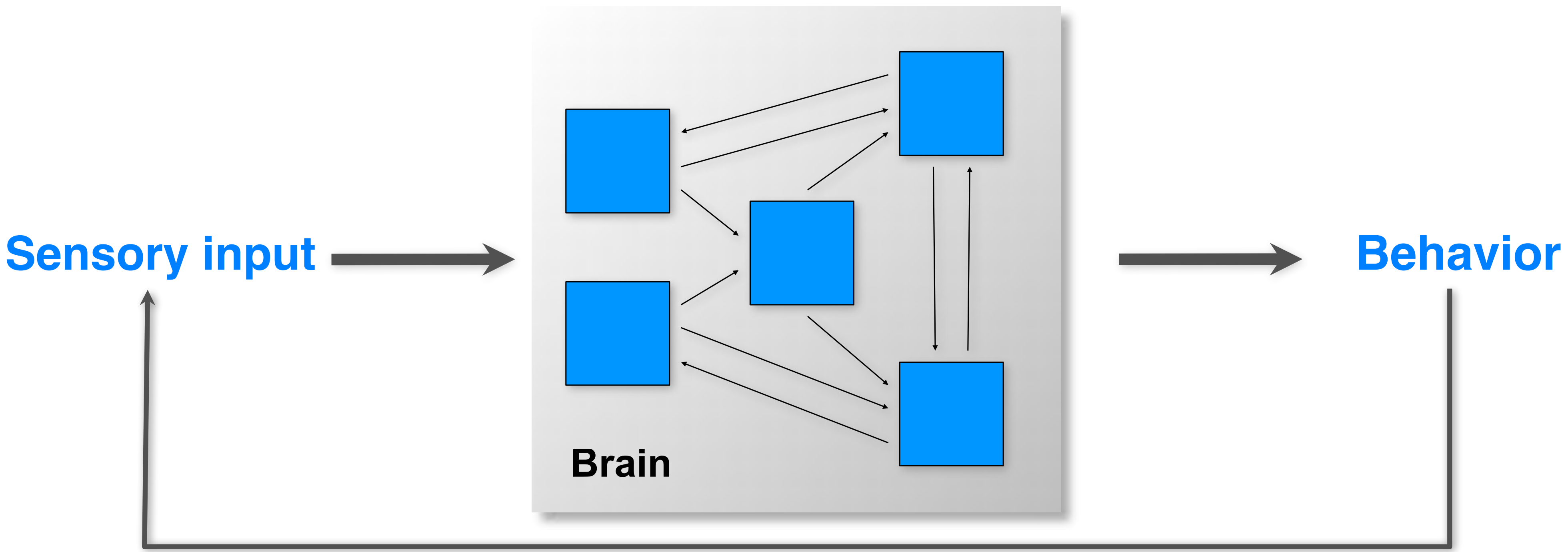
Relating Anatomy and Function Across Brain Scales



Specialized areas and large-scale networks

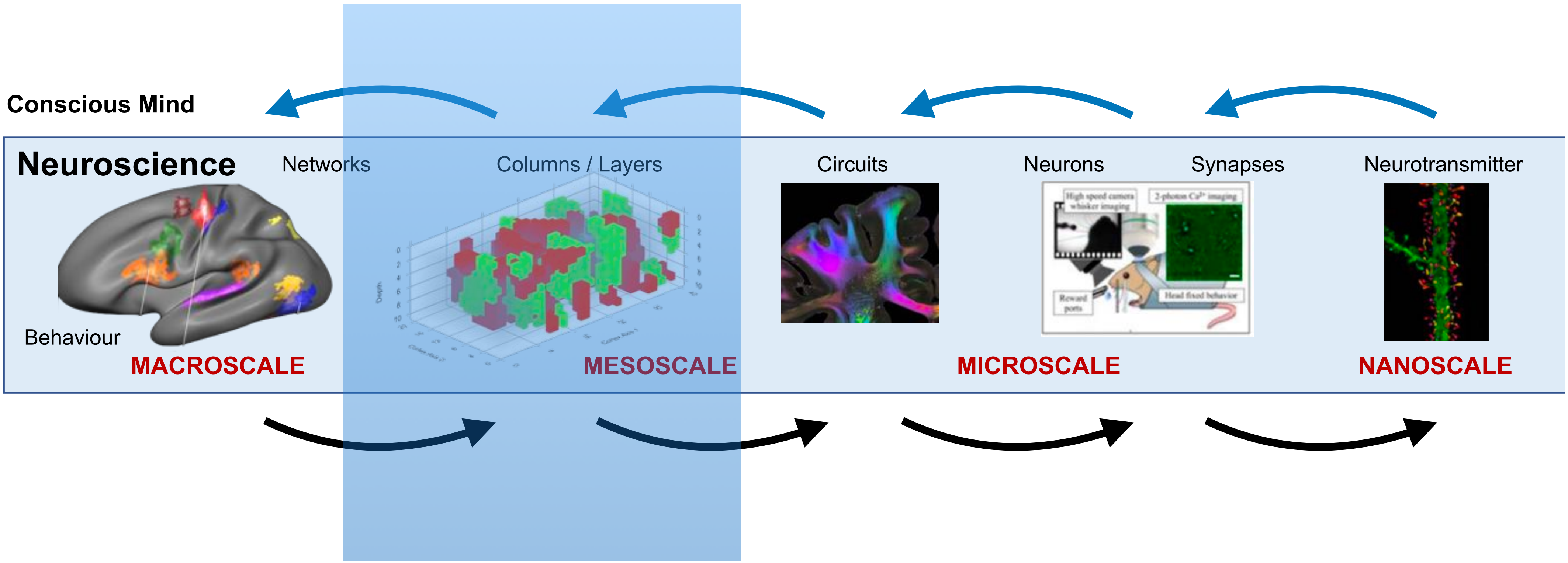
Conventional fMRI @ 3T
(2.0 - 3.0 mm)

Multi-Scale Functional Organization of the Human Brain
Macroscopic Level: Specialized Areas and Large-Scale Networks



- **What are elementary mental/neural functional components?** Understand categorical representations in “modules of the mind” and how they are embedded in areas of the brain (e.g. face area vs house/place area).
- **How do basic components interact and unfold over time?** Understand communication between brain areas, i.e. direction of information flow (anatomical and effective connectivity).

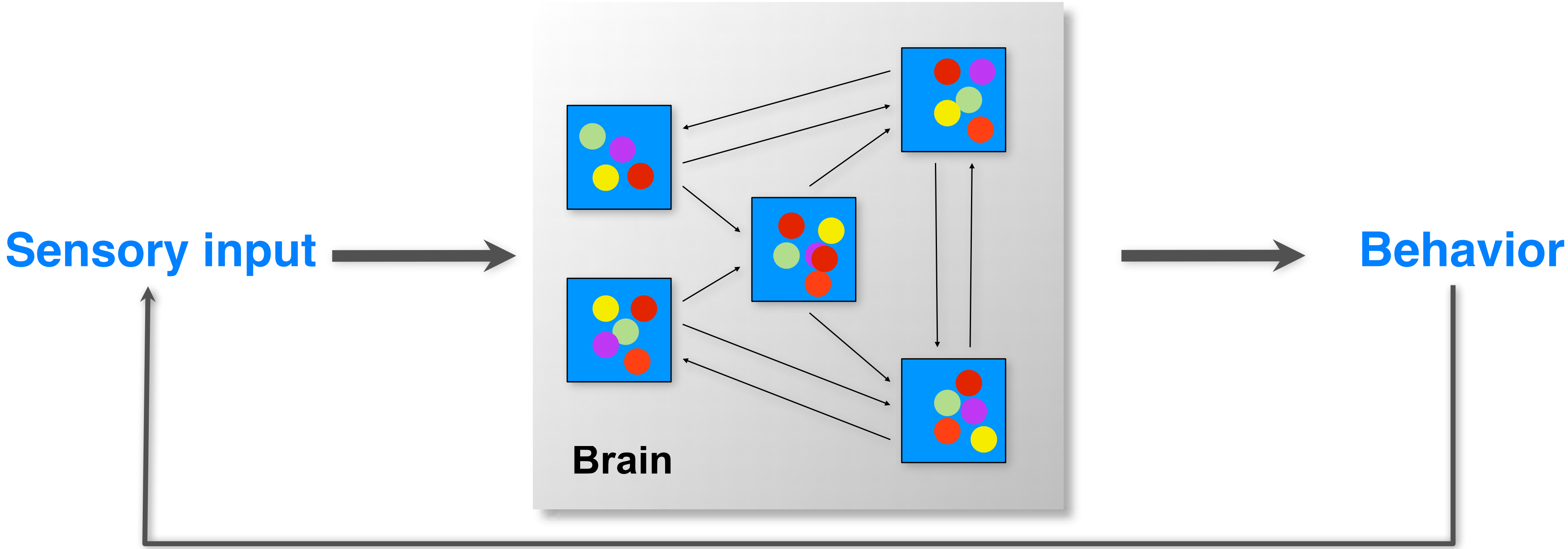
Relating Anatomy and Function Across Brain Scales



Cortical Columns and
Cortical Layers

High-Resolution fMRI @ ≥ 7T
(0.5 - 1.0 mm)

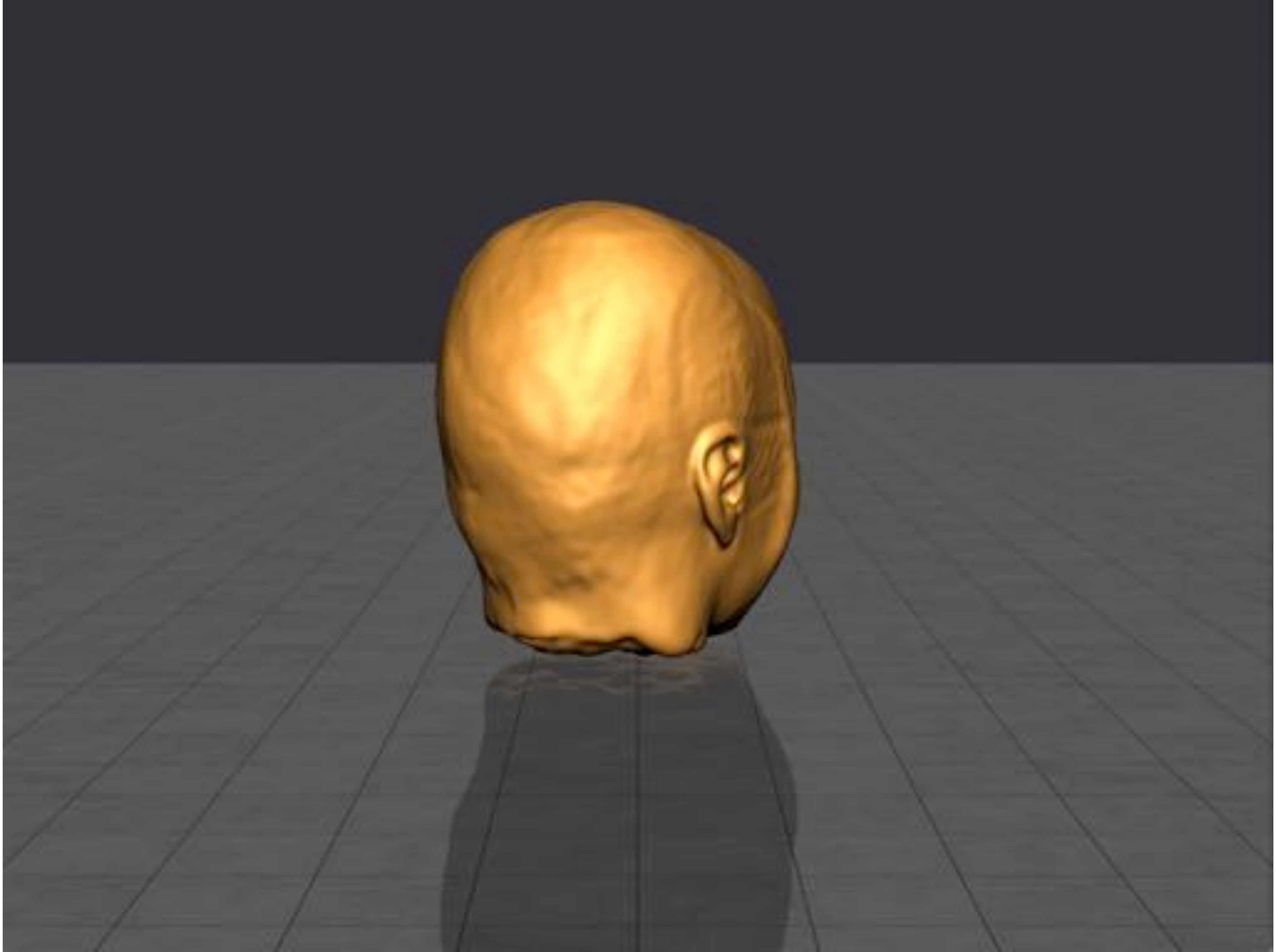
Multi-Scale Functional Organization of the Human Brain
Mesoscopic Level: Features Coded Within Specialized Areas



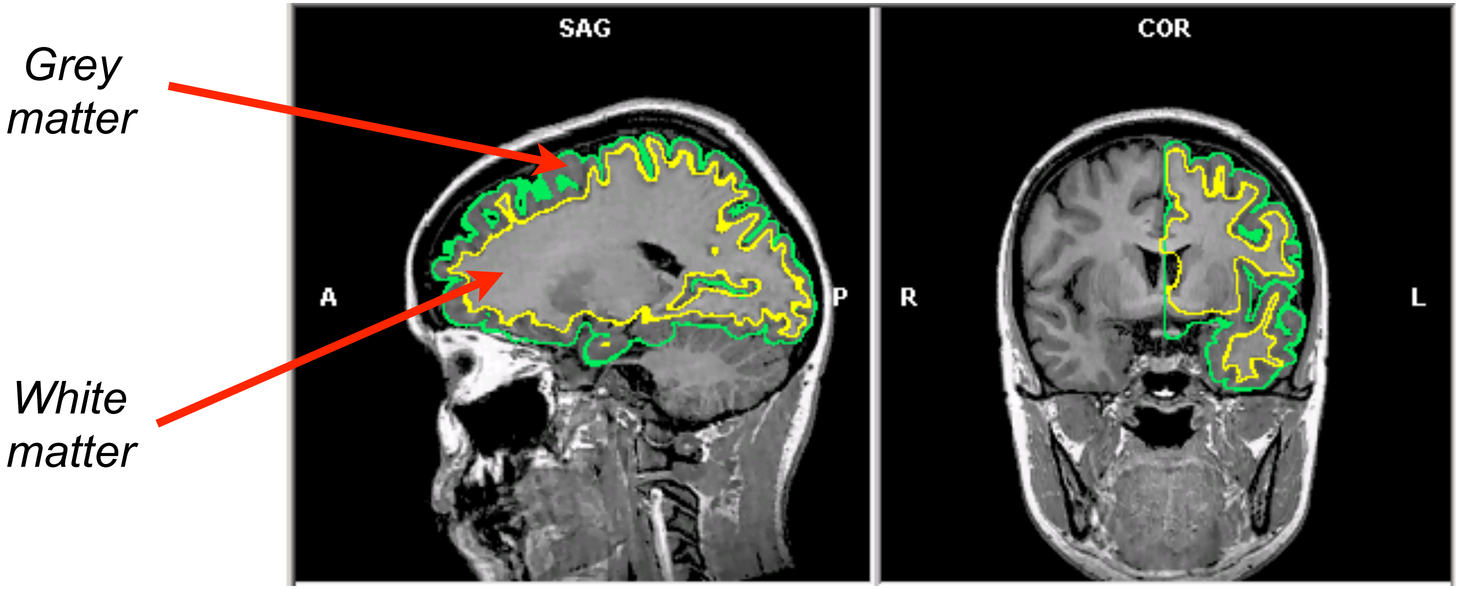
- **What are elementary mental/neural functional components?** Understand "alphabet" of basic features within specialized brain areas (e.g. face area) and how specific "words" (e.g. individual faces) are encoded as distributed patterns across mapped features.
- **How do basic components interact and develop over time?** Understand interactions between features, e.g. how complex feature codes in higher areas emerge from simpler features in lower areas.

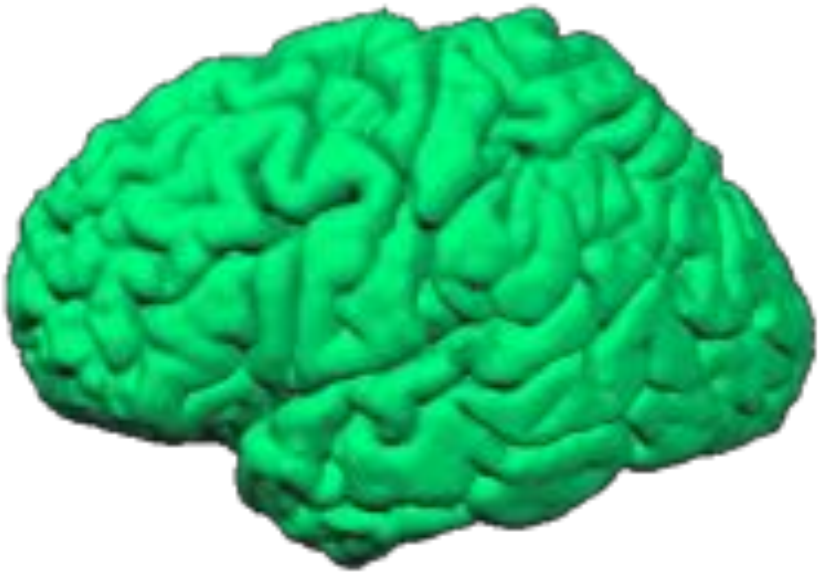
Anatomical Brain Imaging with MRI

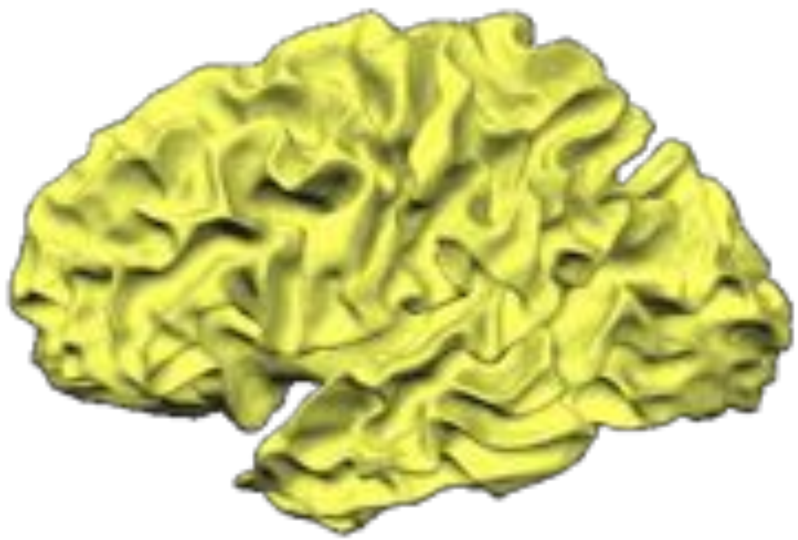
Recorded 2D Slices (sagittal orientation)

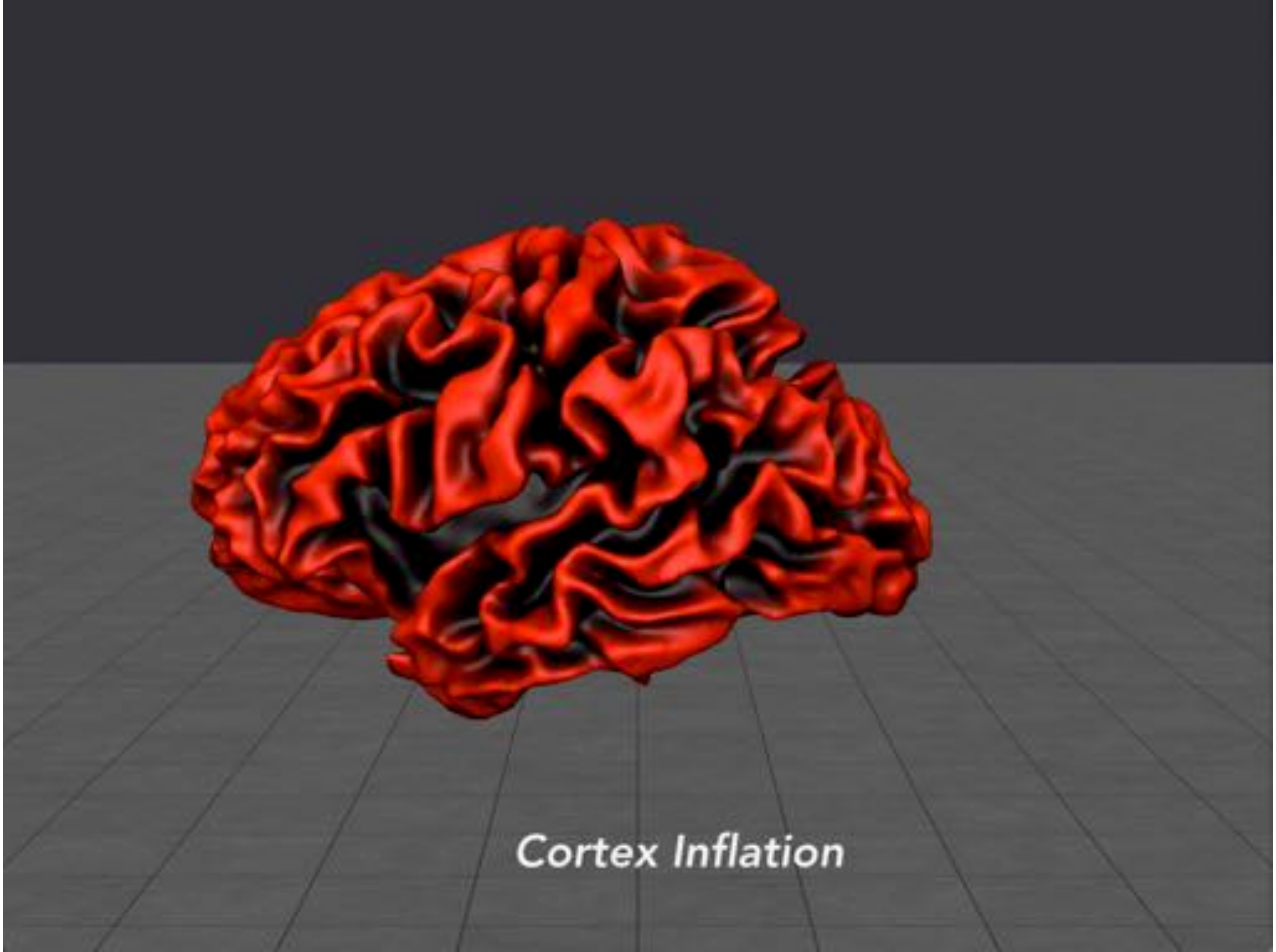


Segmentation of Inner and Outer Boundary of the Cortex

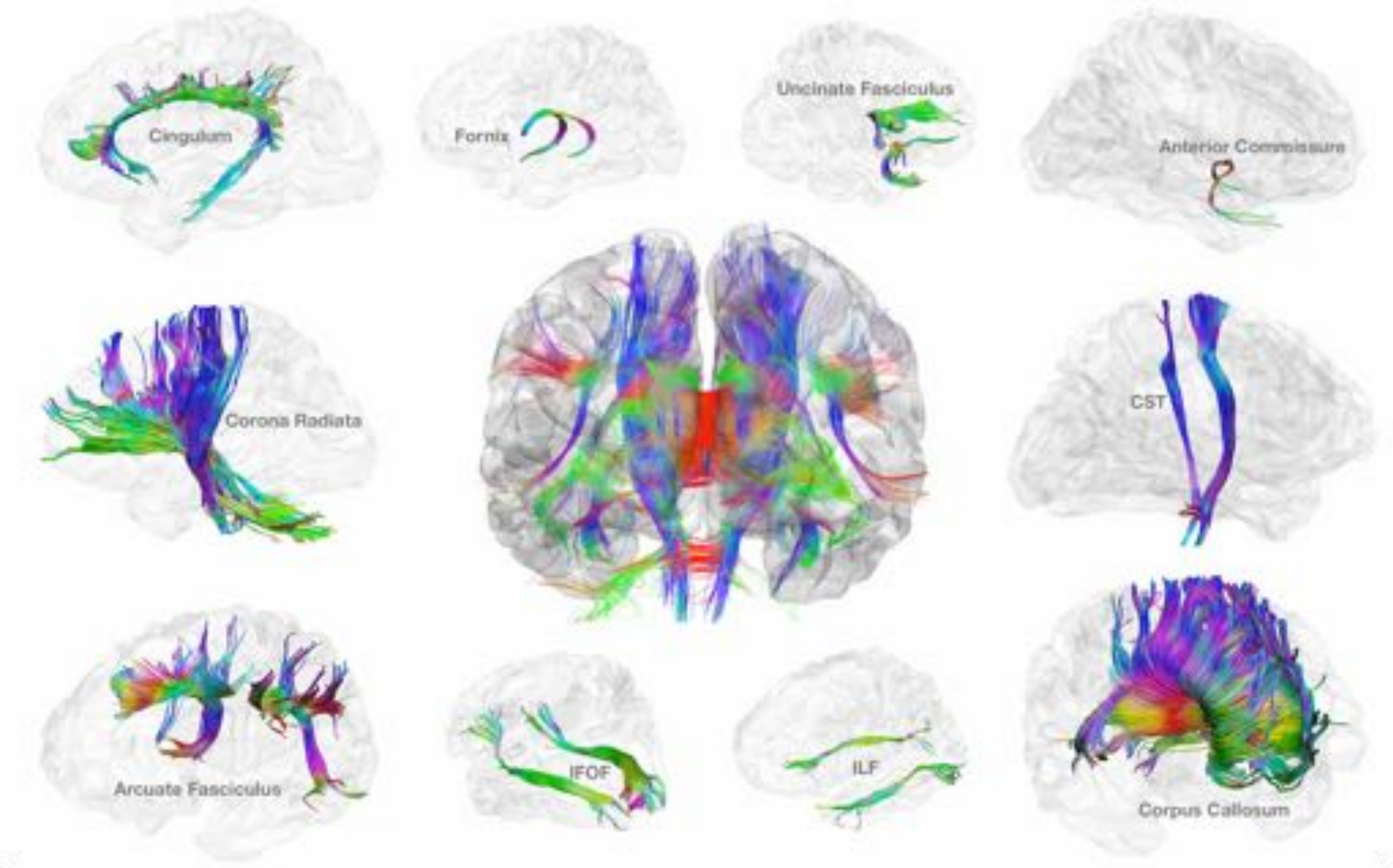







Cortex Inflation

Subset of Major Fiber Tracts Revealed by Computational Tractography

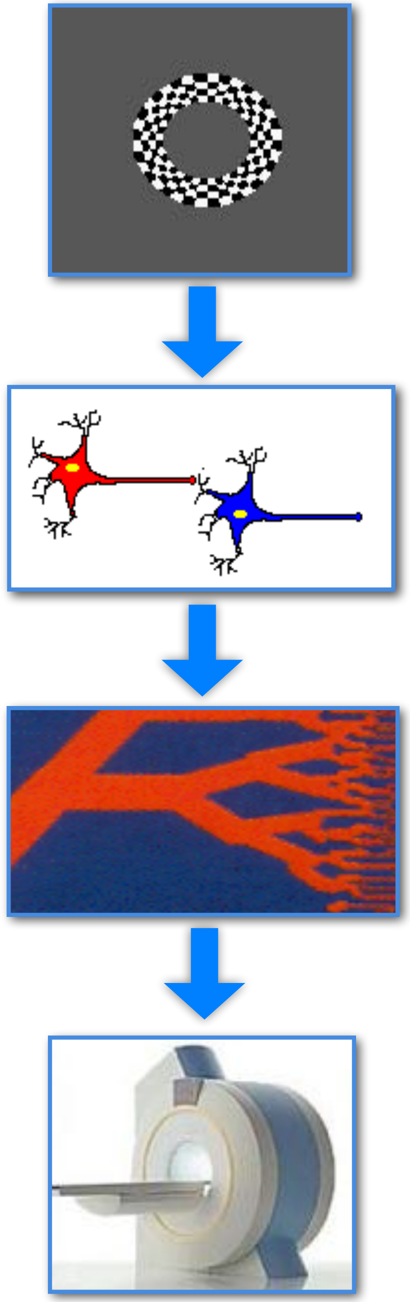


Goebel (2015). Revealing Brain Activity and White Matter Structure Using Functional and Diffusion-Weighted Magnetic Resonance Imaging. In: Stippich C (Ed.), *Clinical Functional MRI – Presurgical Functional Neuroimaging*. Heidelberg: Springer

How Functional MRI Works

fMRI Signal = BOLD (Blood-Oxygenation-Level-Dependent) Signal

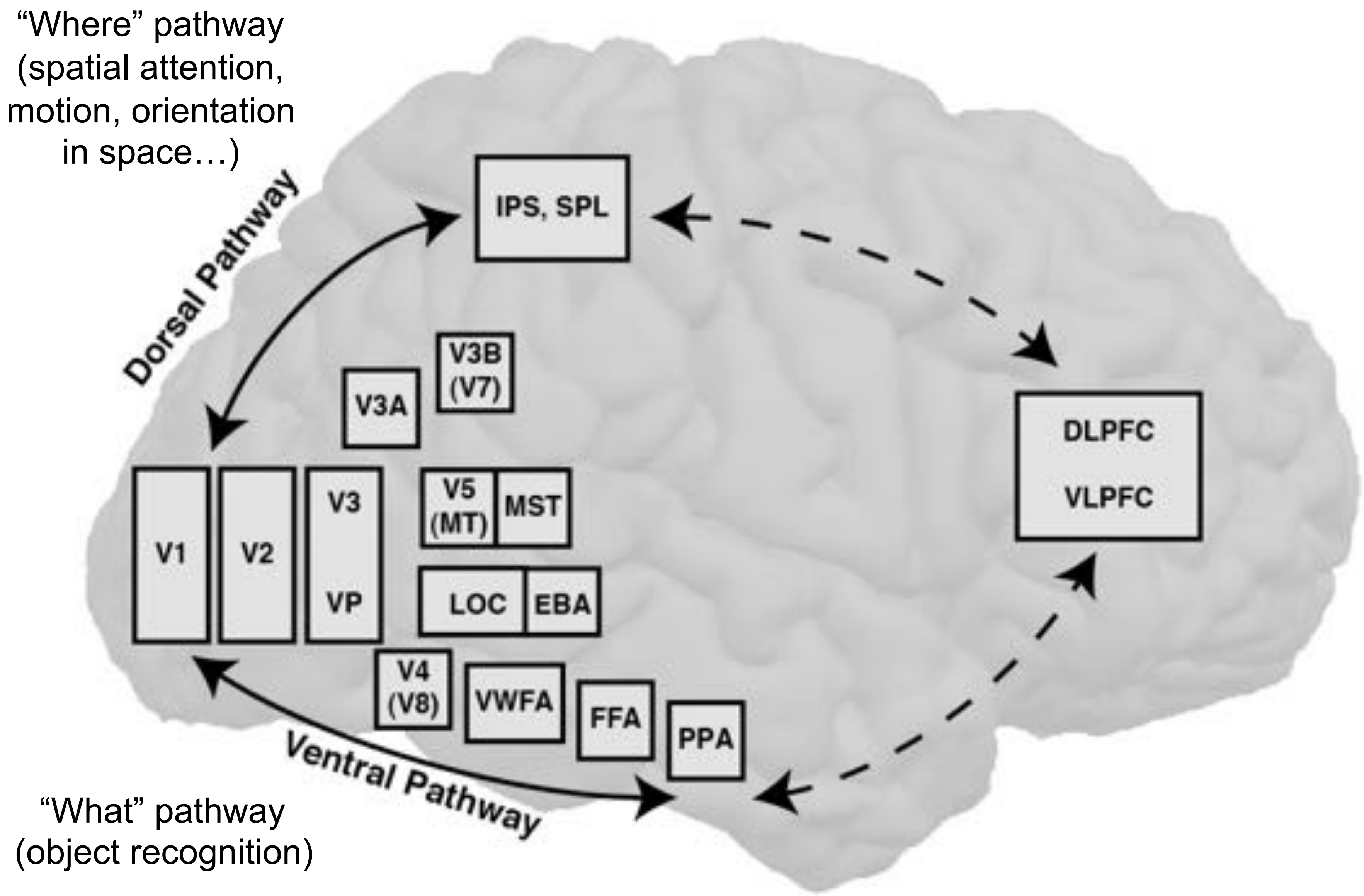
- When the ***neuronal activity*** in an area of the brain increases after stimulation, that brain area consumes more ***energy***.
- The ***neuronal tissue*** gets its energy from ***oxygenated hemoglobin*** in the blood.
- Within a few seconds the ***blood flow*** and the concentration of ***oxygenated hemoglobin*** in the blood ***increases*** in that area - this is called the ***hemodynamic response***.
- Since oxygenated and deoxygenated hemoglobin have ***different magnetic properties***, the hemodynamic response can be ***imaged*** with functional MRI.



How does the Brain Solve Complex Computational Vision Problems?

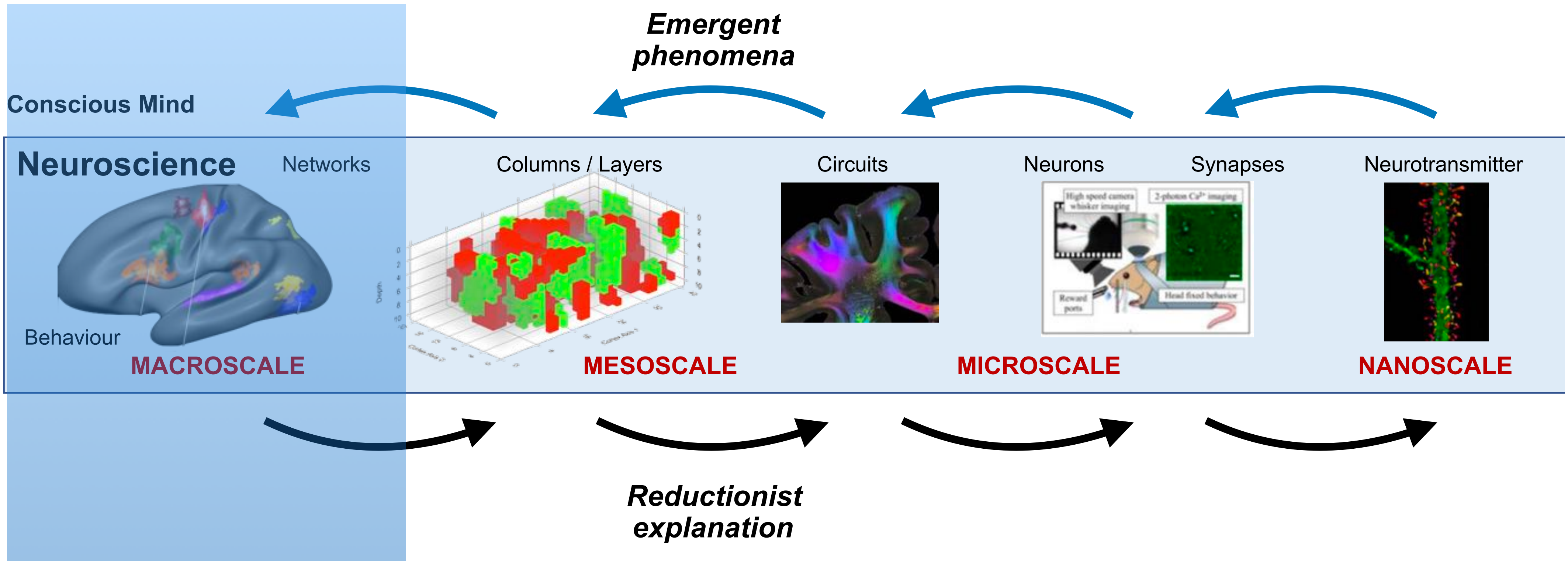
- Visual system covers about 25% of human cerebral cortex containing ~5 billion neurons.
- Divide and conquer strategy:
  - Specialized pathways (“what”, “where”).
  - Specialized areas within pathways (e.g. for color, texture, motion, shape, faces).
  - “Soft” modular processing
  - More than 15 visual areas exhibit full visual field map (retinotopic organization).

Schematic Overview of Visual Cortex (as seen by fMRI)



Goebel et al. (2012) The Visual System. In G.Paxinos,& J.K. Mai (Eds). The Human Nervous System 2nd edition.

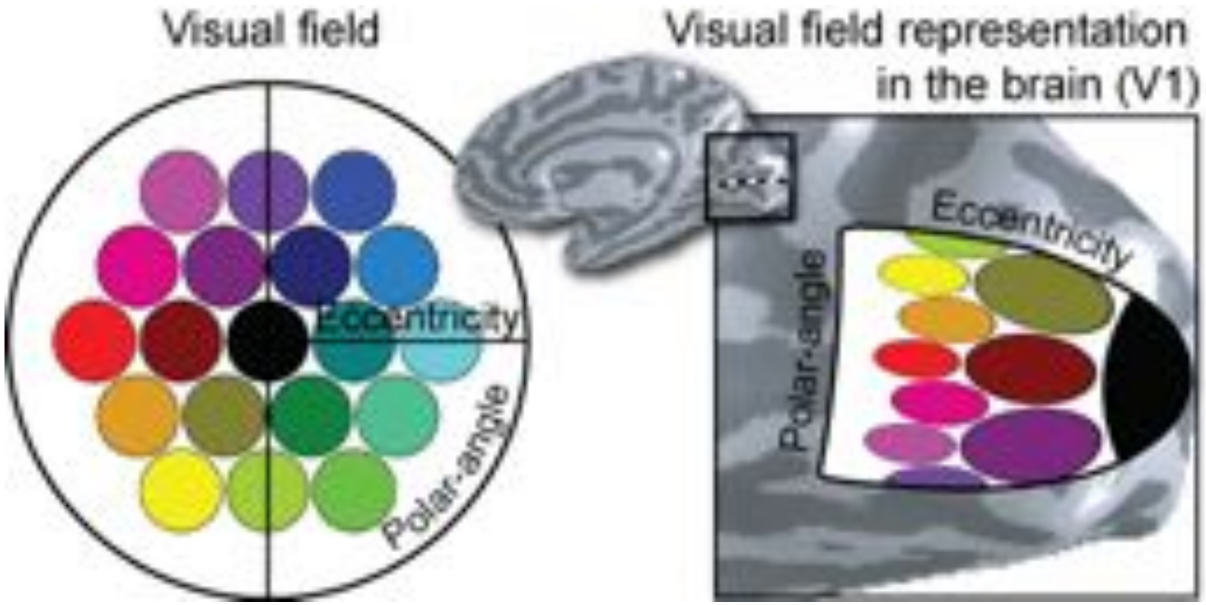
Relating Anatomy and Function Across Brain Scales



Specialized areas and large-scale networks

Conventional fMRI @ 3T
(2.0 - 3.0 mm)

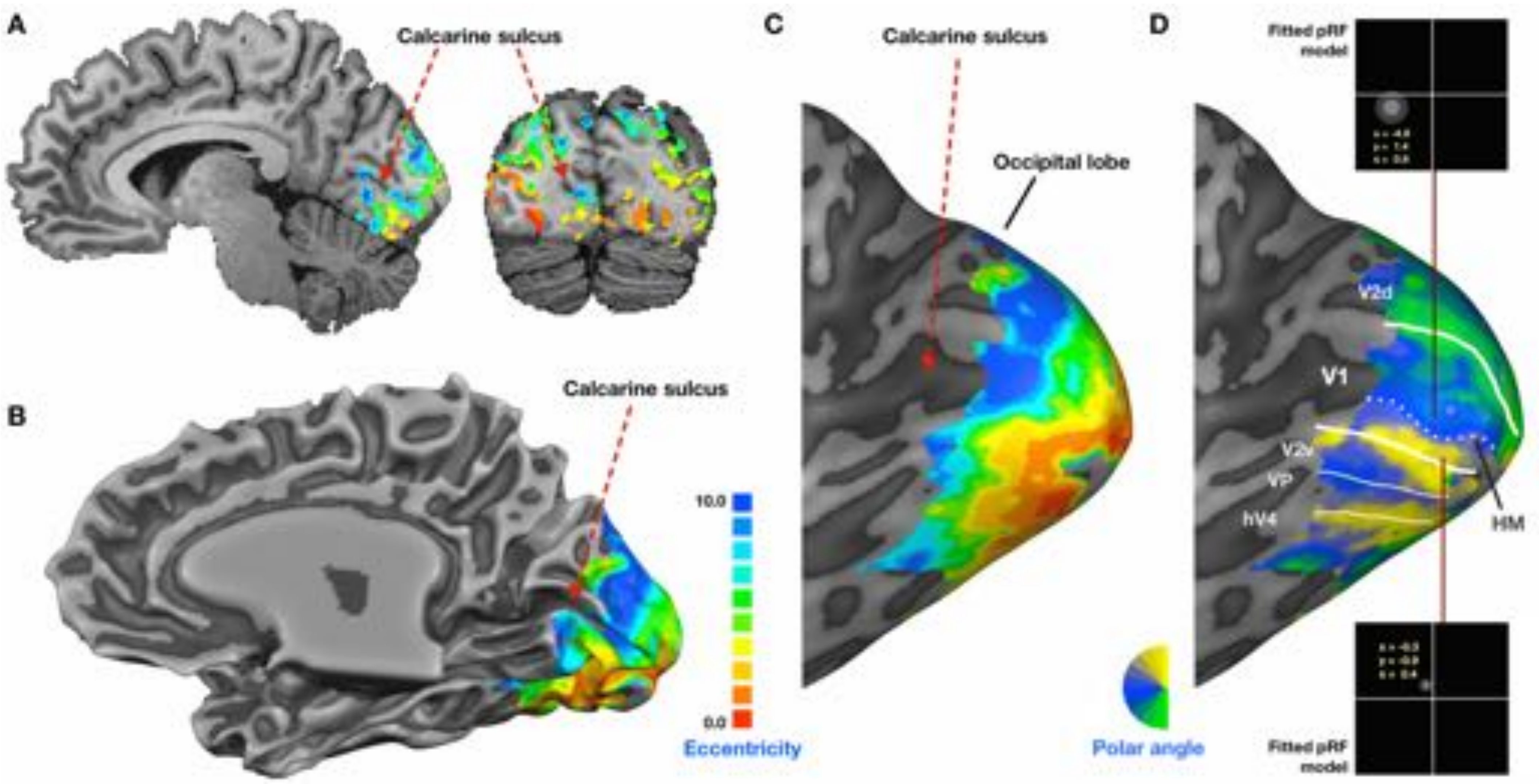
Retinotopic Organization of V1 and Cortical Magnification



Dumoulin (2011)

Schematic illustration of the visual field representation in primary visual cortex (V1). The visual field representation is shown in the left panel; the center of the visual field is at the back circle and the polar-coordinate axes – eccentricity and polar-angle – are identified. V1 lies within and around the Calcarine sulcus (inset, dashed lines). The left visual field (left panel) is represented on the right unfolded cortical surface (right panel) using a mathematical transformation proposed by Schwartz (Schwartz et al., 1985) with cortical magnification (Daniel and Whitteridge, 1961).

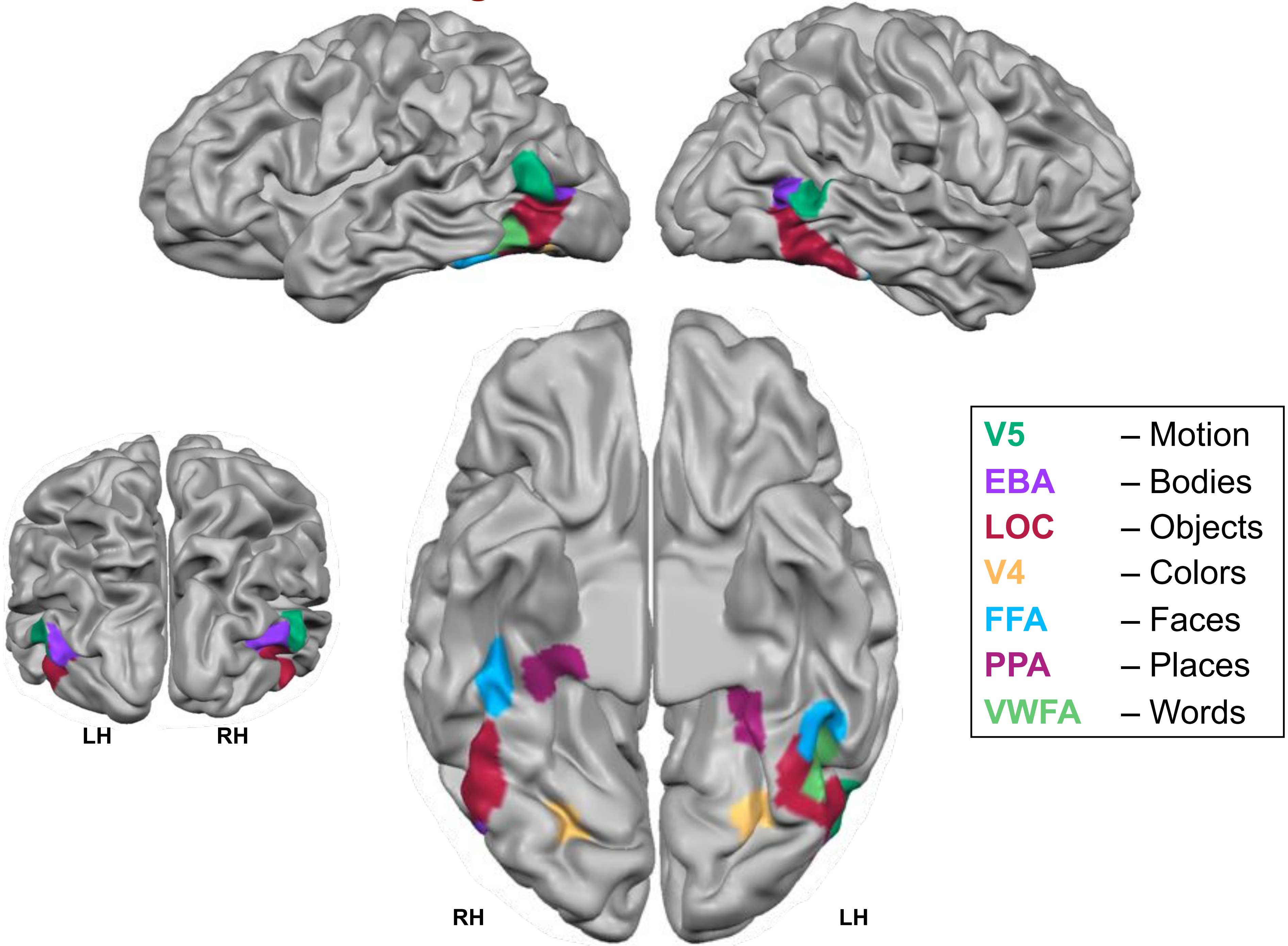
Retinotopic Mapping of Early Visual Areas using the Population Receptive Field (pRF) Estimation Technique (based on Dumoulin & Wandell, 2008)



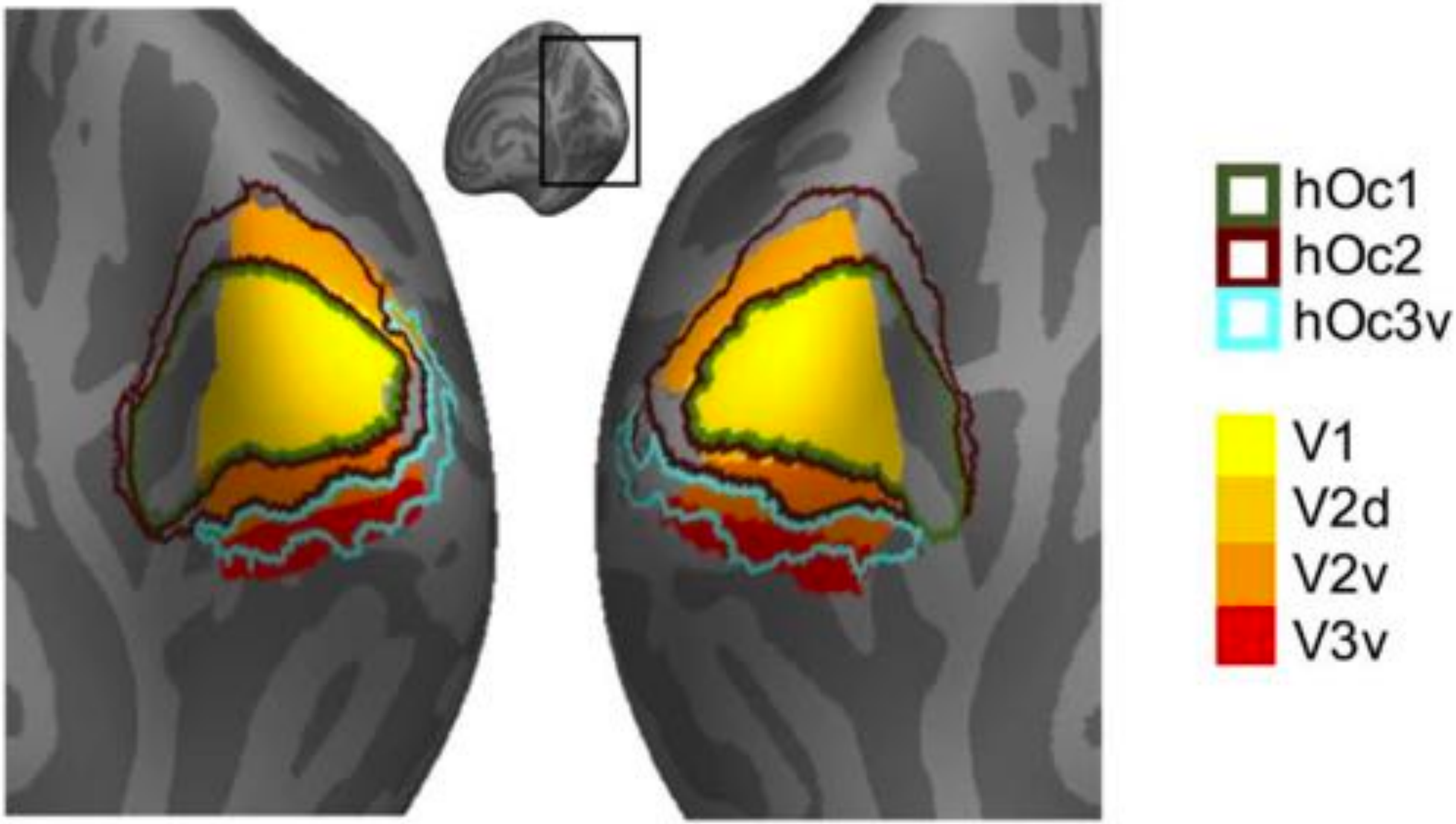
Goebel R (2014). Functional organization of primary visual cortex. In: Brain Mapping: An Encyclopedic Reference.

Major Functionally Segregated Higher-Level Visual Areas

Coding Inside Areas Unknown!



Cytoarchitectonic Cortex-Aligned Probabilistic Atlas - Early Visual Areas

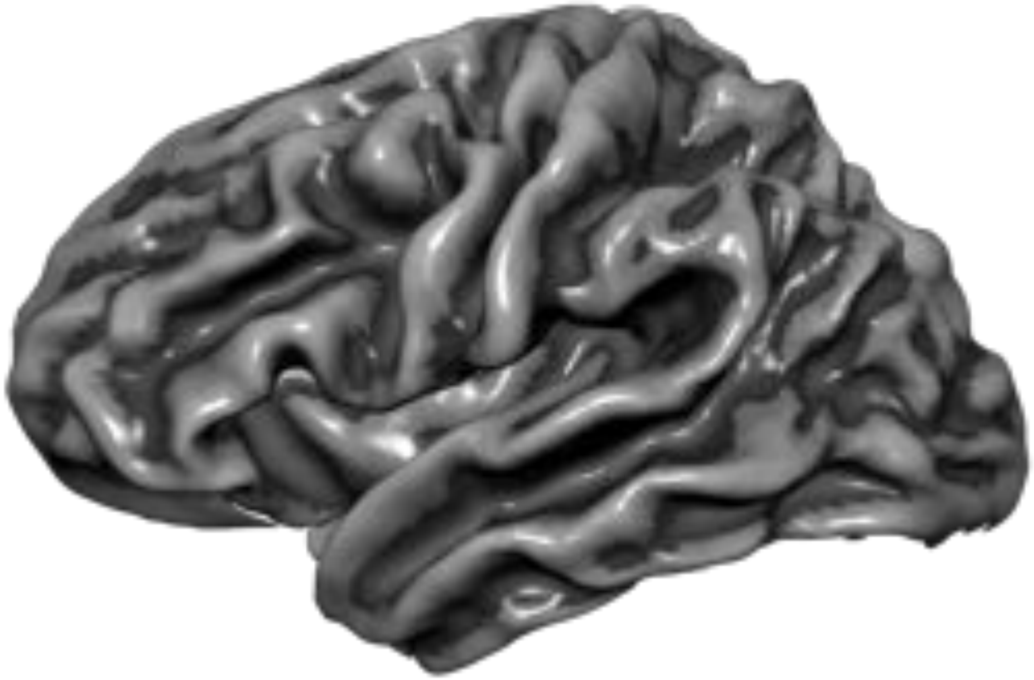


- Reproducible when using leave-one out validation
- overlaps well with retinotopic functional map

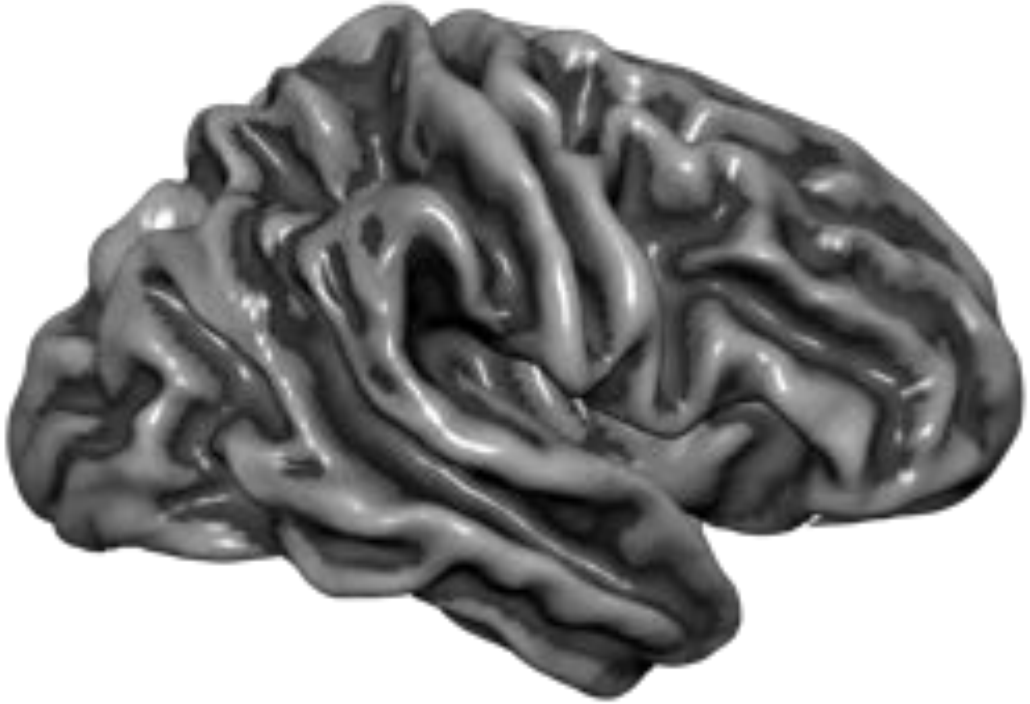
Rosenke, Weiner, Barnett, Zilles, Amunts, Goebel, Grill-Spector (2017) A cross-validated cytoarchitectonic atlas of the human ventral visual stream, Neuroimage,

Functional Parcellation of Occipito-Temporal Visual Cortex

Macro-Anatomically Aligned Average Cortex (N = 19)



Left Hemisphere

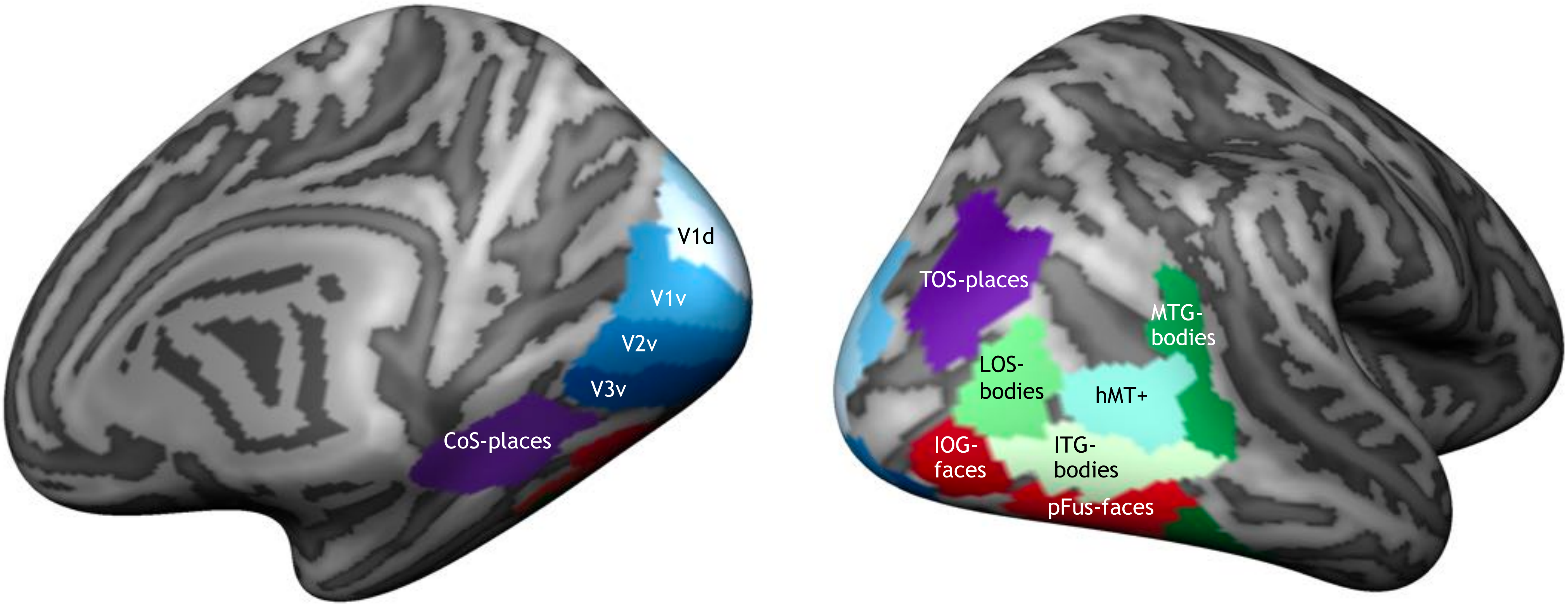


Right Hemisphere

Rosenke, van Hoof, Frost, van den Hurk, Goebel (2018). Functional parcellation of occipito-temporal cortex – A probabilistic atlas in volume and surface space, *under review*.

Functional Parcellation of Occipito-Temporal Visual Cortex

Probabilistic map after cortex (curvature) alignment of 19 subjects, 20% threhsold, RH



Medial view

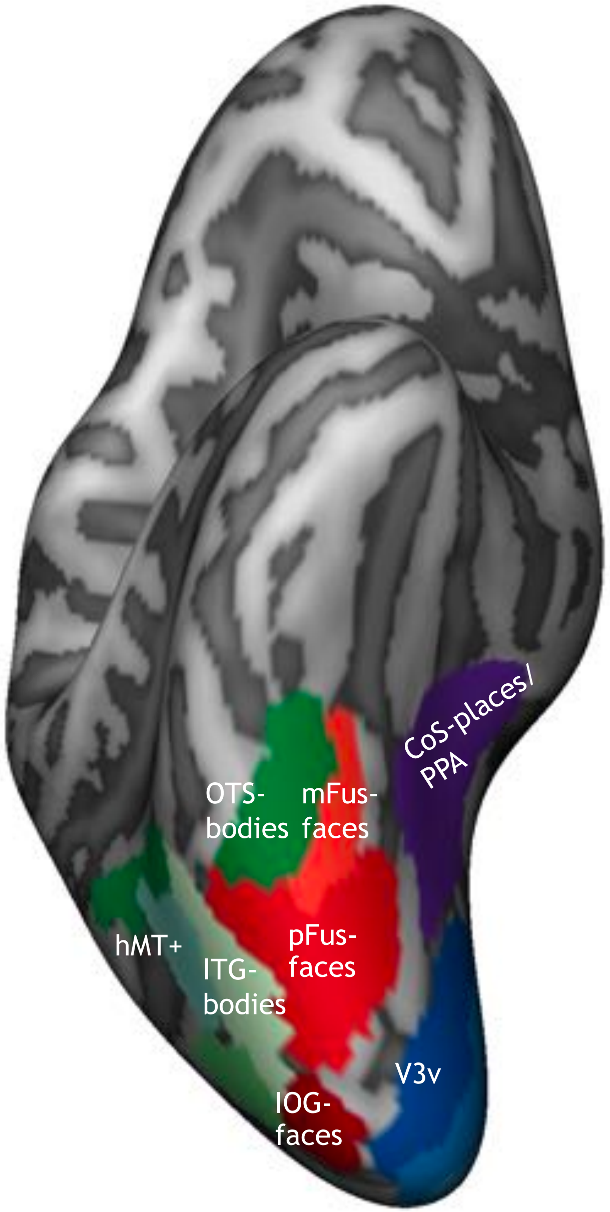
Lateral view

Functional parcellation will be contributed to the HBP Atlas

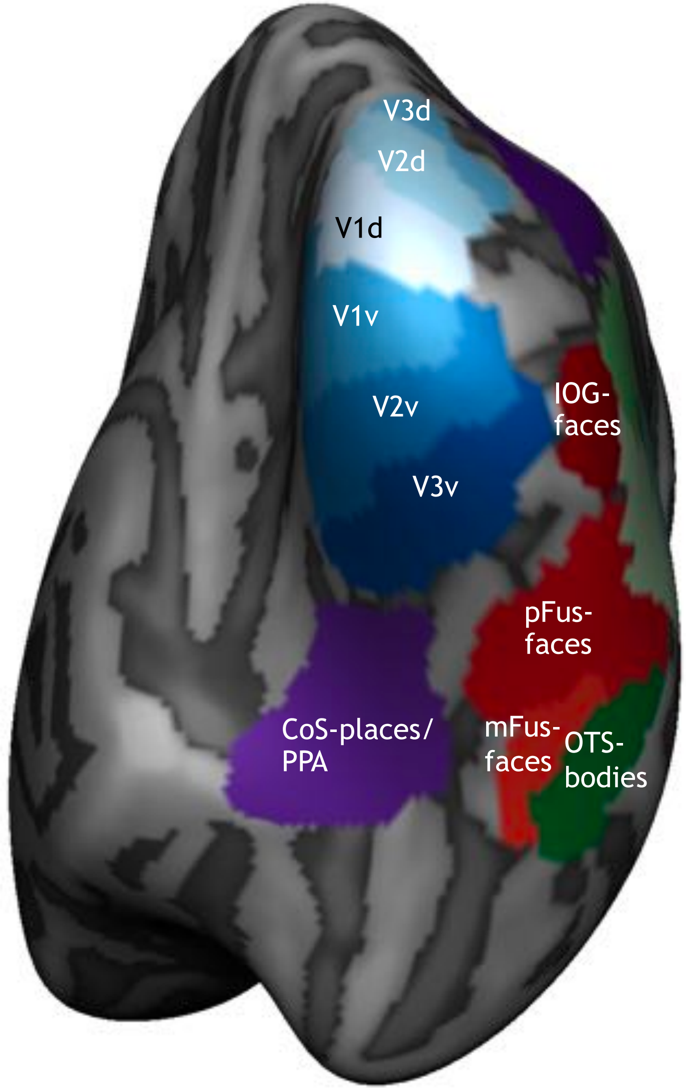
Rosenke, van Hoof, Frost, van den Hurk, Goebel (2018). Functional parcellation of occipito-temporal cortex – A probabilistic atlas in volume and surface space, *under review*.

Functional Parcellation of Occipito-Temporal Visual Cortex

Probabilistic map after alignment of 19 subjects, 20% threhsold, RH



Ventral view

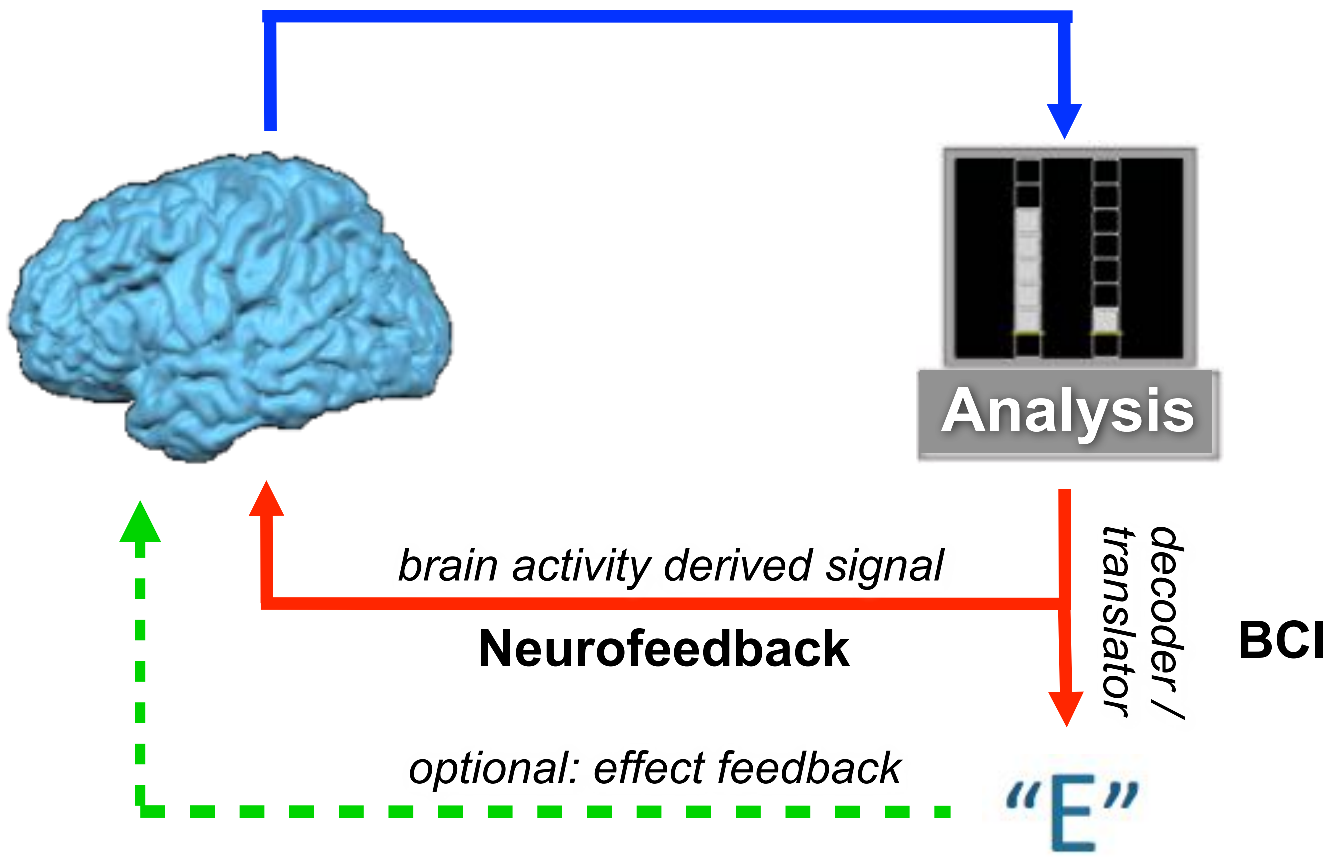


Posterior-ventral view

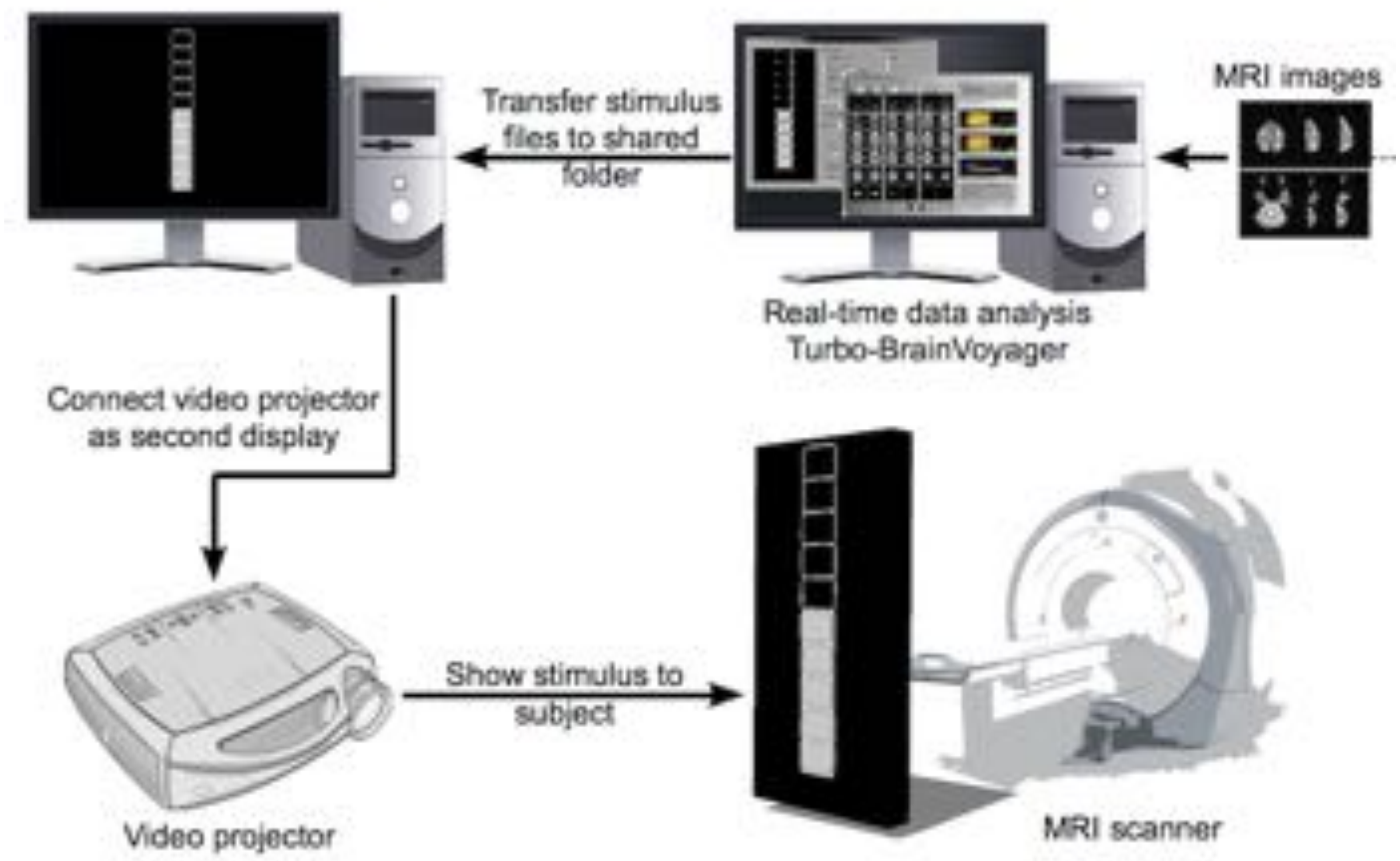
Rosenke, van Hoof, Frost, van den Hurk, Goebel (2018). Functional parcellation of occipito-temporal cortex – A probabilistic atlas in volume and surface space, *under review*.

Applications of Real-Time fMRI Data Analysis

- Neural activity is transformed into digital code
- Feedback for learning of self-regulation of brain activity
- Decoding / translating brain activity for BCI application

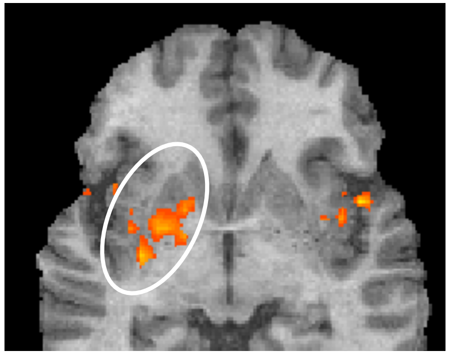


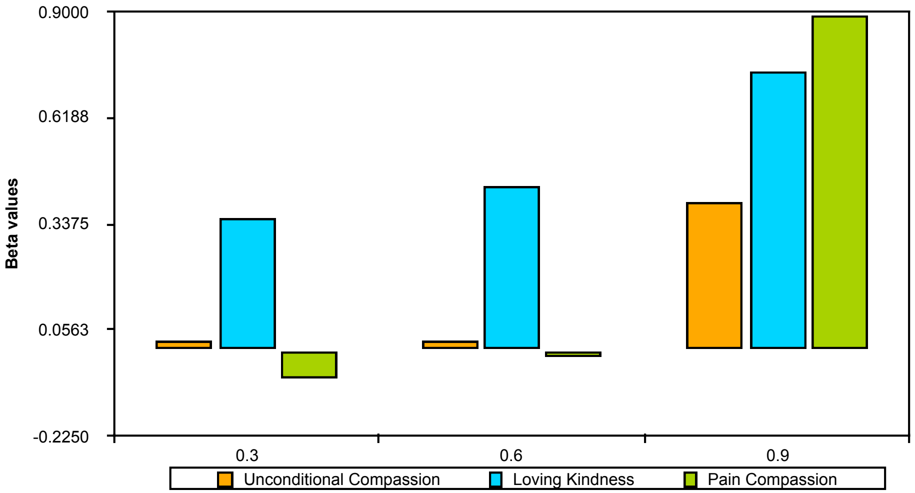
fMRI Neurofeedback / BCI Technical Setup

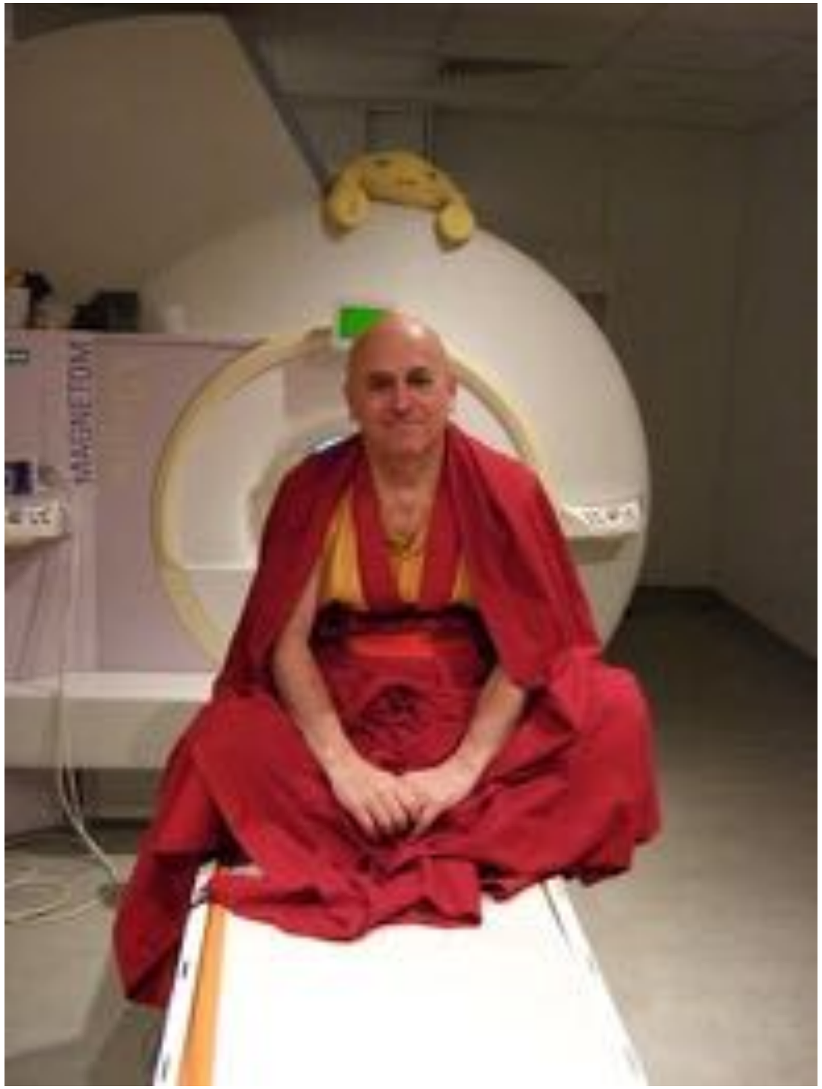


Learning from a Meditation Expert

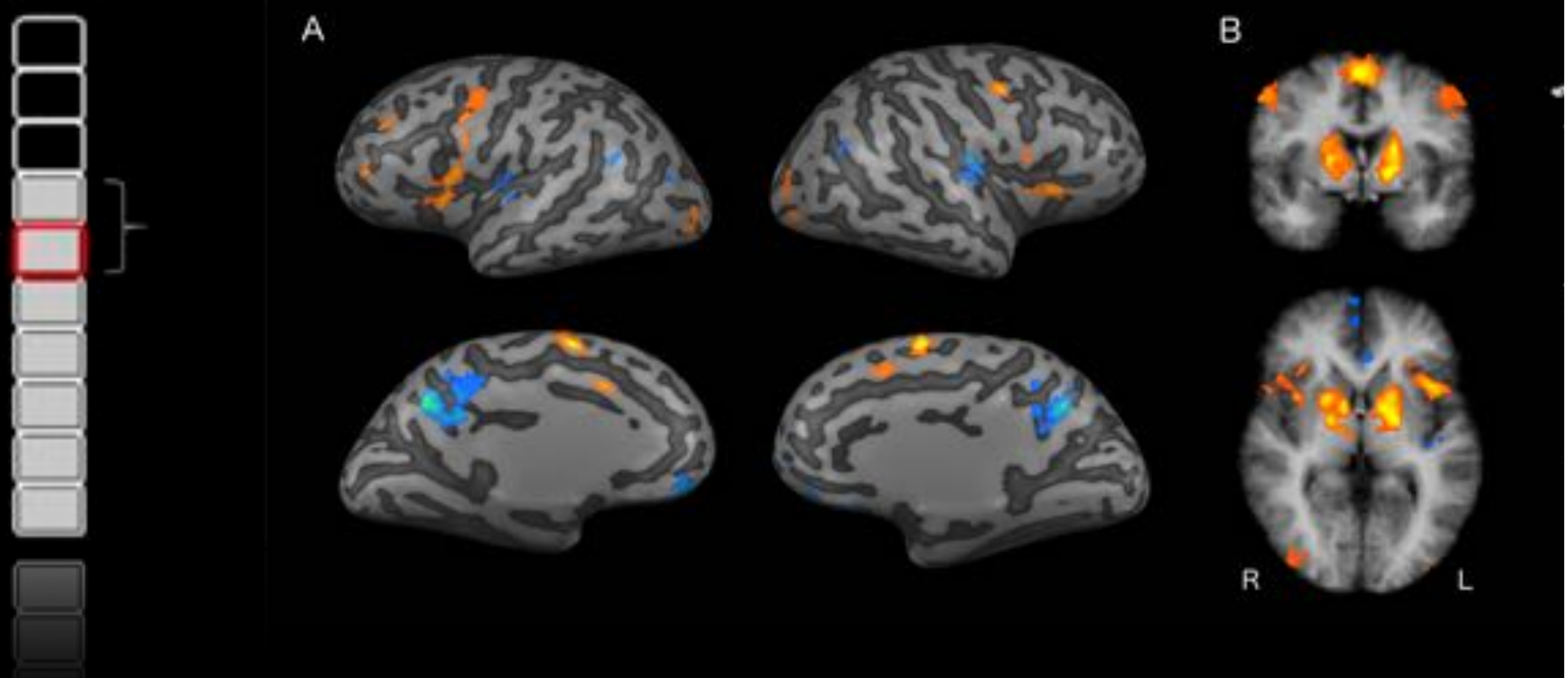
Subject: Matthieu Ricard
Ventral striatum activation is modulated by intensity of positive mental states.







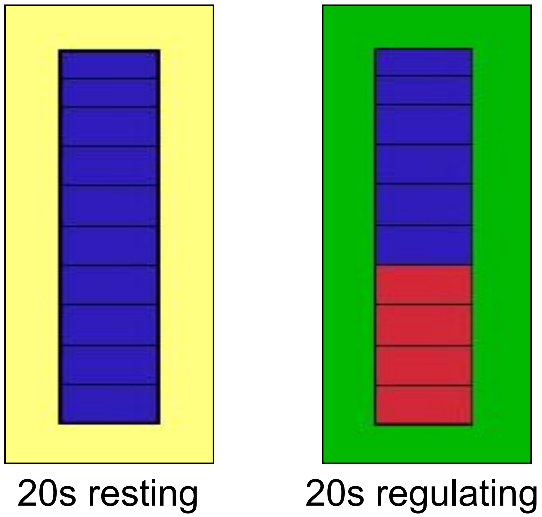
Neurofeedback and Reward Processing in the Ventral Striatum

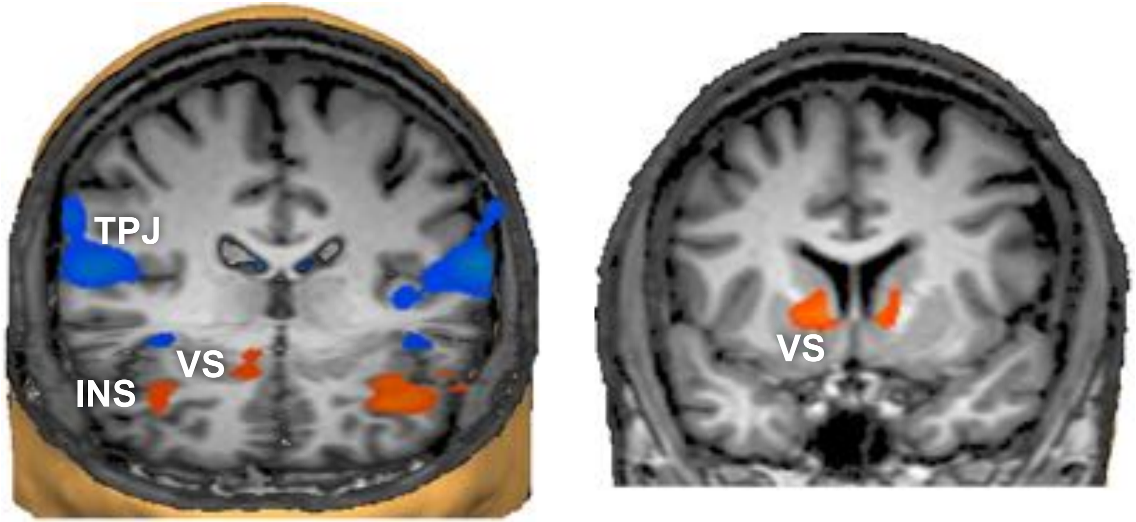


Skottnik, Sorger, Kamp, Goebel (2018). Success and failure of controlling the fMRI-neurofeedback signal are reflected in the striatum, submitted.

Neurofeedback Therapy for Patients with Depression

- Patients with recurrent depressive episodes after unsuccessful conventional therapy
- Neurofeedback design
  - learning to up-regulate brain activation within the emotion network (amygdala, prefrontal cortex *etc.*)
  - 4 sessions (within 4 weeks)
  - one session = 3 runs (1h)



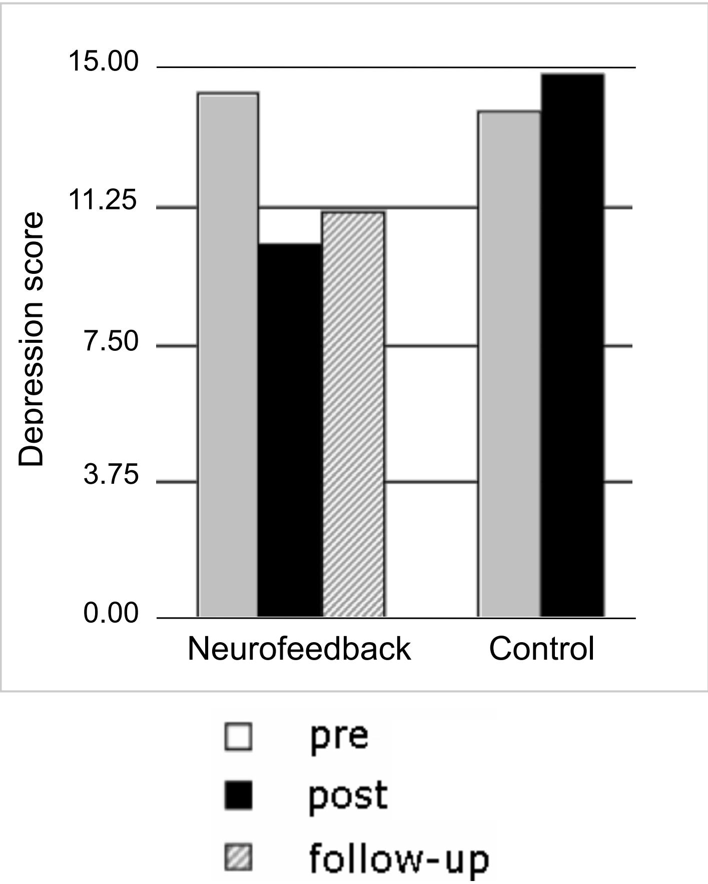


Linden, D.E.J., Habes, I., Johnston, S.J., Linden, S., Tatineni, R., Subramanian L., Sorger, B., Healy, D., Goebel, R. (2012). Real-time Self-regulation of Emotion Networks in Patients with Depression. *PLOS One*, **7**, e38115.

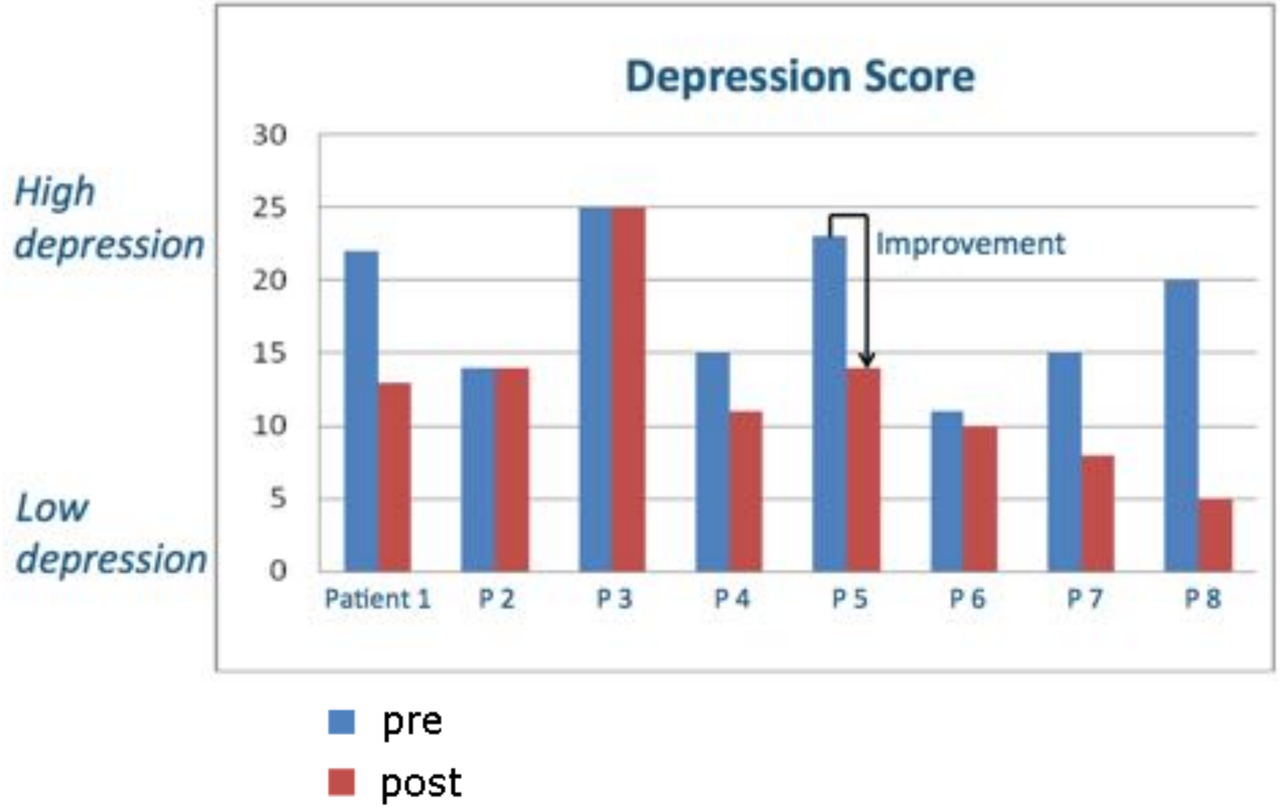
Neurofeedback Therapy for Patients with Depression

Behavioral effects of neurofeedback training after 4 sessions (HRSD score)

group results



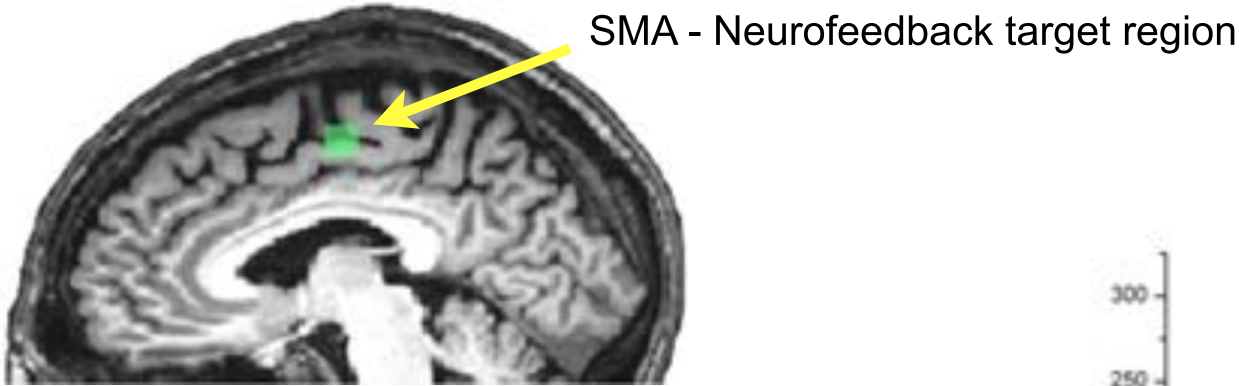
single-subject results

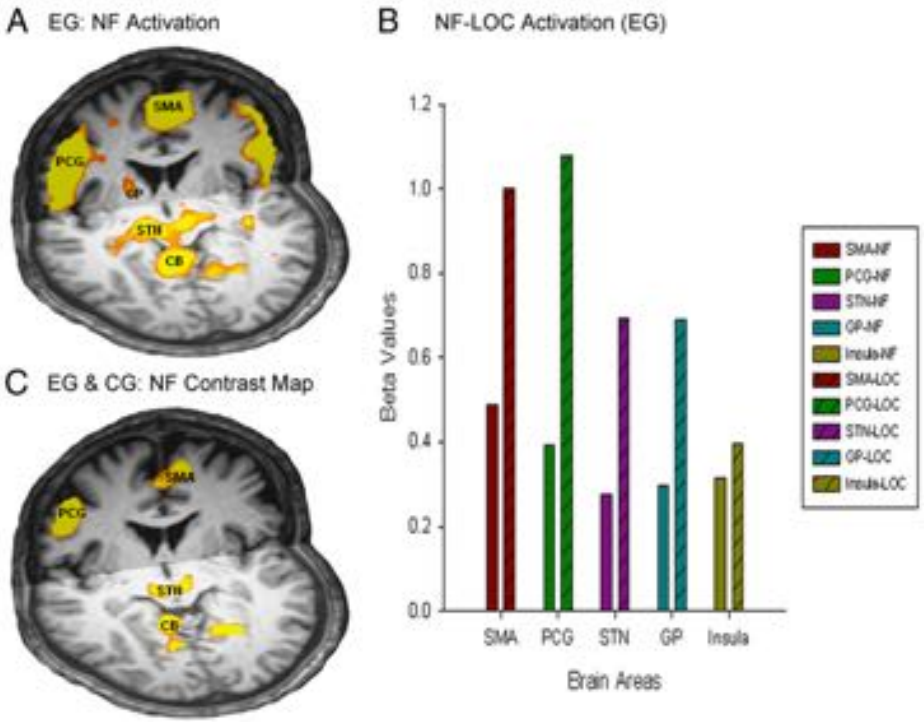


-> First clinical trial study in UK

Linden, D.E.J., Habes, I., Johnston, S.J., Linden, S., Tatineni, R., Subramanian L., Sorger, B., Healy, D., Goebel, R. (2012). Real-time Self-regulation of Emotion Networks in Patients with Depression. *PLOS One*, **7**, e38115.

Neurofeedback Therapy for Parkinson Patients





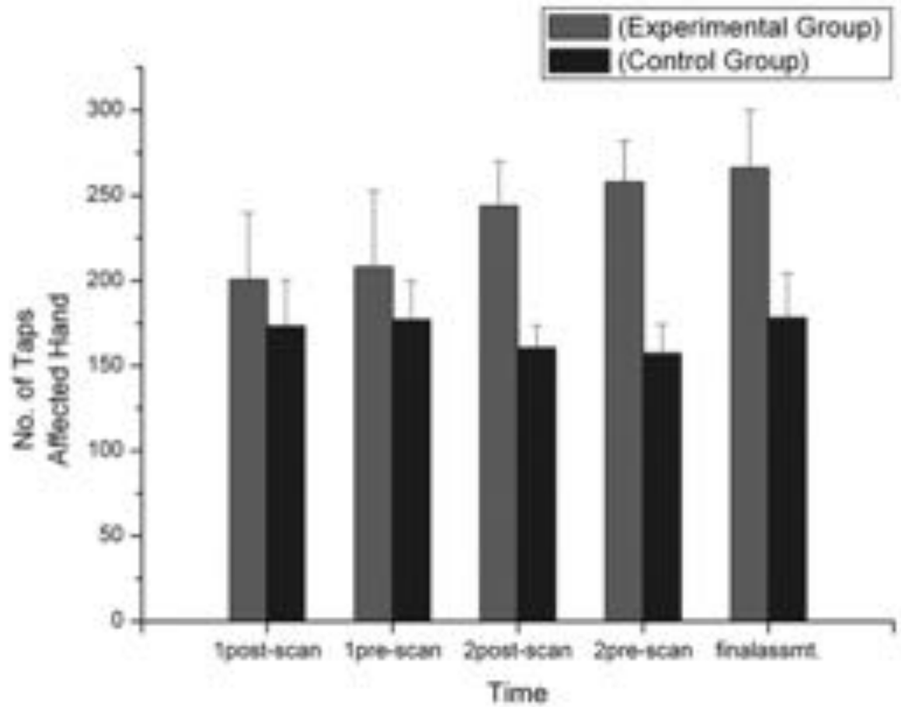
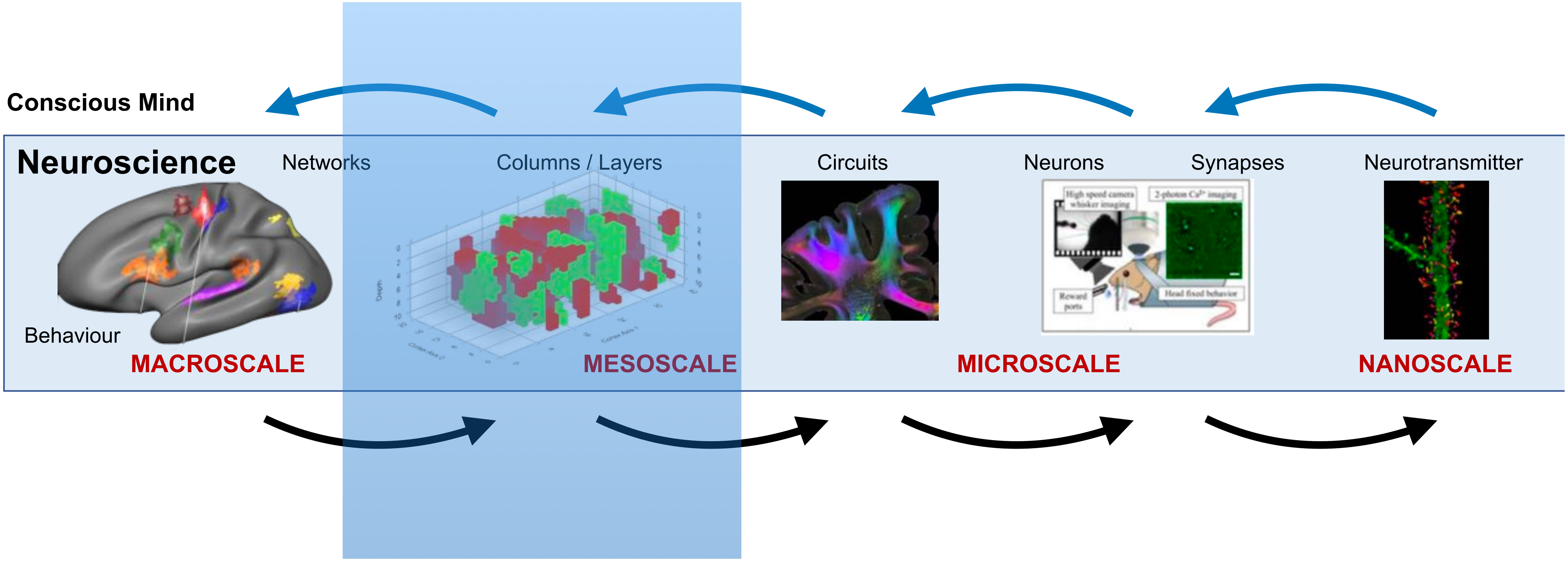


Figure 5. The functional improvement was apparent from the increase in finger-tapping frequency. Mean number of finger taps is shown for all sessions, with error bars showing the SD. Patients in the experimental group were able to increase the number of finger taps from session 1 to session 3 (the final assessment) ($p < 0.05$).

Subramanian, Hindle, Johnston, Roberts, Husain, Goebel, Linden (2011) *The Journal of Neuroscience*, **31**, 16309-16317.

Relating Anatomy and Function Across Brain Scales



Cortical Columns and
Cortical Layers

High-Resolution fMRI @ ≥ 7T
(0.5 - 1.0 mm)

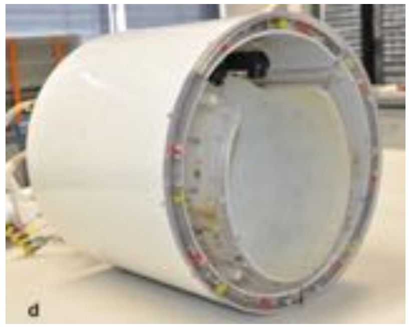
Ultra-High Field (UHF) MRI Center in Maastricht

Neuropartner / Incubator

Cognitive Neuroscience Department

Ultra-high field (UHF) imaging center "Scannexus"
(3 Tesla, 7 Tesla, 9.4 Tesla human MRI)

Scannexus Ultra-High Field MRI Center — The 9.4T

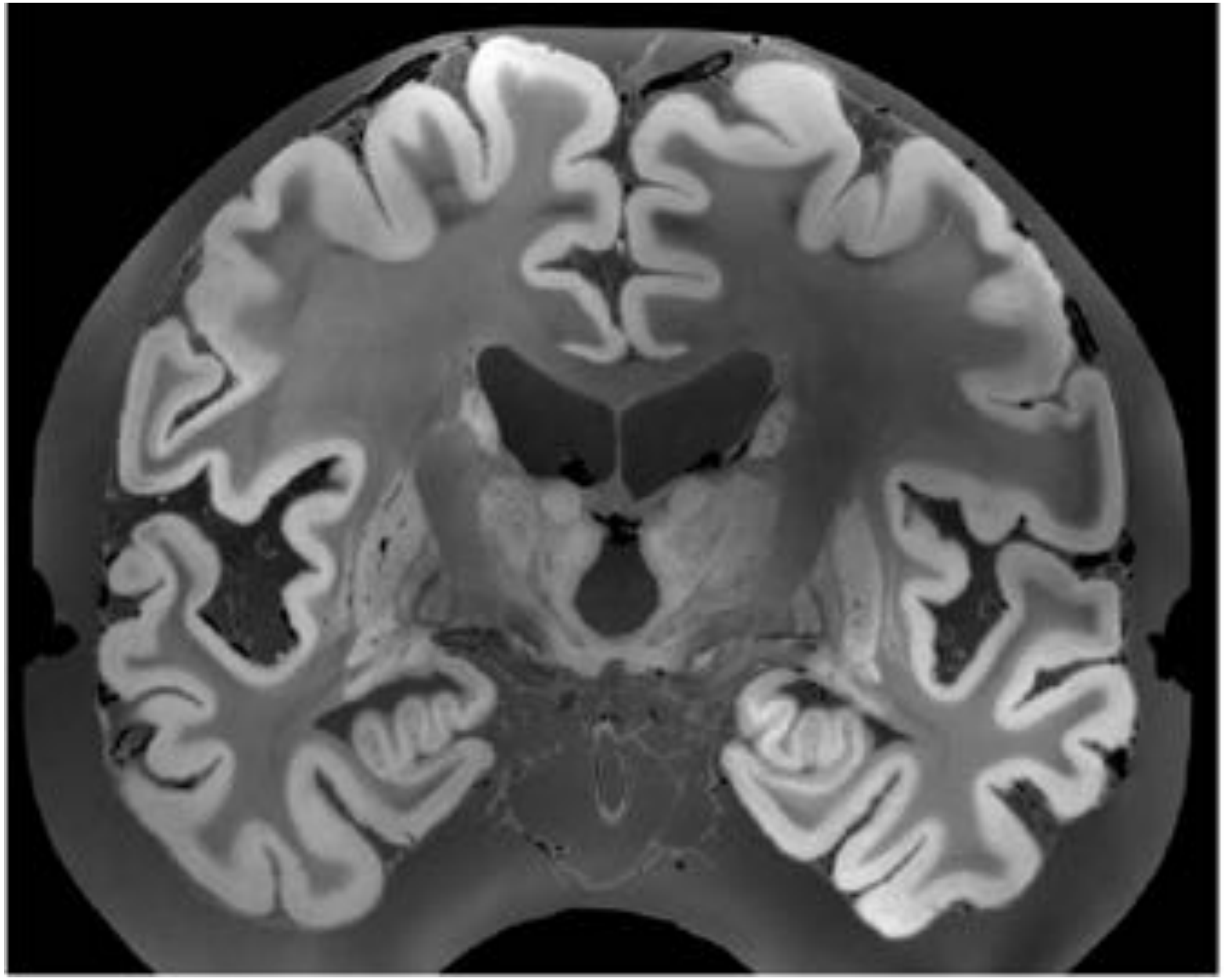


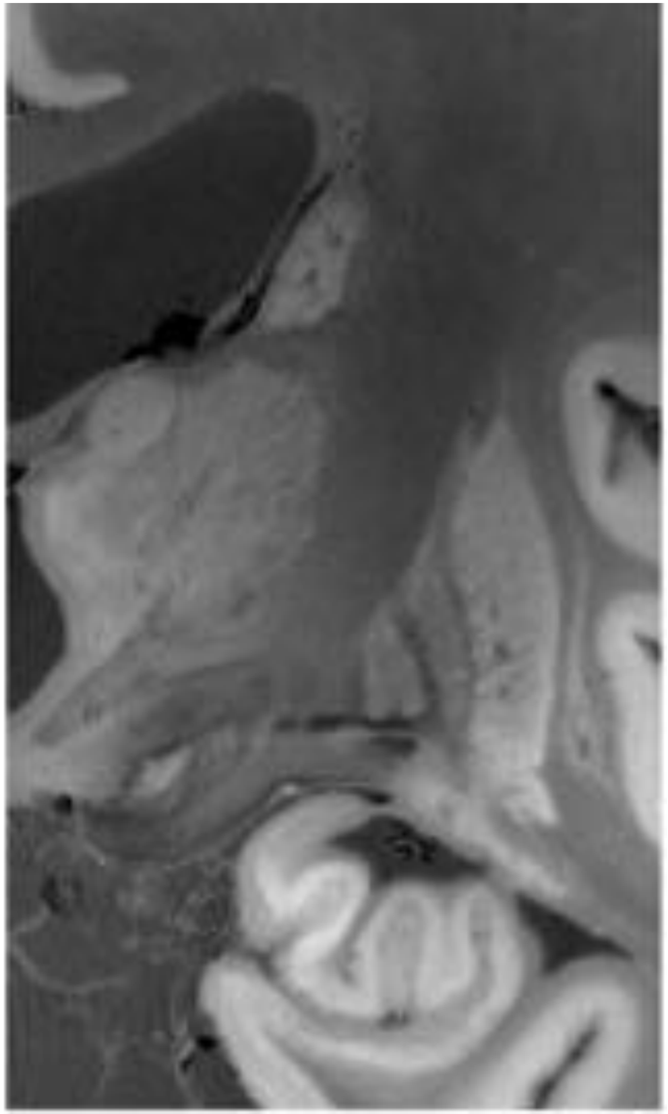
Head-only gradient coil (max. 80 mT/m at 400 mT/m/s slew rate)

Shajan et al, Magn Reson Med. 2014 Feb;71(2):870-9

Acknowledgements to Benedikt Poser, Desmond Tse, Chris Wiggins, Klaus Scheffler and Life Services (among others) to make it ready for Neuroscience applications!

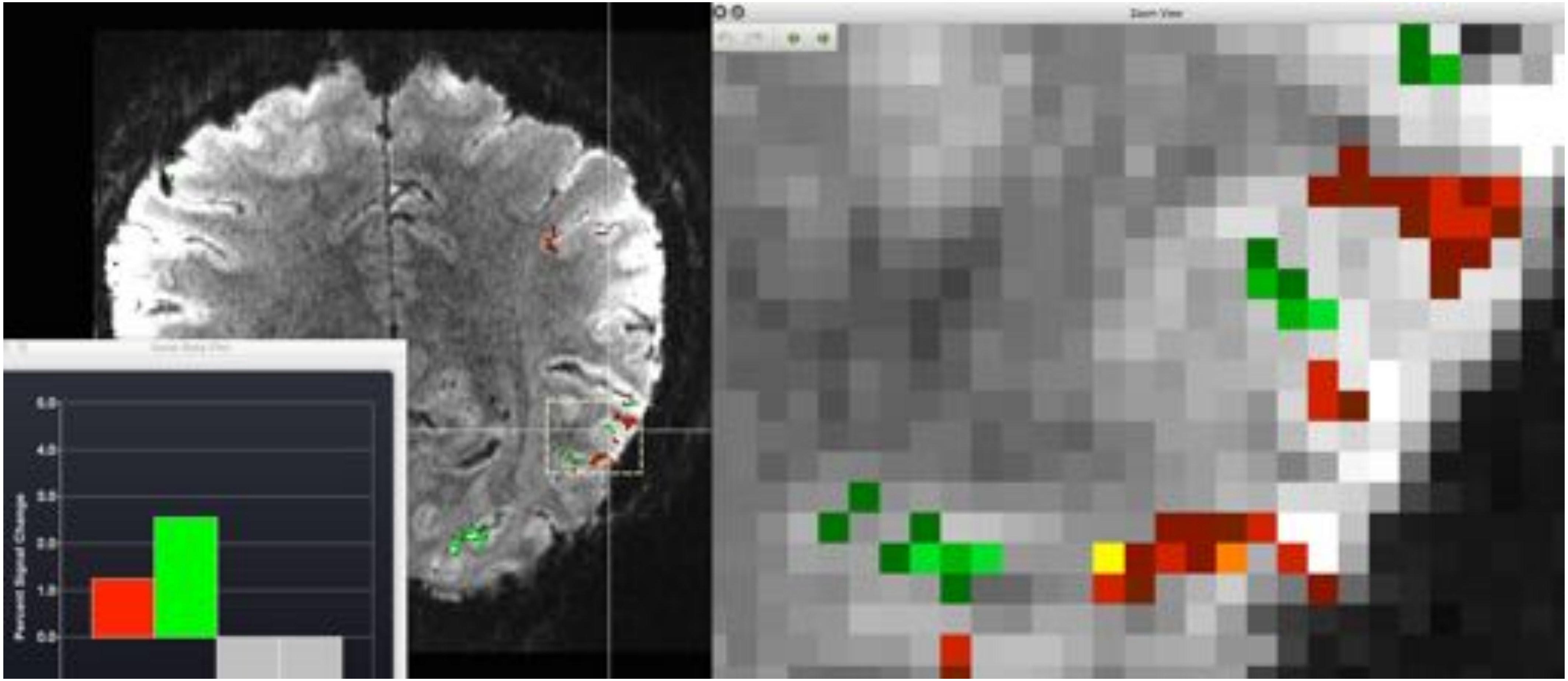
Ex-Vivo MRI @ 9.4T — 200 Mircon T2*w Isotropic





Courtesy Alard Roebroeck

Functional Sub-Millimeter fMRI at 7 Tesla

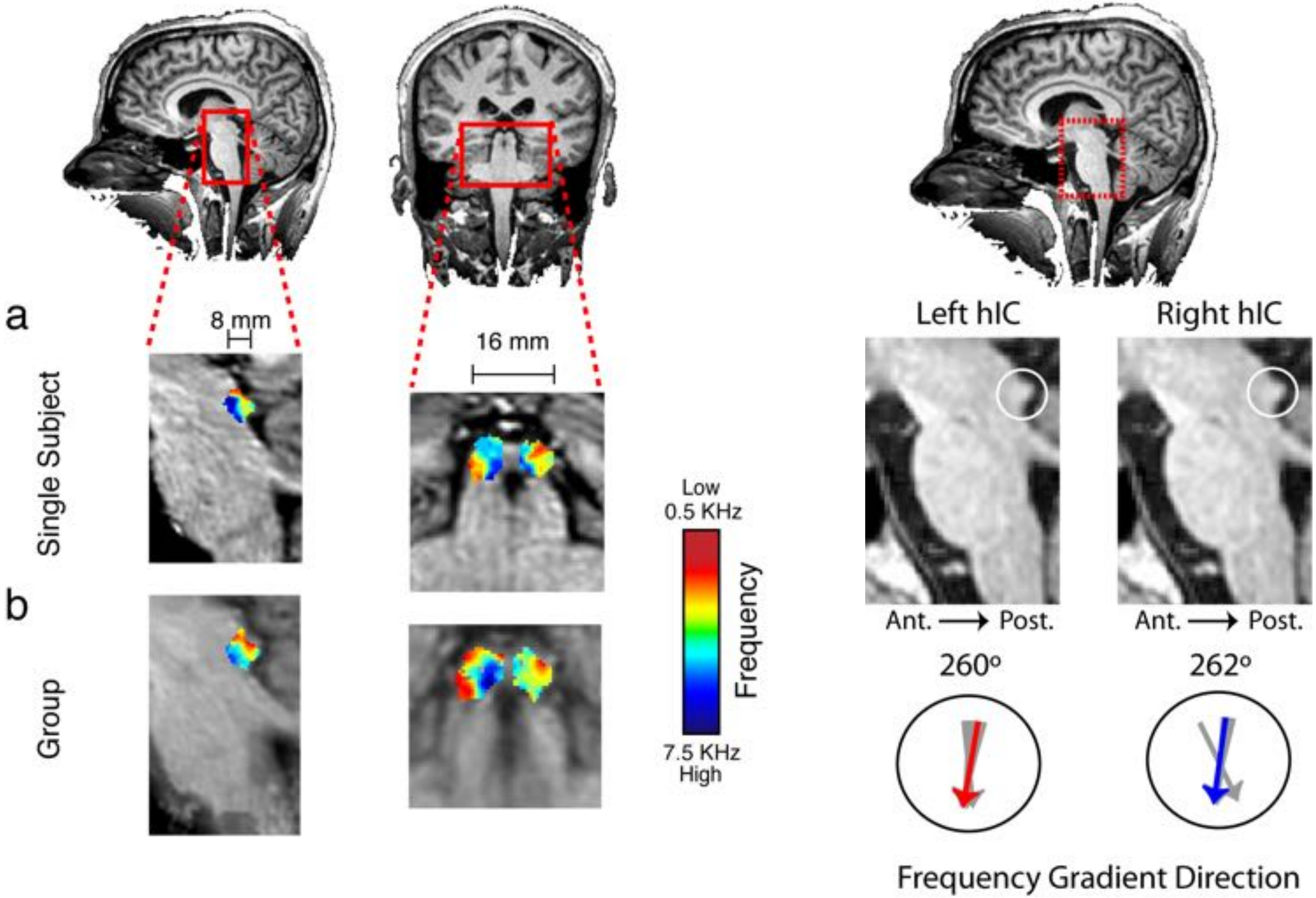


Non-smoothed (motion corrected) data at 0.8 mm isotropic resolution (0.512 mm^3)
Red and green colours indicate voxel preference for horizontal vs vertical motion

Goebel R, Schneider M, Ugurbil K, De Martino F, Yacoub E.(2017). in preparation.

Tonotopic Maps in the Inferior Colliculus @ 7 T

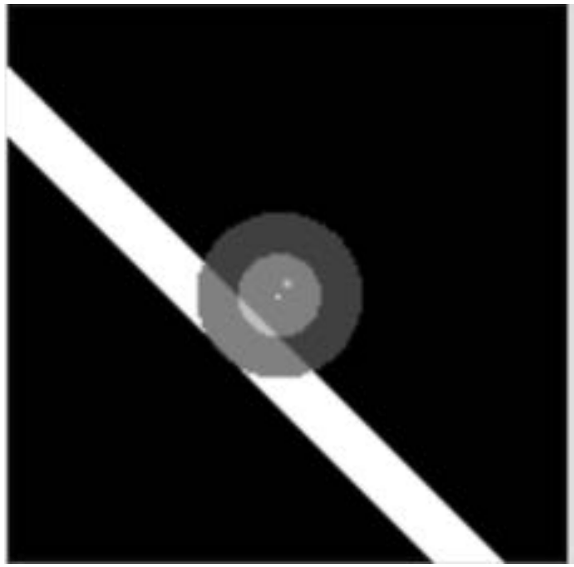
UHF fMRI reveals a feature map in a small structure that shows only unspecific response at conventional resolution



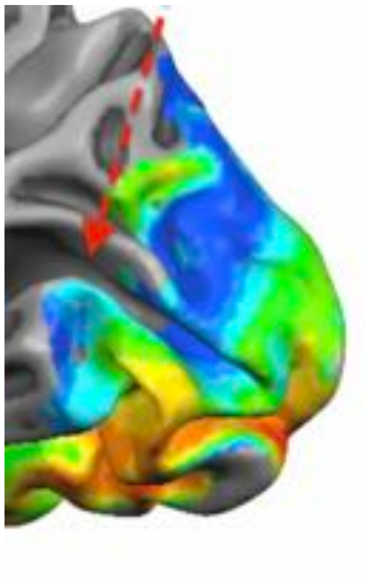
De Martino, Moerel, van de Moortele, Ugurbil, Goebel, Yacoub, Formisano (2013). Spatial organization of frequency preference and selectivity in the human inferior colliculus. *Nature Communications*, **4**, 1386.

From Encoding to Decoding the Visual Field

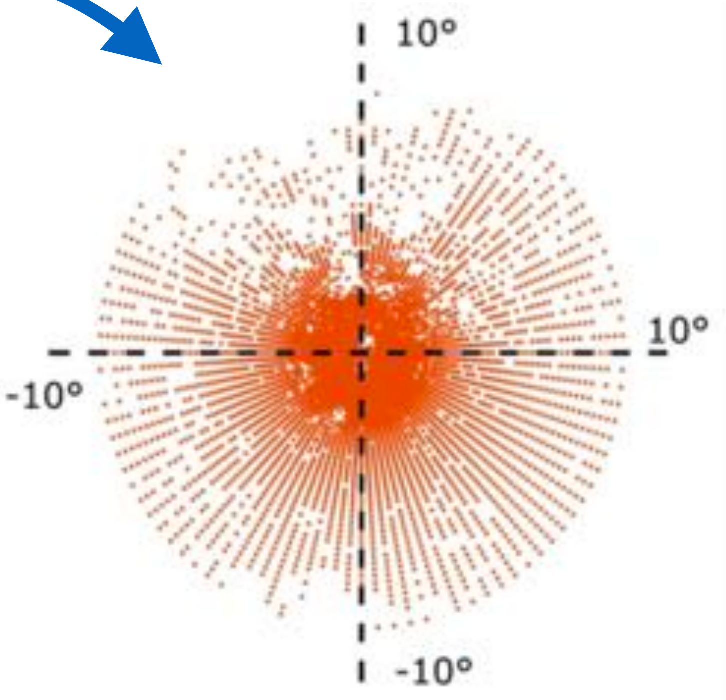
Encoding *Decoding*



Visual Stimulus



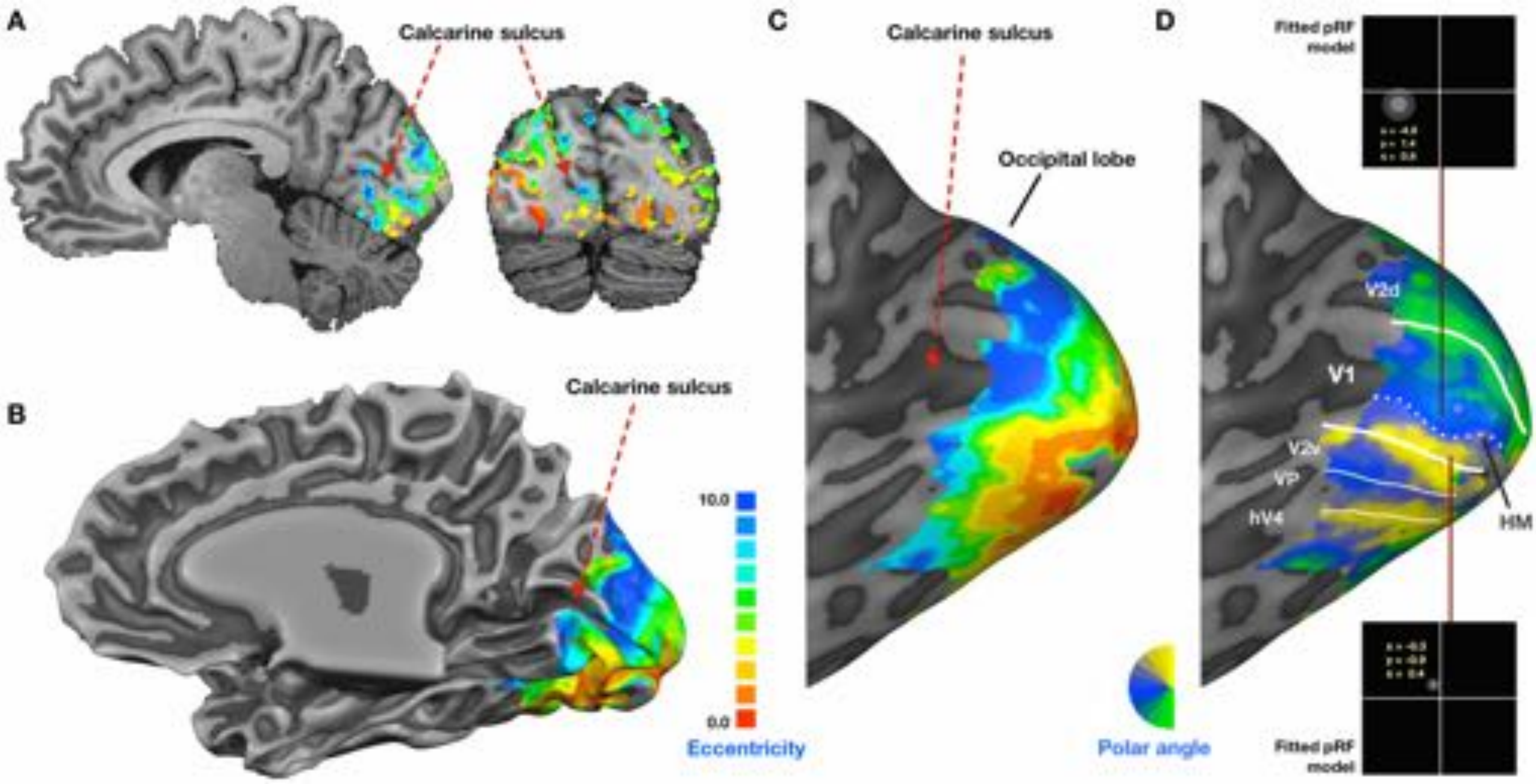
Visual Field
Mapped on Brain



Voxels pRFs Back-
Projected in Visual Field

ERC Proof-Of-Concept Grant (2018) “7 Tesla Mind’s Eye BCI”
Follow-up grant of Advanced ERC grant “ColumnarCodeCracking”

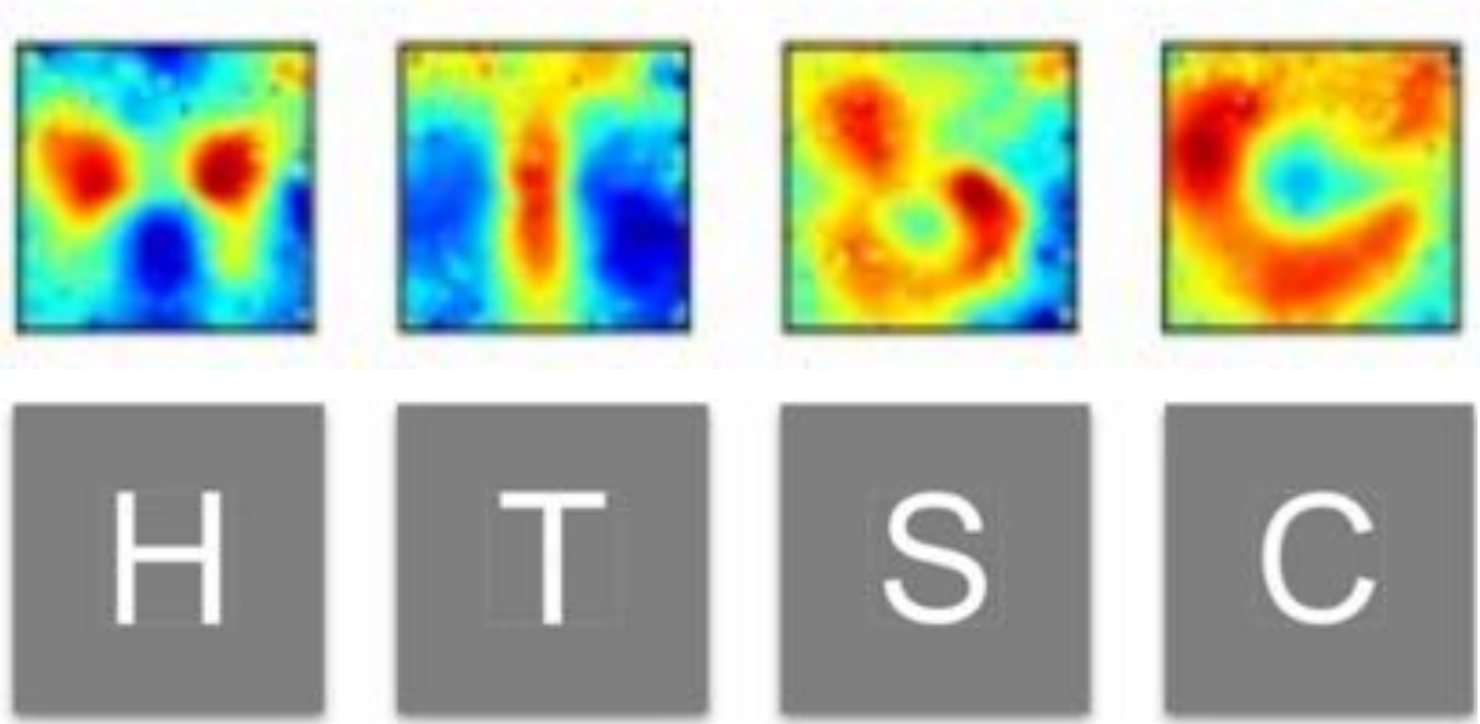
Retinotopic Mapping of Early Visual Areas using Population Receptive Field (pRF) Estimation (based on Dumoulin & Wandell, 2008)



Goebel R (2015). Functional organization of primary visual cortex. In: A. Toga (Ed). Brain Mapping: An Encyclopedic Reference.

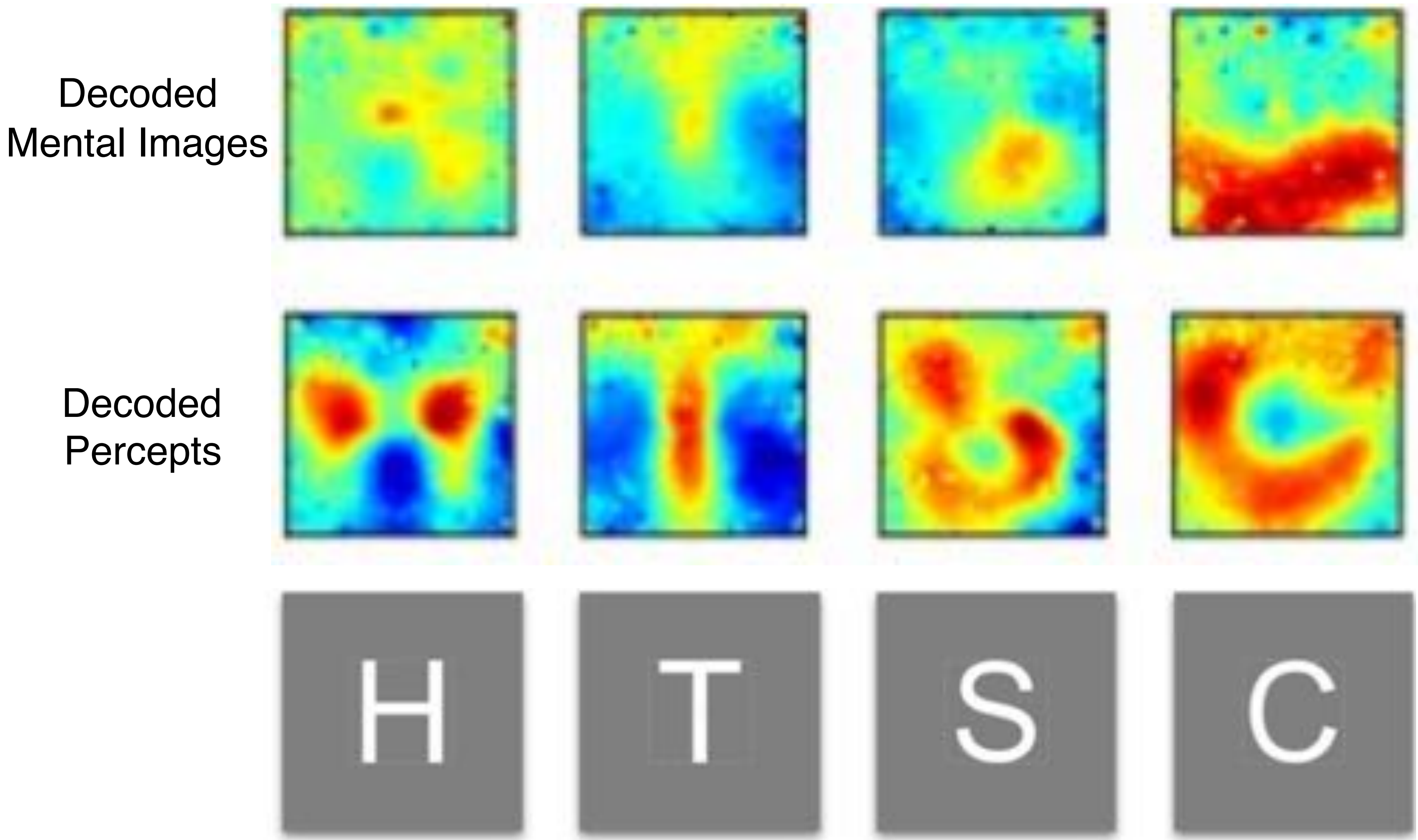
Decoding Imagined Letter Shapes from V1-V3 Activity @ 7T

Decoded Percept



Senden, Emmerling, van Hoof, Frost, Goebel (2018) Under review.

Decoding Imagined Letter Shapes from V1-V3 Activity @ 7T



Senden, Emmerling, van Hoof, Frost, Goebel (2018) Under review.

De-Noising Brain Patterns using Multi-Layered Auto-Encoder

Pre-training

We used a de-noising autoencoder in order to learn efficient letter features (figure 2). The autoencoder was trained to reproduce letter-typical voxel co-activations (voxel patterns, VPs).

Voxel patterns within each ROI were obtained from perceptual data. First, single trial VPs were obtained by averaging BOLD activations in the range from +2 until +4 volumes after trial onset. Grand average VPs per letter were subsequently obtained by averaging over all single trial VPs of a letter and z-normalizing. These grand average VPs were used for training.

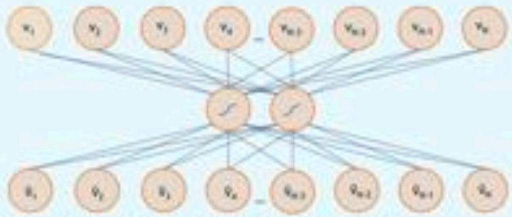


Figure 2: De-noising autoencoder.
An single-layer autoencoder was trained to reproduce VPs after adding Gaussian noise ($\sigma = 12$). The number of units in the hidden layer was 10% of ROI voxels. Hidden units had a sigmoid activation function while output units activated linearly. The learning rate was 10^{-6}, momentum was 0.9, batches had a size of 100, and loss was measured by the sum of squared distances. Training lasted 2500 iterations.

Reconstruction

Based on the mapping from visual field to cortex given by pRFs, we obtained weights mapping the cortex to a visual field image (VFI):

$$\mathbf{W}_{VFI} = \mathbf{W}^{T}_{pRF}\mathbf{D}_{pRF}$$

where $\mathbf{D}_{pRF}$ is a diagonal matrix of the inverse outdegree of each pixel in the VFI.

Using these weights, VFIs were calculated from grand average VPs ($\mathbf{VFI}=\mathbf{W}_{VFI}\mathbf{VP}$). Since activations for imagery runs were noisy compared to perceptual runs, they were cleaned using the pre-trained autoencoder prior to extracting grand average VPs.

Classification

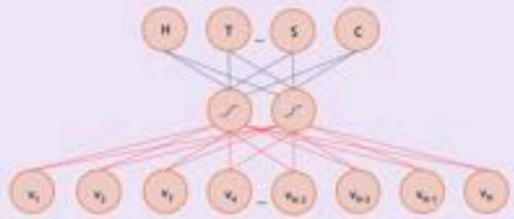
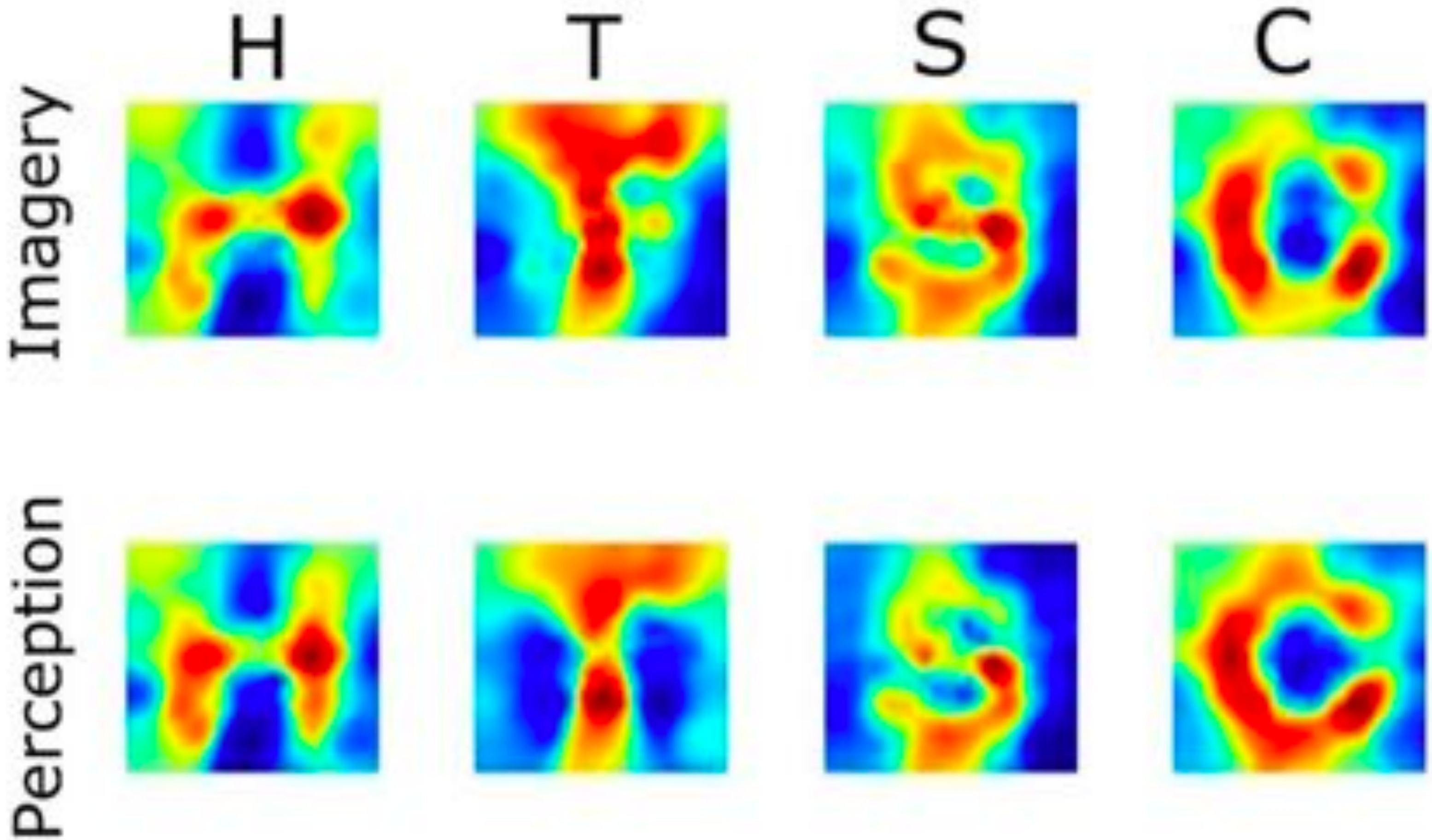


Figure 3: Letter-classifier.
A four unit softmax classifier was stacked on the pretrained hidden layer (red weights). The network was then trained to classify single trial VPs in imagery runs. These runs were split into training and testing datasets in a leave-one-run-out procedure. The learning rate was 10^{-4}, momentum was 0.9, batches had a size of 96, and loss was measured by cross-entropy. Training lasted 250 iterations.

Senden, Emmerling, Frost, Goebel (2017). Faithful reconstruction of imagined letters from 7T fMRI measures in early visual cortex. Poster presented at Organization of Human Brain Mapping Meeting, Vancouver, Canada.

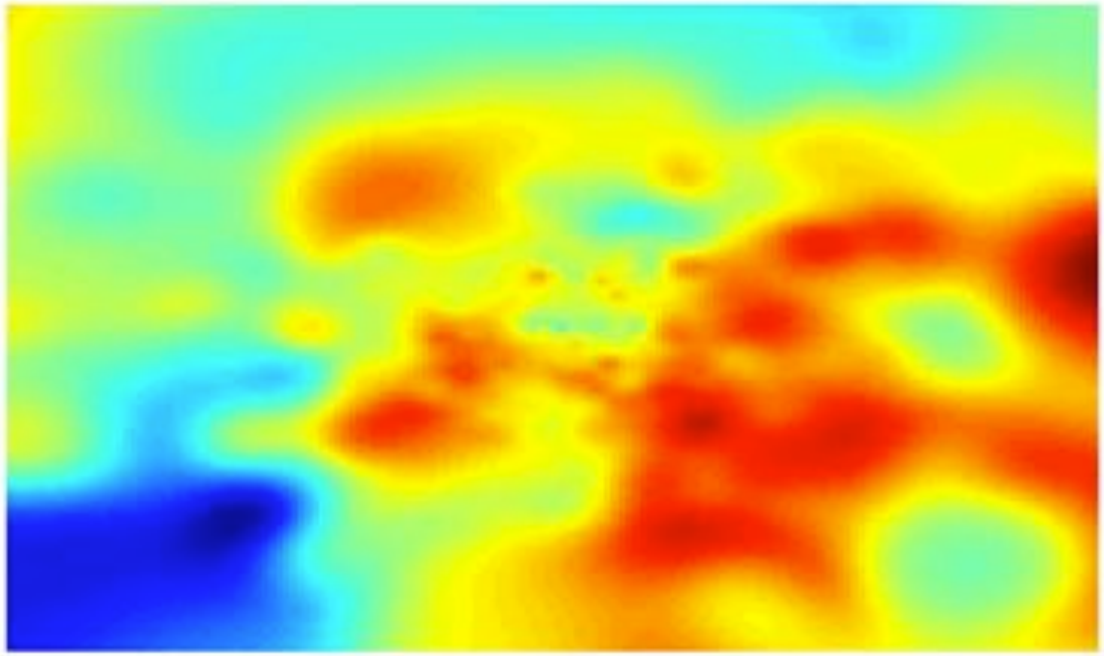
Decoding Letter Shapes from V1 Activity @ 7T



Decoded Images of the “mind’s eye” (top row) when using deep auto-encoder network for “de-noising”

Senden, Emmerling, van Hoof, Frost, Goebel (2018) Under review.

Combining Neurofeedback and BCI Application



Time course of letter decoding when using
deep auto-encoder network for “de-noising”

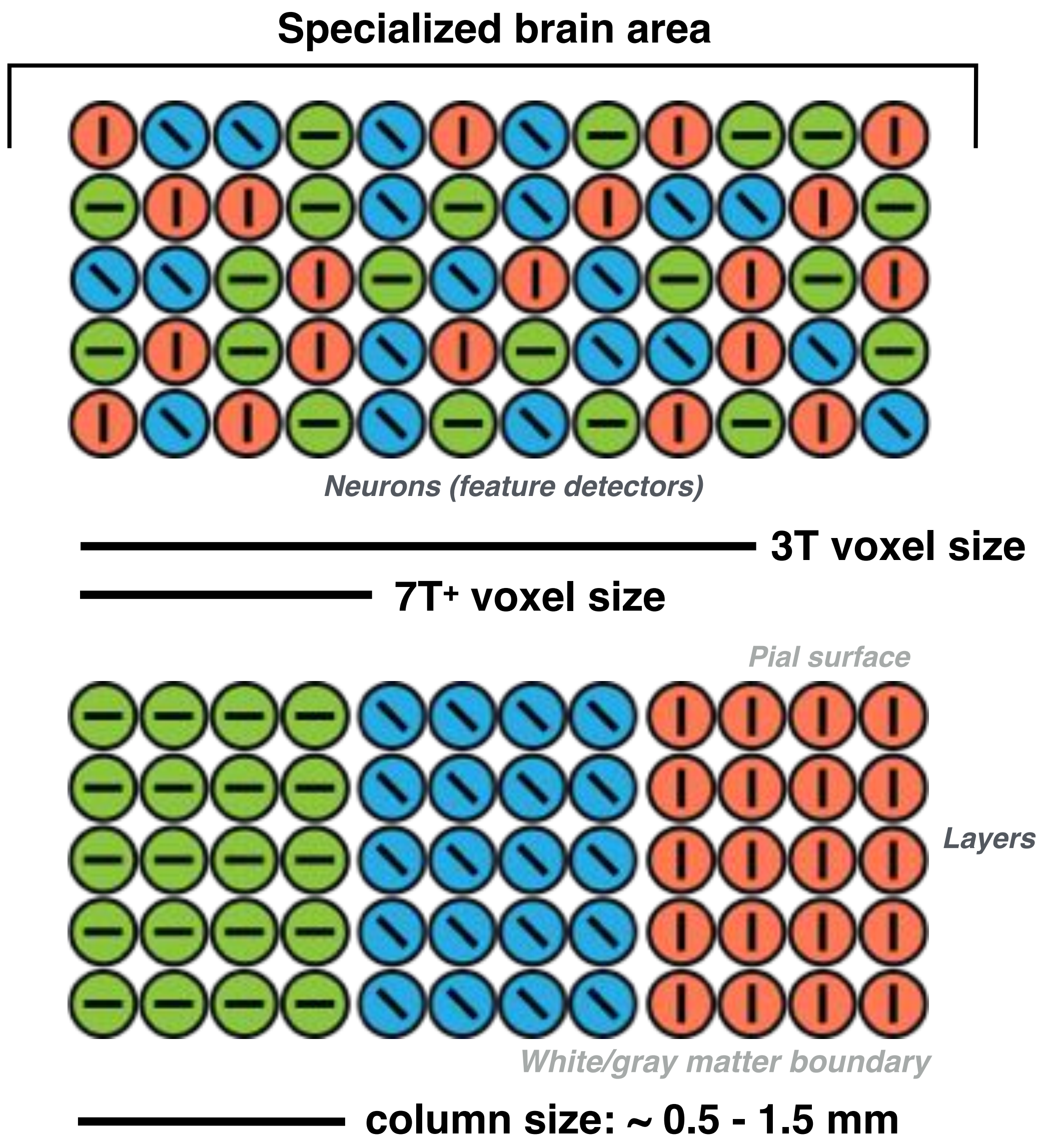
ERC Proof-Of-Concept Grant (2018) “7 Tesla Mind’s Eye BCI”
Follow-up grant of Advanced ERC grant “ColumnarCodeCracking”

Mixed Neurofeedback-BCI: Letter shapes decoded and visualized to participant are “frozen” and (local) imagery used to correct (add / remove features) of letter shape

Columnar- And Laminar-Level Imaging with fMRI at 7+ Tesla

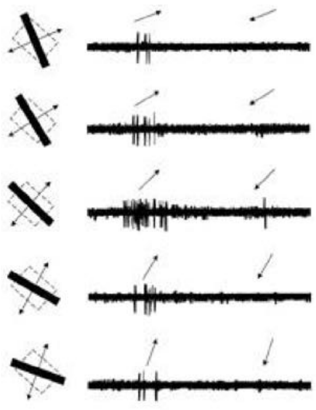
When a Quantitative Improvement of Spatial Resolution Turns into a Qualitative Change

- **Individual neurons** code features but they are **too small** to be detected with high-resolution human fMRI.
- If **neurons** would be **distributed randomly**, ultra-high field imaging would provide no qualitative improvement.
- If neurons **cluster into functional units**, we might be able to reveal fine-grained "neuron-like" representations at the columnar level.
- There is indeed substantial evidence that many areas of the cortex are organized in vertically extending **columns** that contain neurons with rather similar response profiles.



Features at Mesoscopic Scale: From Neurons to Columns

Prime example: *Orientation selectivity in primary visual cortex*

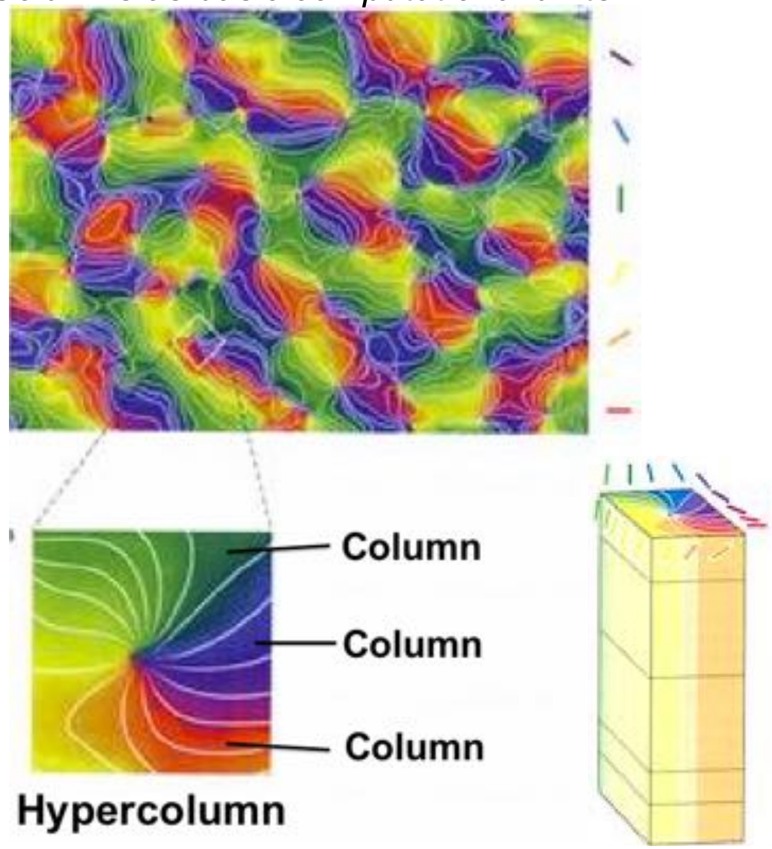


- Responses of most V1 neurons are sharply tuned for the orientation of a stimulus in a small region of the visual field
- Discovered by Hubel & Wiesel during microelectrode recordings

They observed that neurons with similar response preference cluster in "cortical columns"

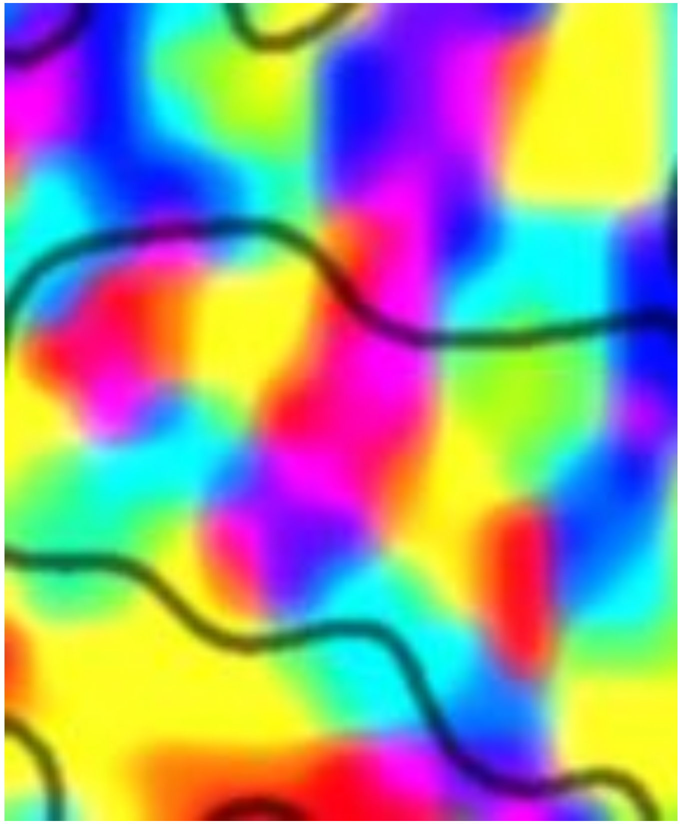
Torsten Wiesel

Columns as basic computational units

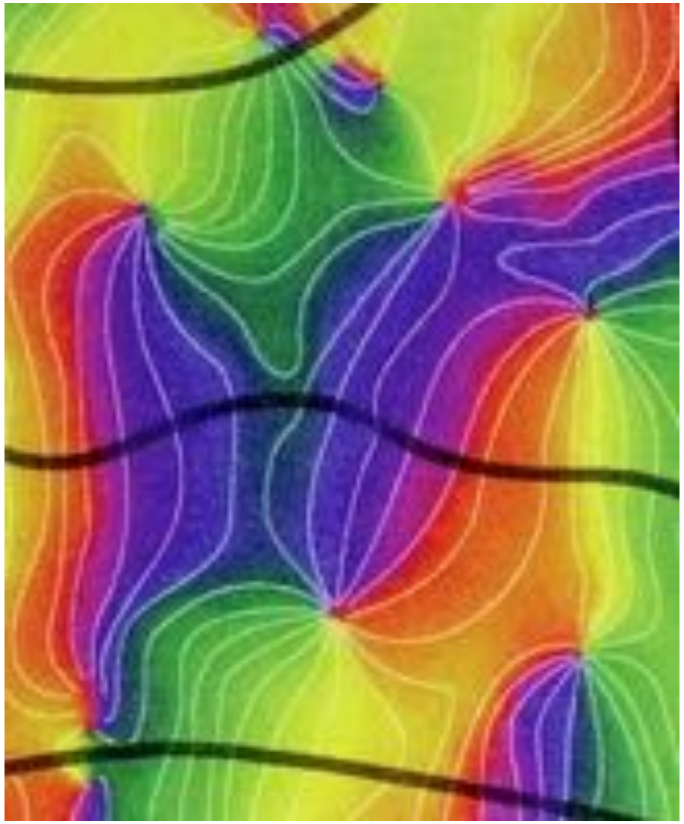


High-Resolution fMRI Reveals Orientation Columns in V1

Human - fMRI (SE, 7T)



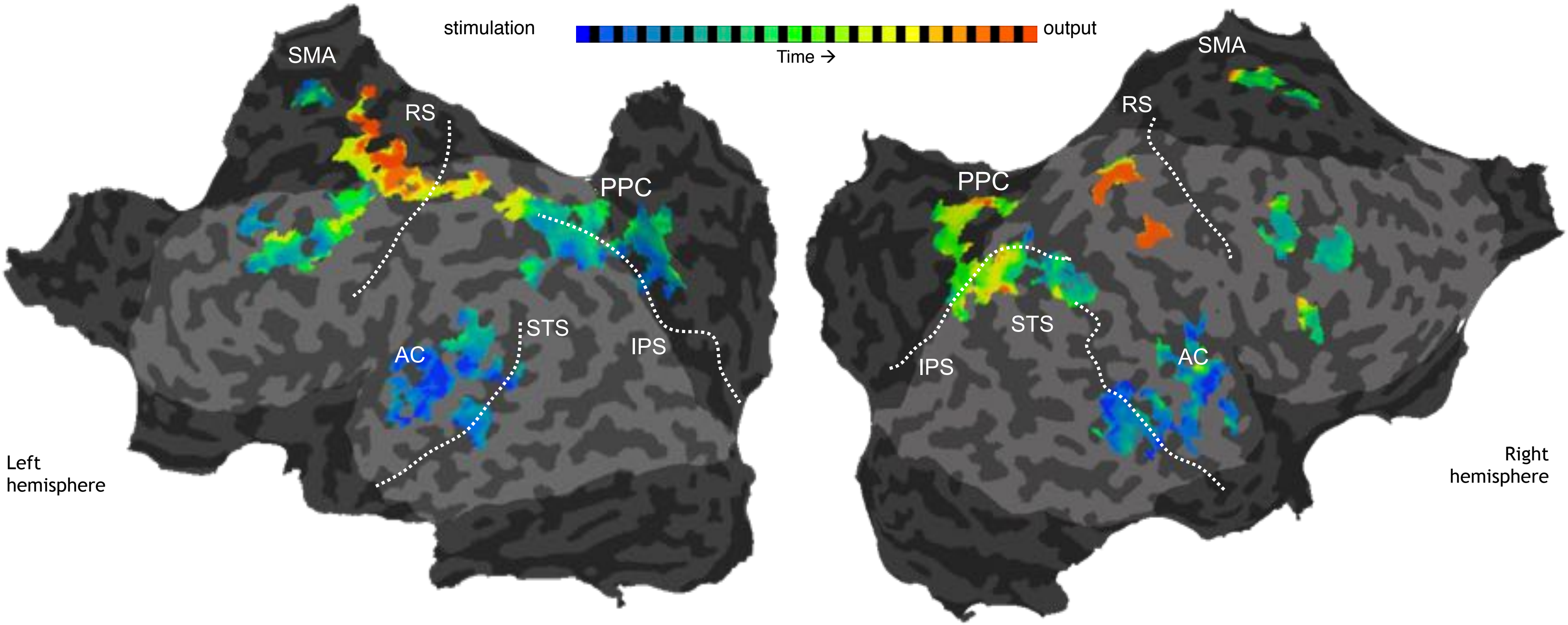
Monkey - Optical Imaging



Yacoub, Harel, Ugurbil (2008) *Proc Natl Acad Sci USA,* **105**, 10607-10612.

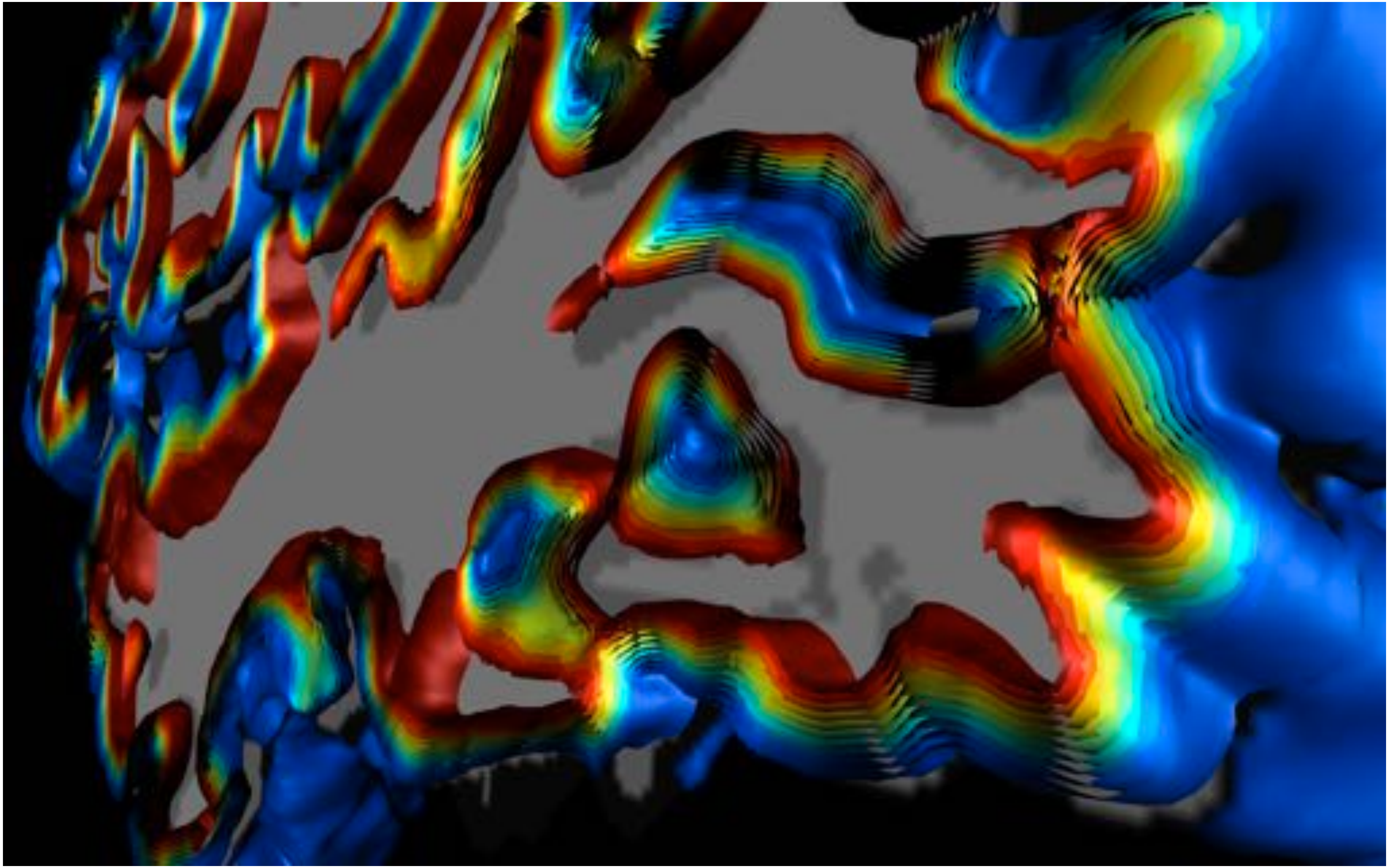
Mapping of the (larger) ocular dominance columns had already been reported earlier (e.g. Cheng et al., 2001; Goodyear and Menon, 2001; Yacoub et al., 2007) but this spin echo (SE) EPI study was the first study revealing detailed maps of the much smaller orientation columns!

The Cortex as a 2D Sheet - Mapping Brain Activity on Flat Maps (3 Tesla)

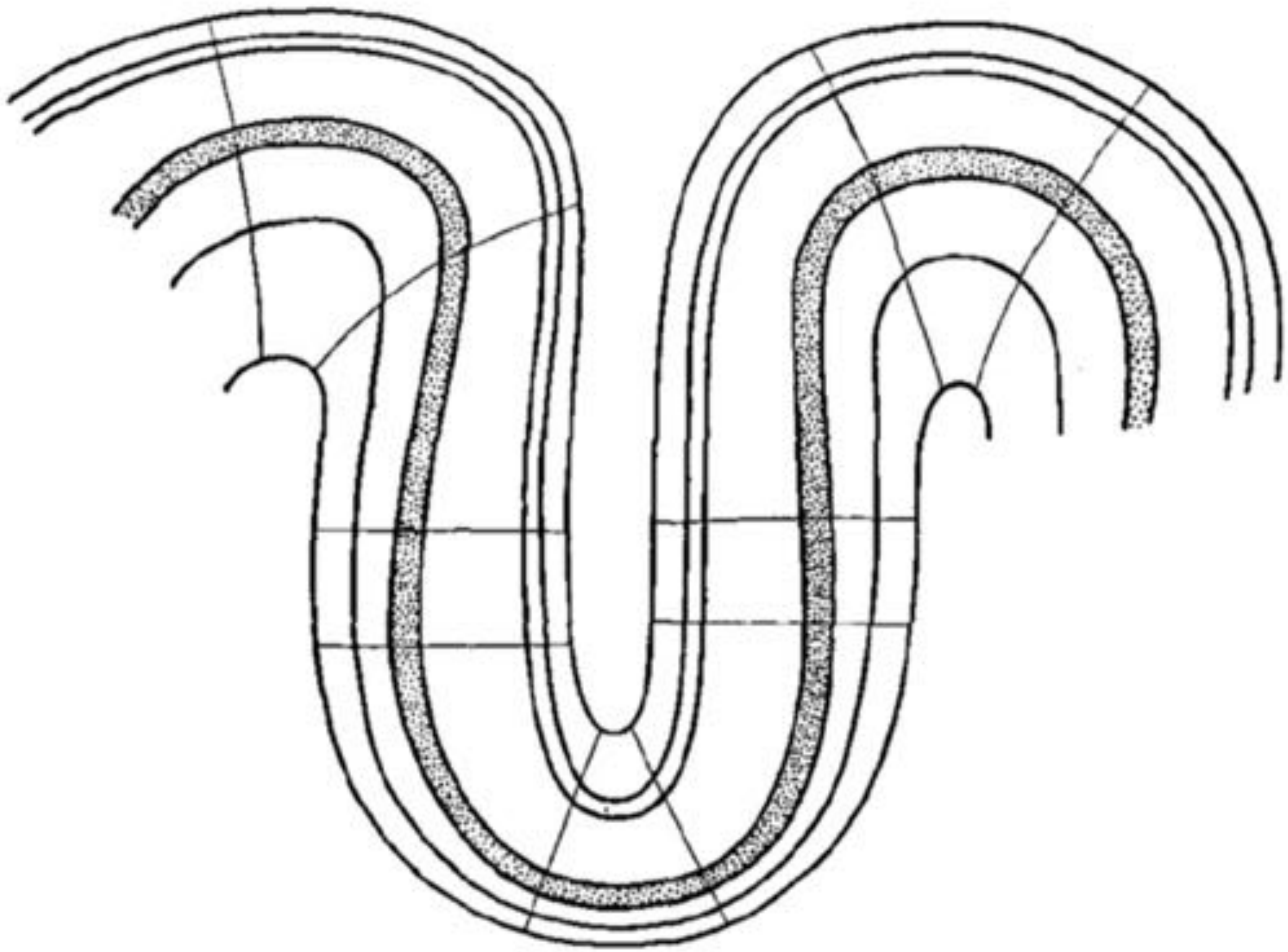


Sack,A, Camprodon, JA, Pascual-Leone, A & Goebel, R (2005). The dynamics of inter-hemispheric compensatory processes in mental imagery. ***Science***, 308, 702-704.

The Cortex Modelled as a 3D Structure (7+ Tesla)

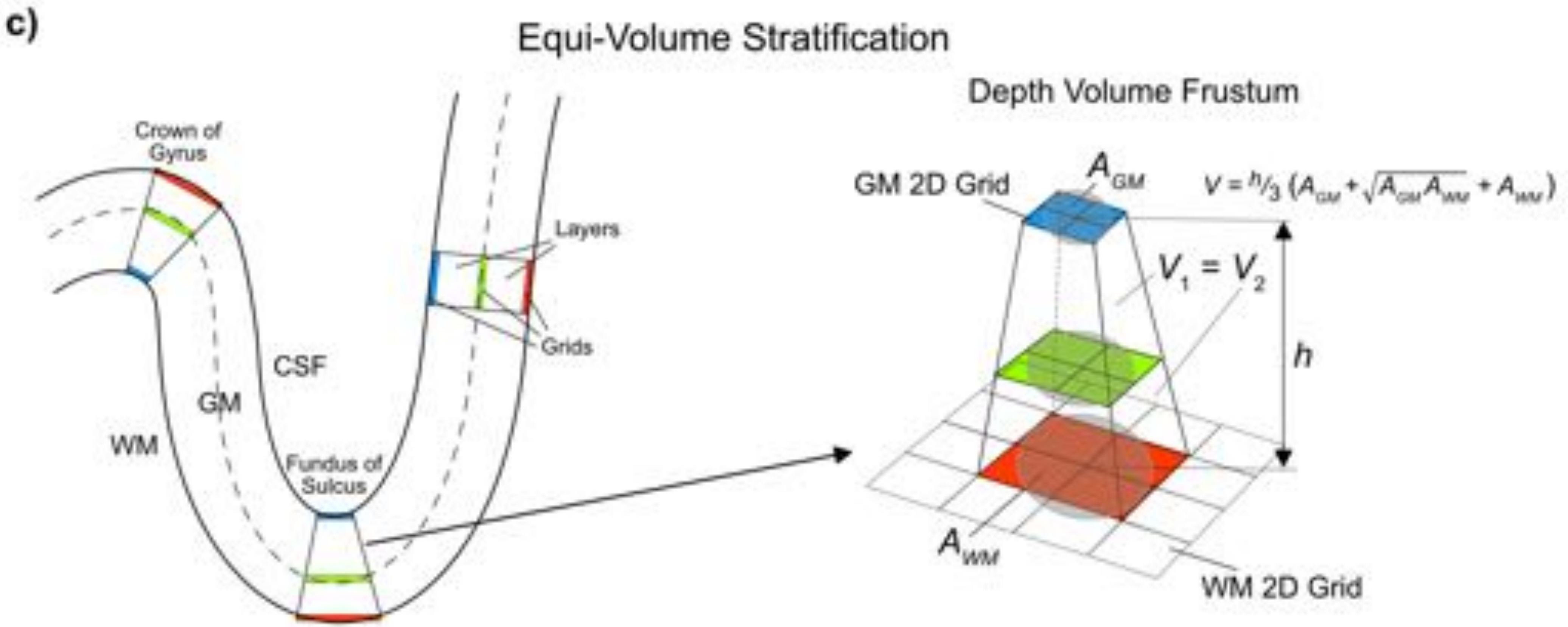


Layer Sampling - The Book Principle



Bok (1929). A cortical cross section depicting six cytoarchitectonic layers. The volume fraction of a segment is constant across the whole layer. This is possible because the thickness of the layer changes to compensate the curvature.

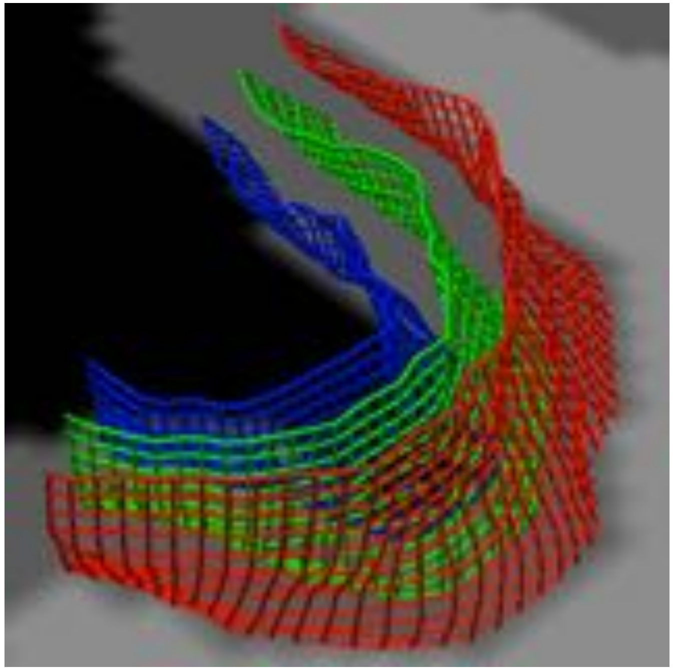
Isotropic High-Resolution Scans and Grids for Advanced Analysis

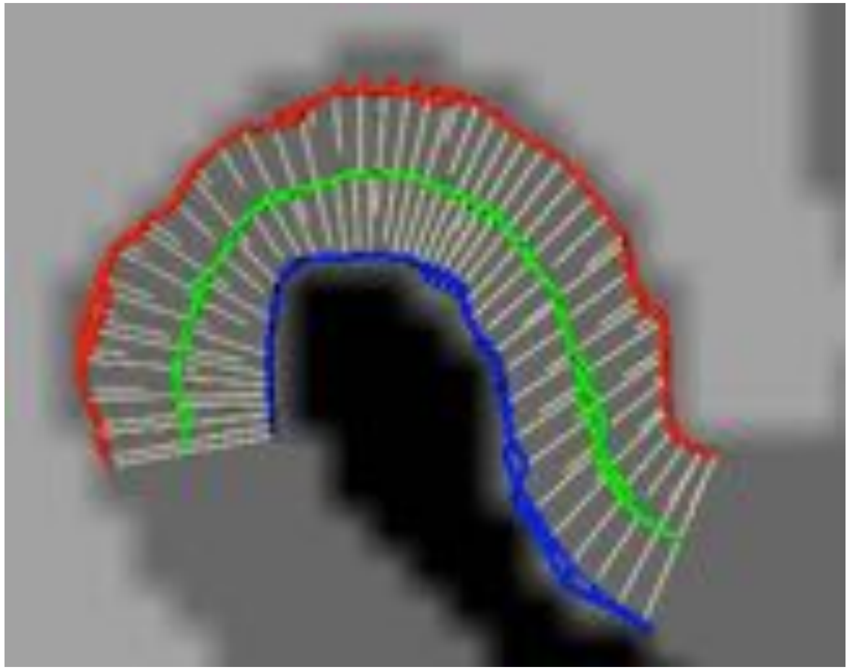


- 2D regular grid sampling using equi-volume model (Bok, 1925, Waehnert et al., 2014)
- Layers (voxels between depth grids) can be filled in voxel space

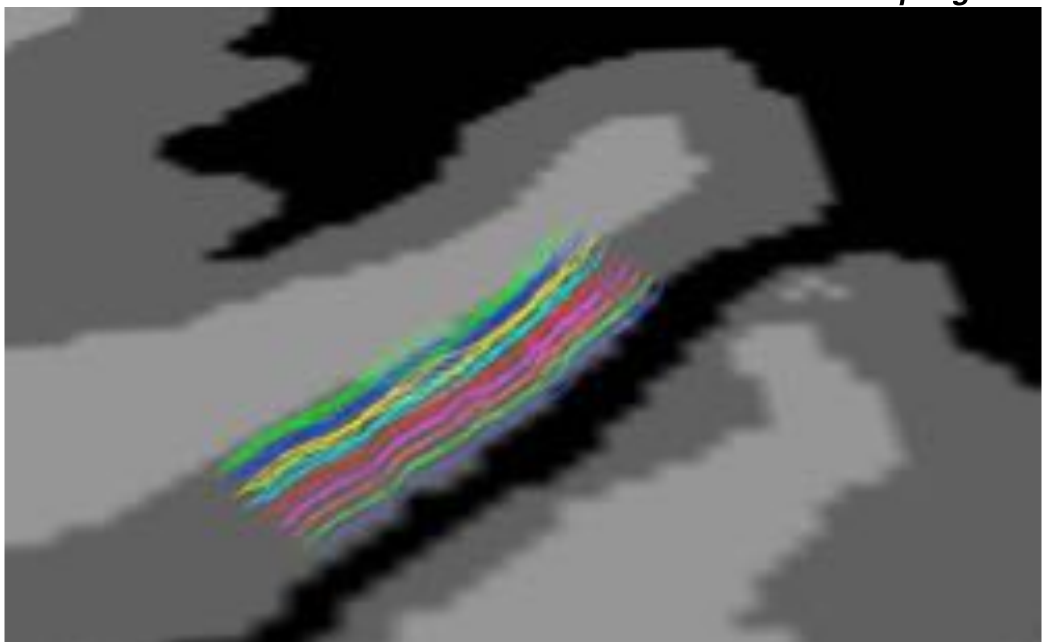
Kemper, De Martino, Emmerling, Yacoub, Goebel (2017). High-resolution data analysis strategies for mesoscale human functional MRI at 7 and 9.4 Tesla. Neuroimage, Accepted.

High-Resolution 2D Grid Sampling At Multiple Cortical Depth Levels



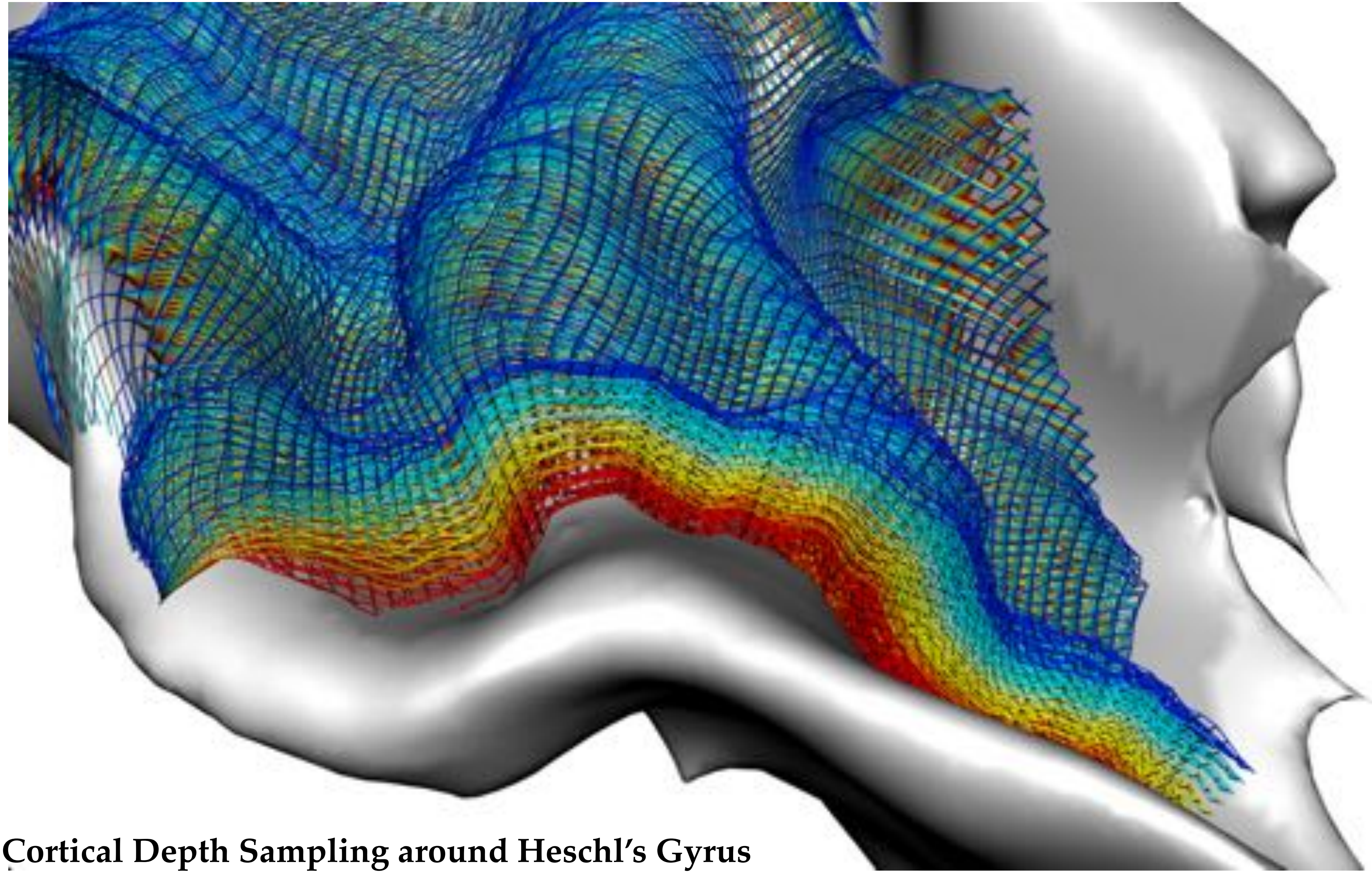


9 depth grids



- Precisely aligned functional data is sampled at each 2D grid point
- Sampled data can be directly visualized in 2D space using grids
- A 2D grid coordinate refers to the same vertical unit across levels ("column")
- Distance, area and volume values can be easily calculated

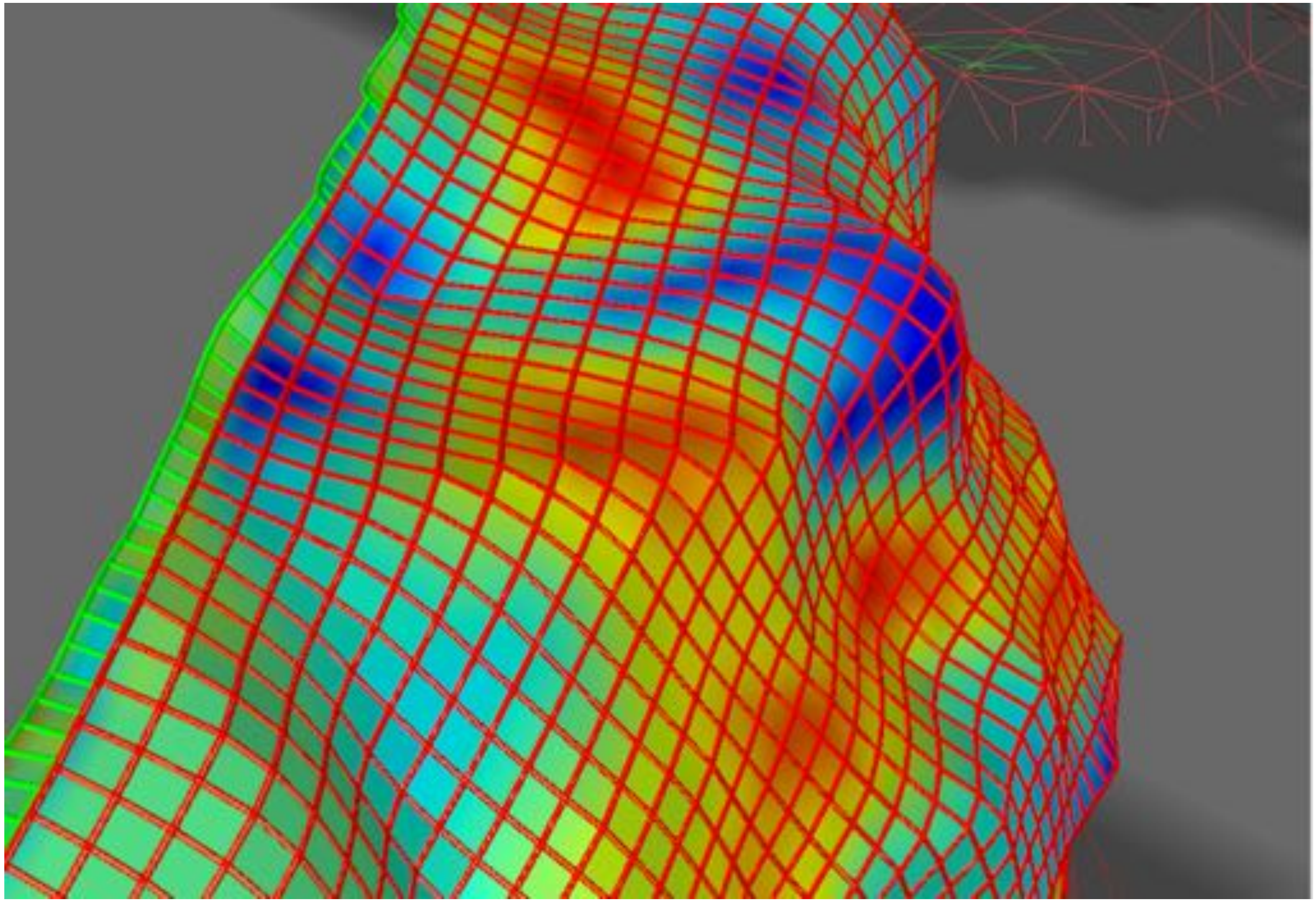
High-Resolution 2D Grid Sampling At Multiple Cortical Depth Levels



Cortical Depth Sampling around Heschl's Gyrus

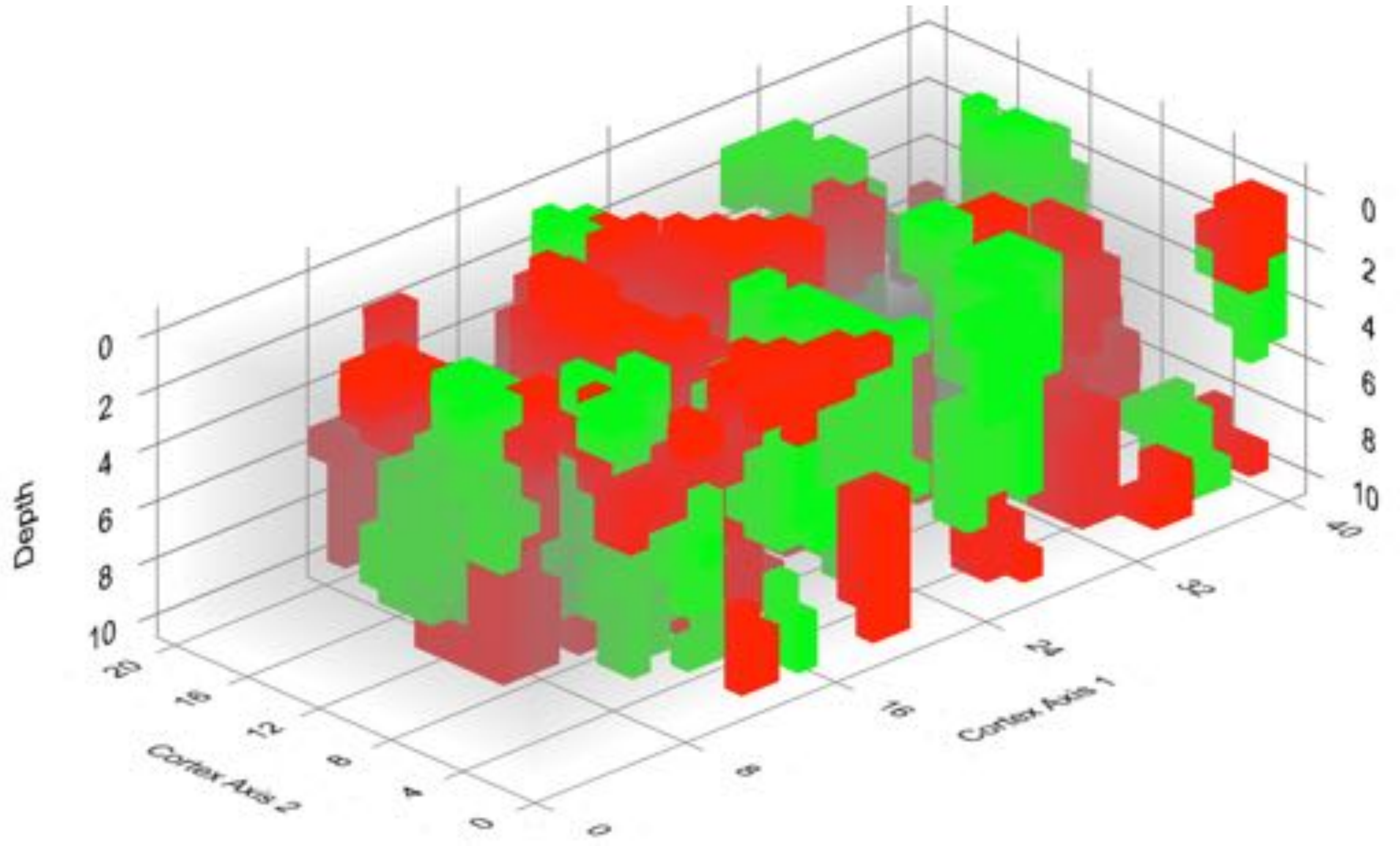
De Martino, Moerel, Ugurbil, Yacoub, Goebel, Formisano (2015). *PNAS*, **112**, 16036-1604.

Functional Grid Sampling and Methods for Alignment of Functional Volumes



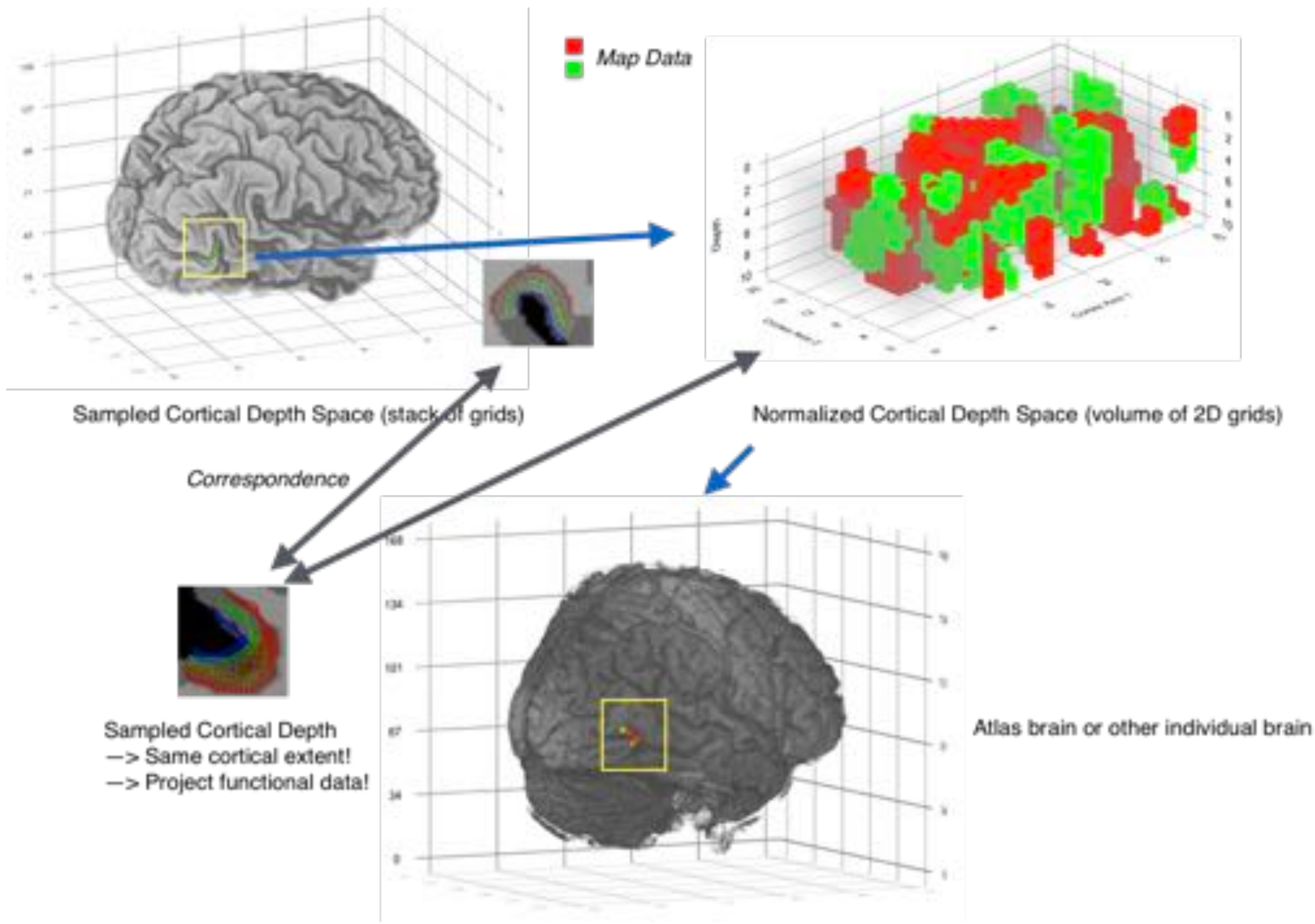
- Sample functional data on cortical depth surface grids.
- Requires precise alignment of anatomy and function and/or creation of cortical depth maps directly in functional data
- Requires also optimal within-run (motion correction), across-run, across-session alignment of functional data volumes

Sampled Functional Grids Represented as Flat Depth Volumes



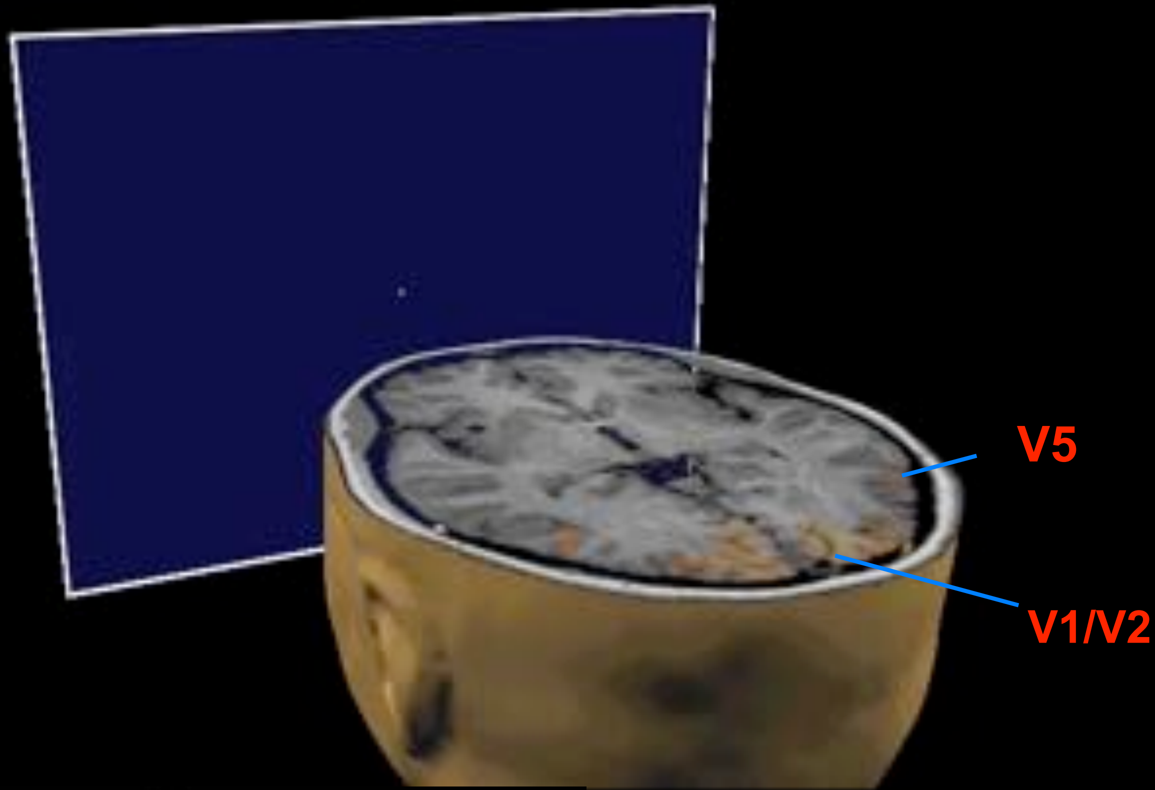
- Visualising stack of grids as conventional volumetric data
- Allows application of conventional analysis tools

Transfering Sub-MM Layer and Columnar-Level fMRI Data into Atlas

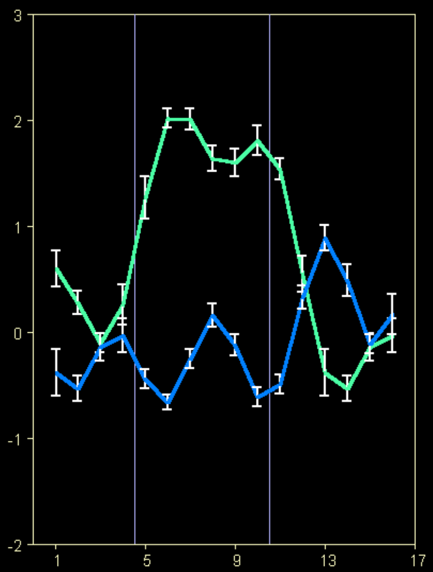


Localizing hMT+/V5 at 3T: "Moving vs Static" Contrast

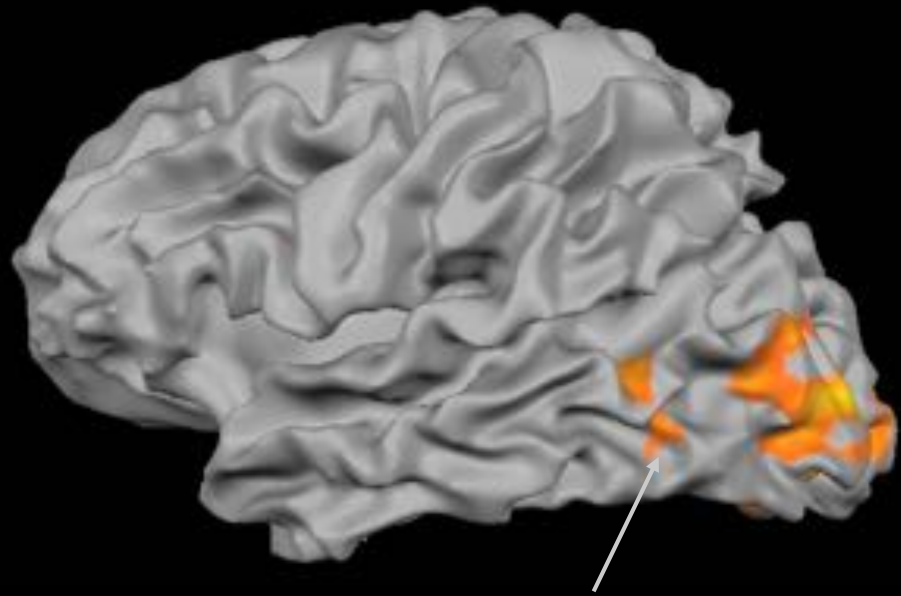
Can we map features in hMT with 7T fMRI?



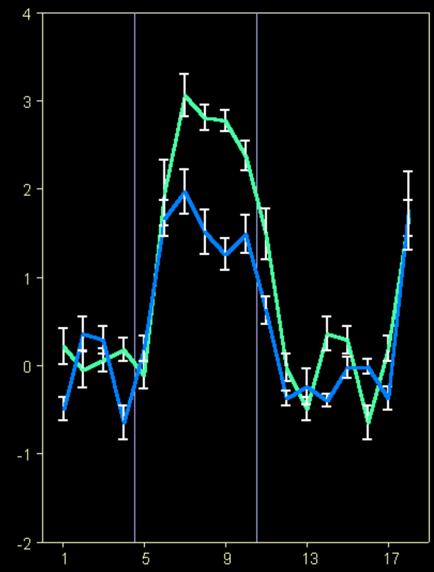
Flowfield
Stationary dots



V5

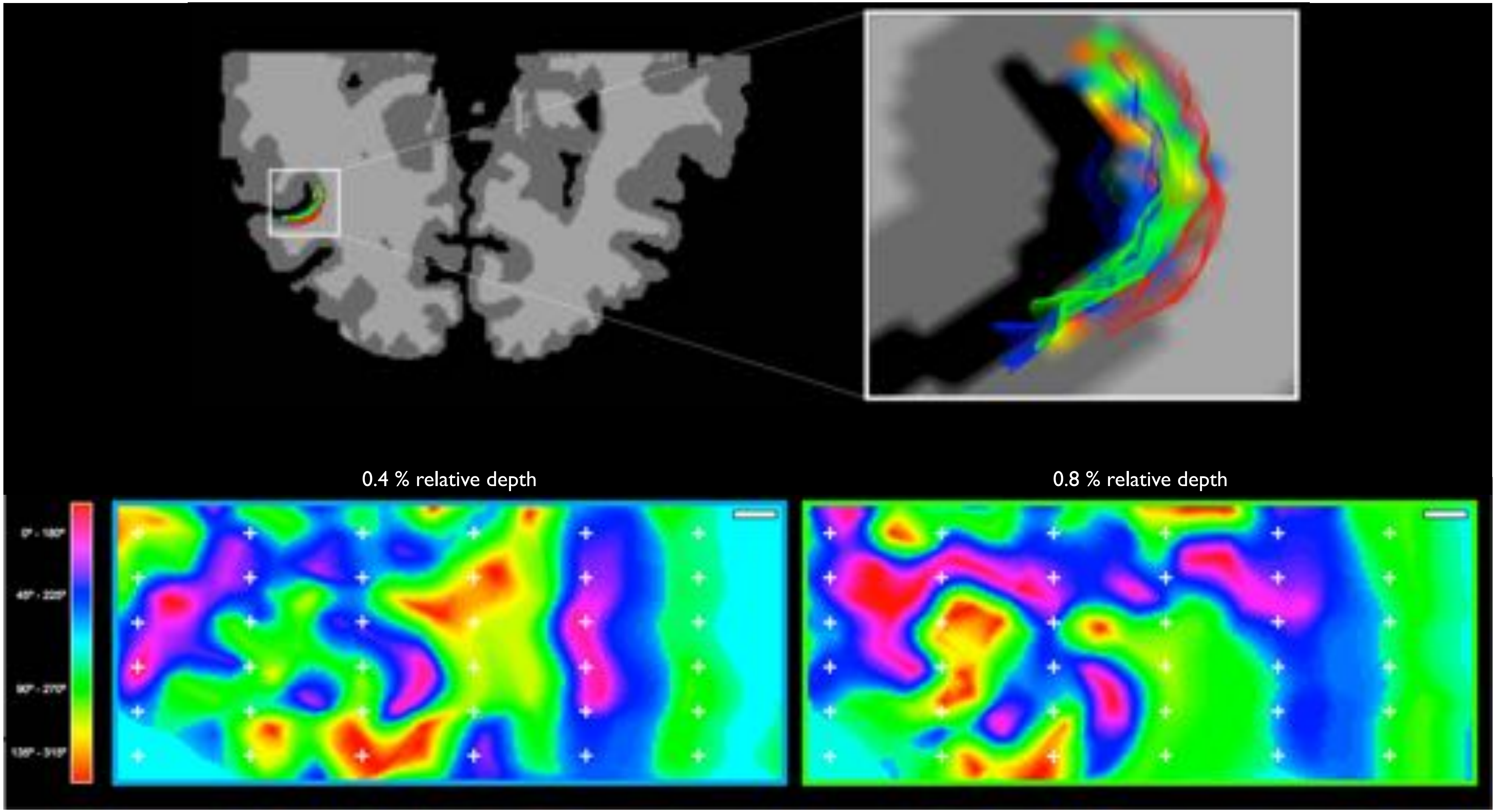


V5



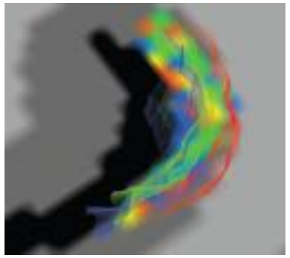
V1/V2

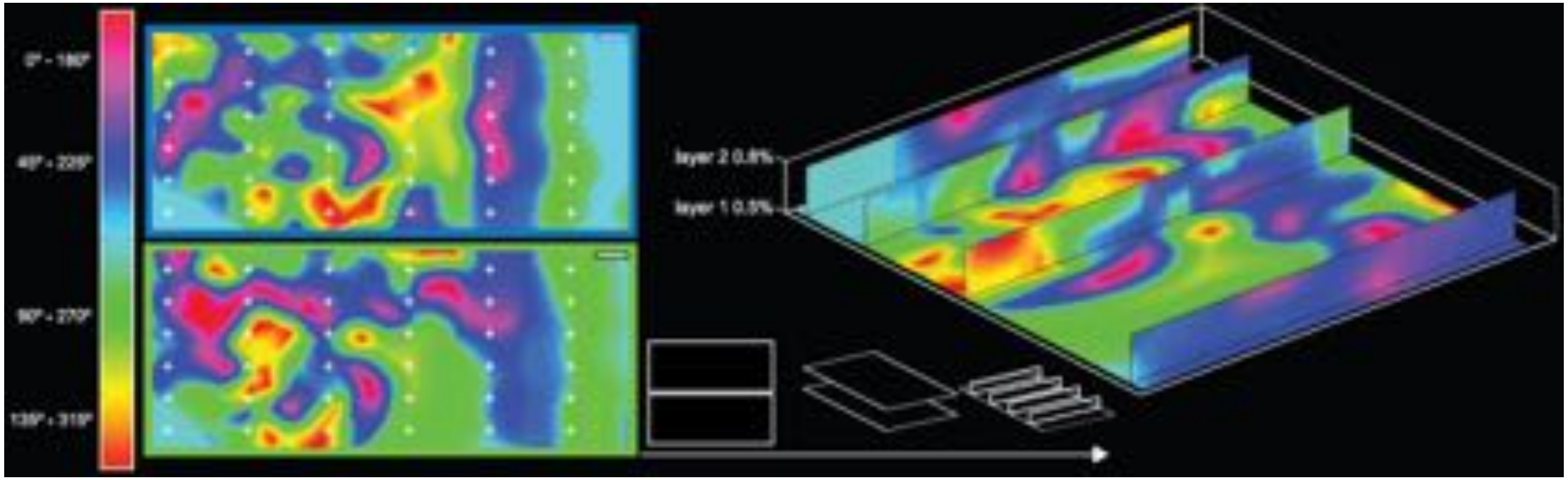
Mapping Axis-of-Motion Columns in hMT/V5 at Different Cortical Depth Levels using High-Resolution Grid Sampling (GRASE)

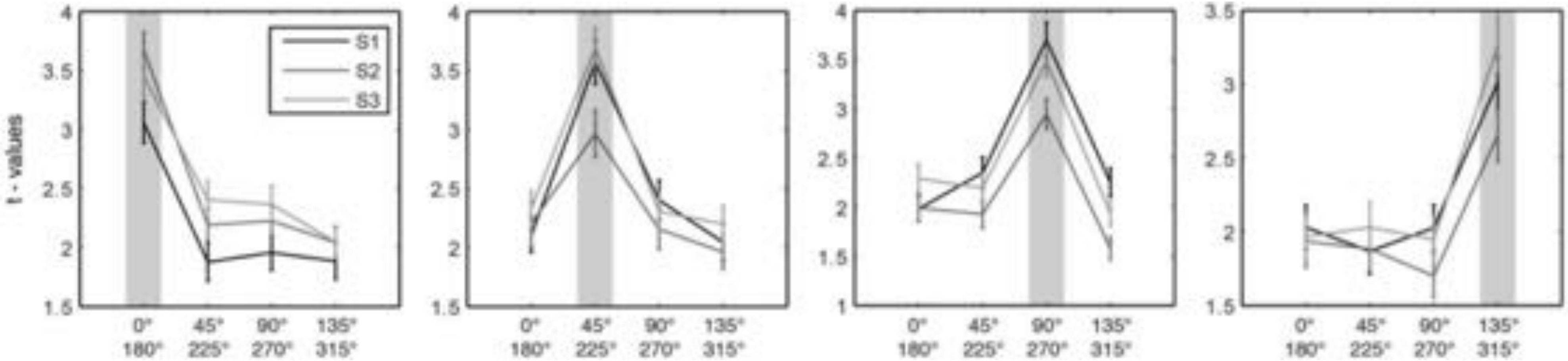


Zimmermann, Goebel, De Martino, Adriani, Van de Moortele, Feinberg, Chaimov, Shmuel, Ugurbil, Yacoub (2011). PLoS One, ***6****(12), e28716.*

Mapping Axis-of-Motion Columns in hMT/V5 at Different Cortical Depth Levels using High-Resolution Grid Sampling (GRASE)



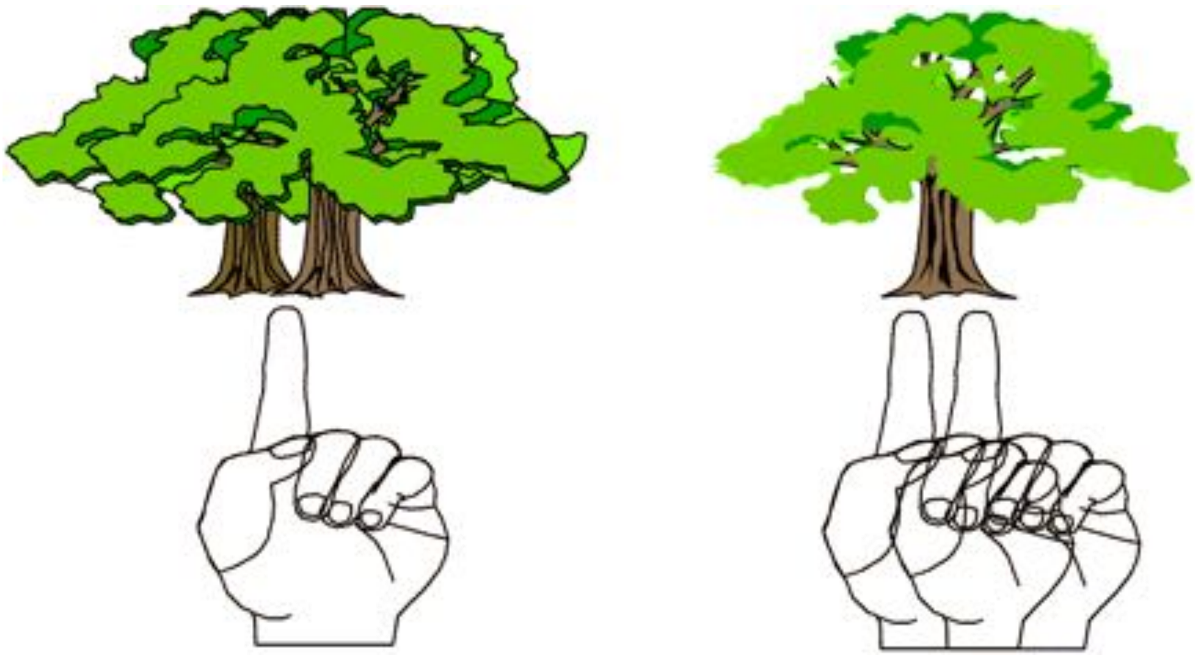


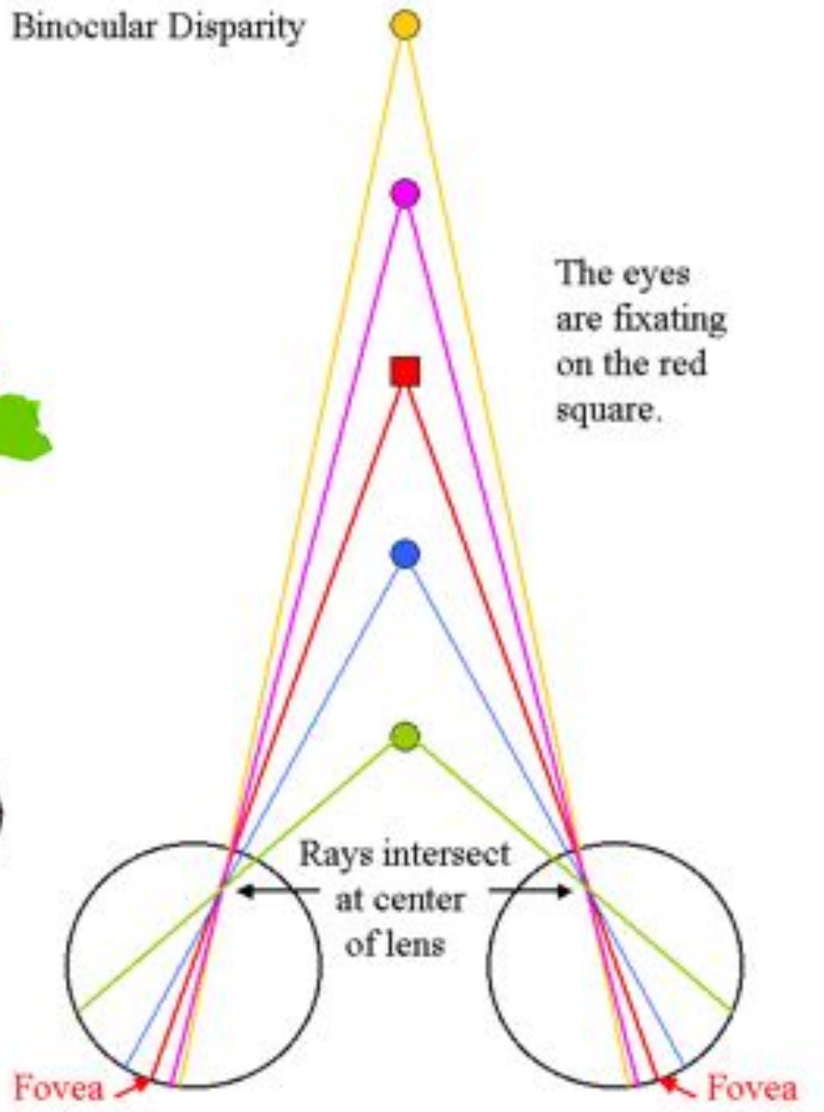


*Zimmermann, Goebel, De Martino, Adriani, Van de Moortele, Feinberg, Chaimov, Shmuel, Ugurbil, Yacoub (2011). PLoS One, **6**(12), e28716.*

Measuring Binocular Disparity Tuning in hMT

Background





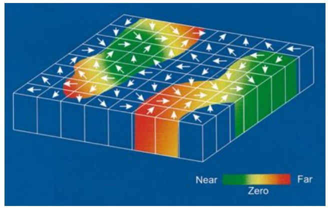
Emmerling, Frost, Goebel (2016). work in progress.

Measuring Binocular Disparity Tuning in hMT

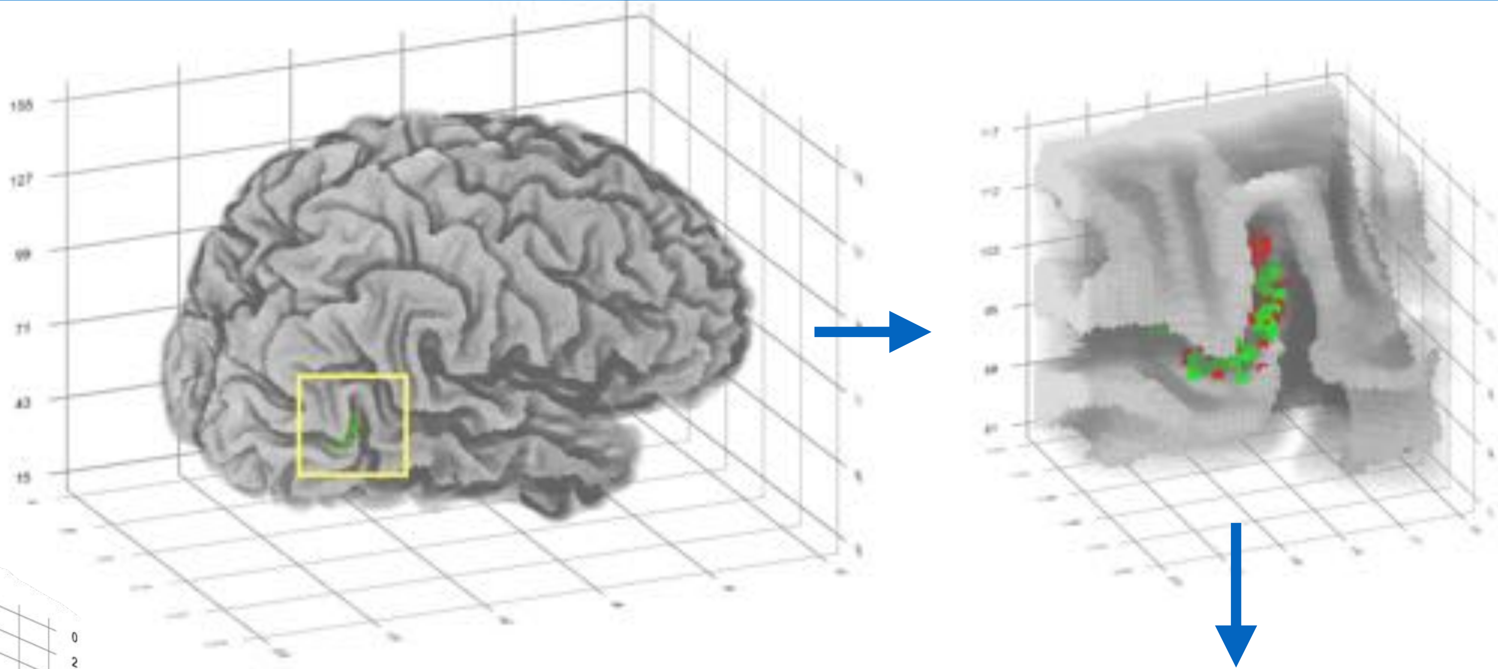
Disparity

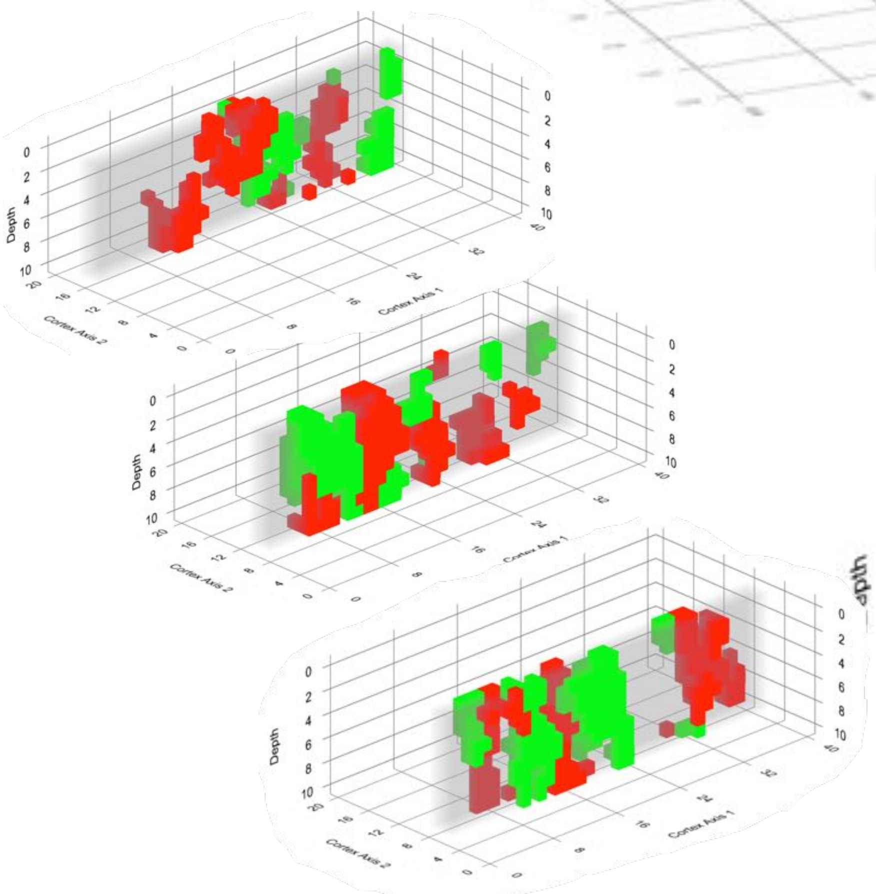
Emmerling, Frost, Goebel (2016). work in progress.

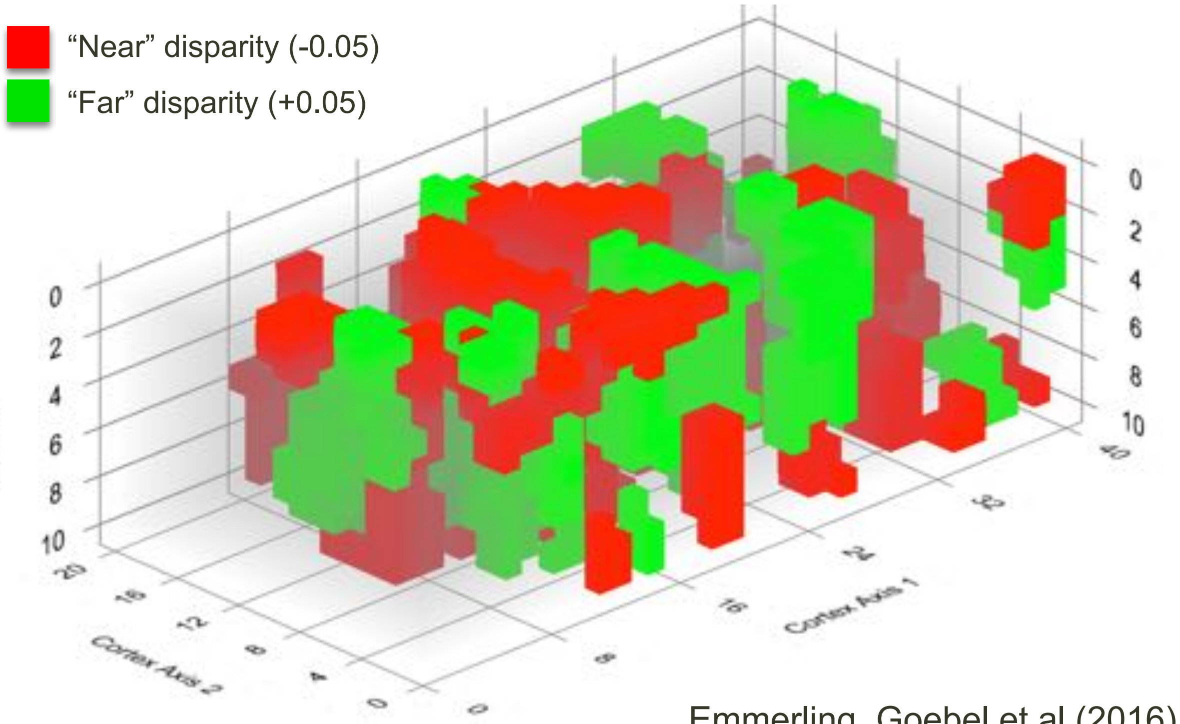
Disparity Columns in Human Area hMT @ 7T



Disparity map in macaque MT.
De Angelis & Newsome (1999).

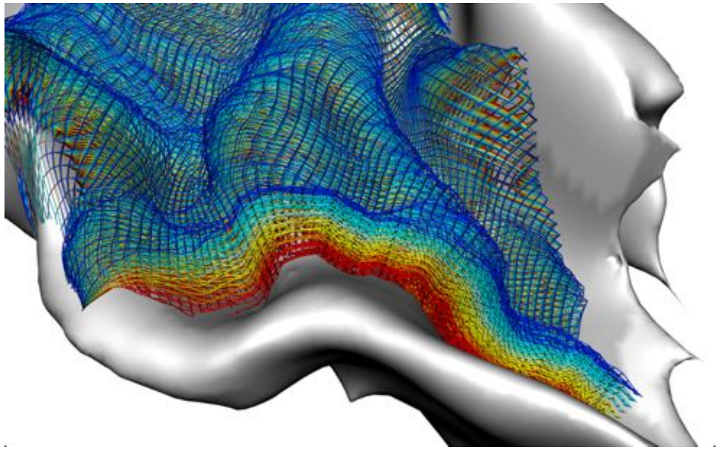


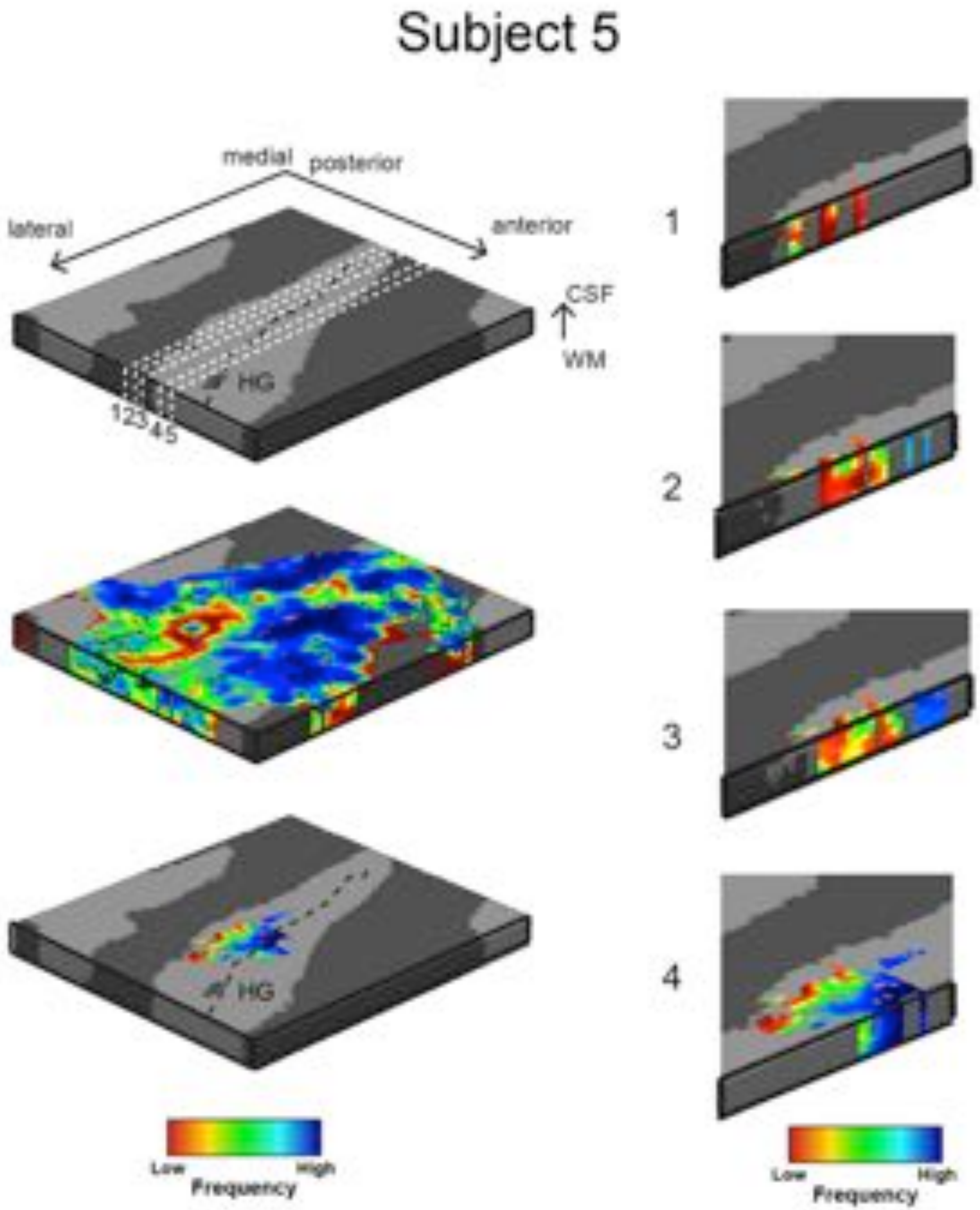




Emmerling, Goebel et al (2016).

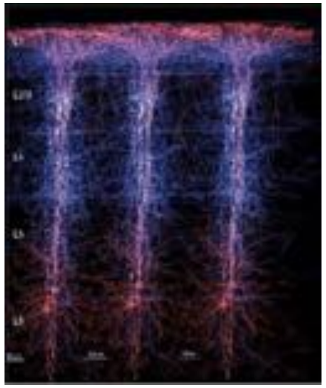
Columnar Coding in Primary Auditory Cortex

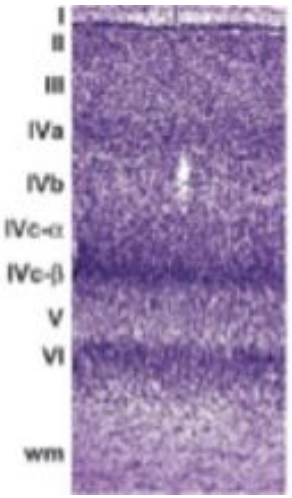


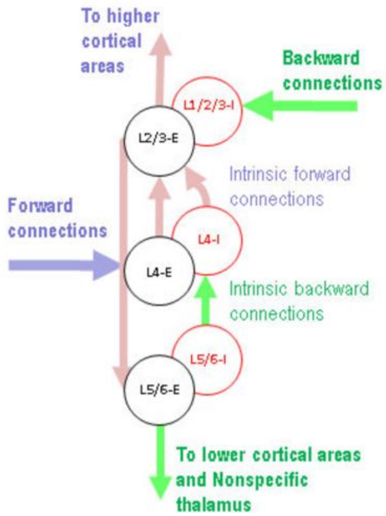


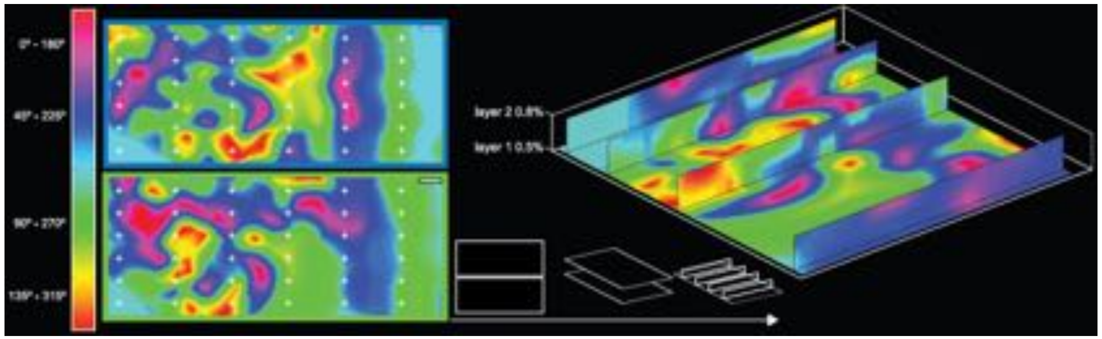
De Martino, Moerel, Ugurbil, Yacoub, Goebel, Formisano (2015). *PNAS*, **112**, 16036-1604.

Going Beyond Feature Mapping: Using Mesoscopic 7T+ fMRI to Study Human Visual Cognition



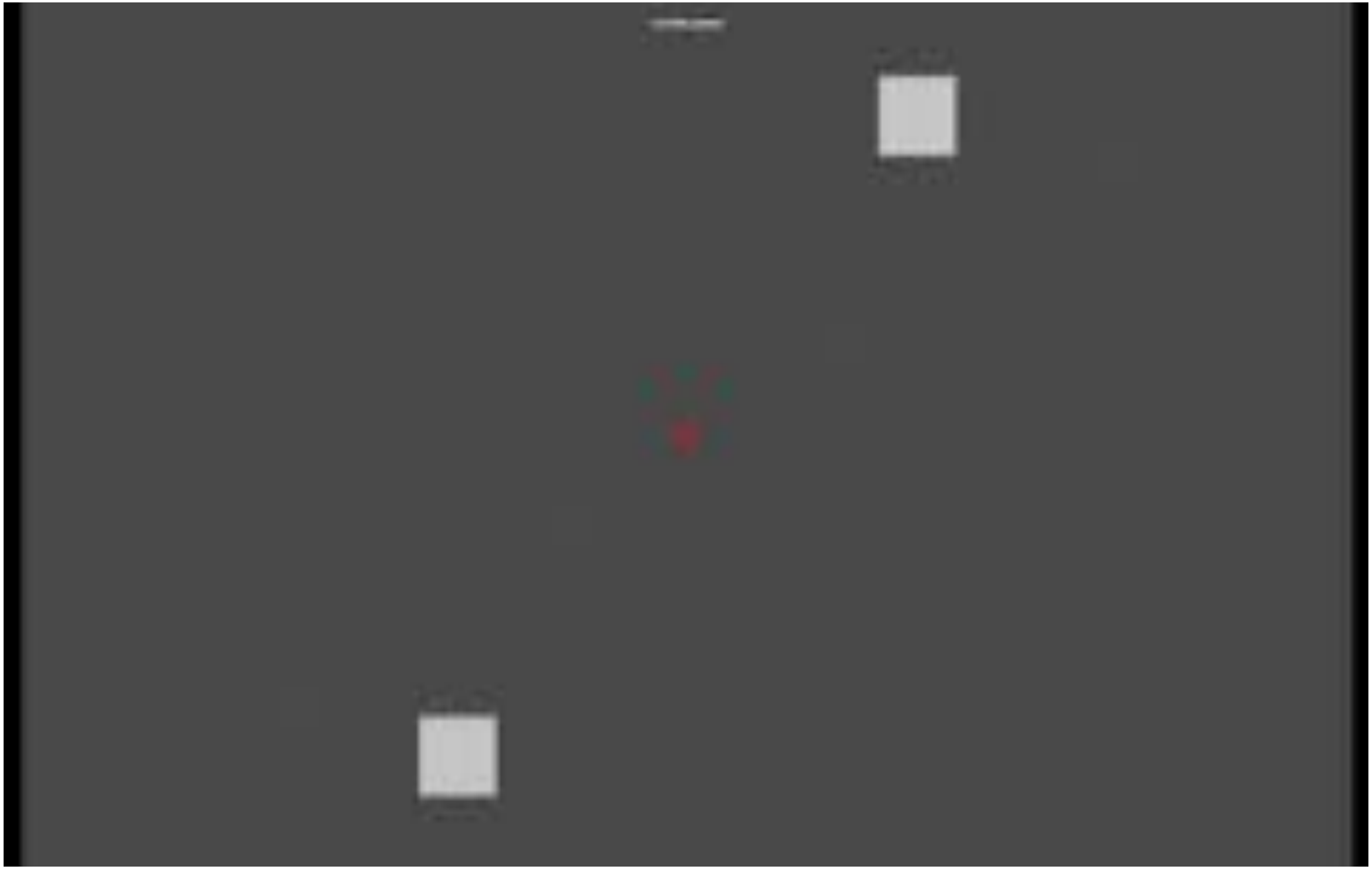






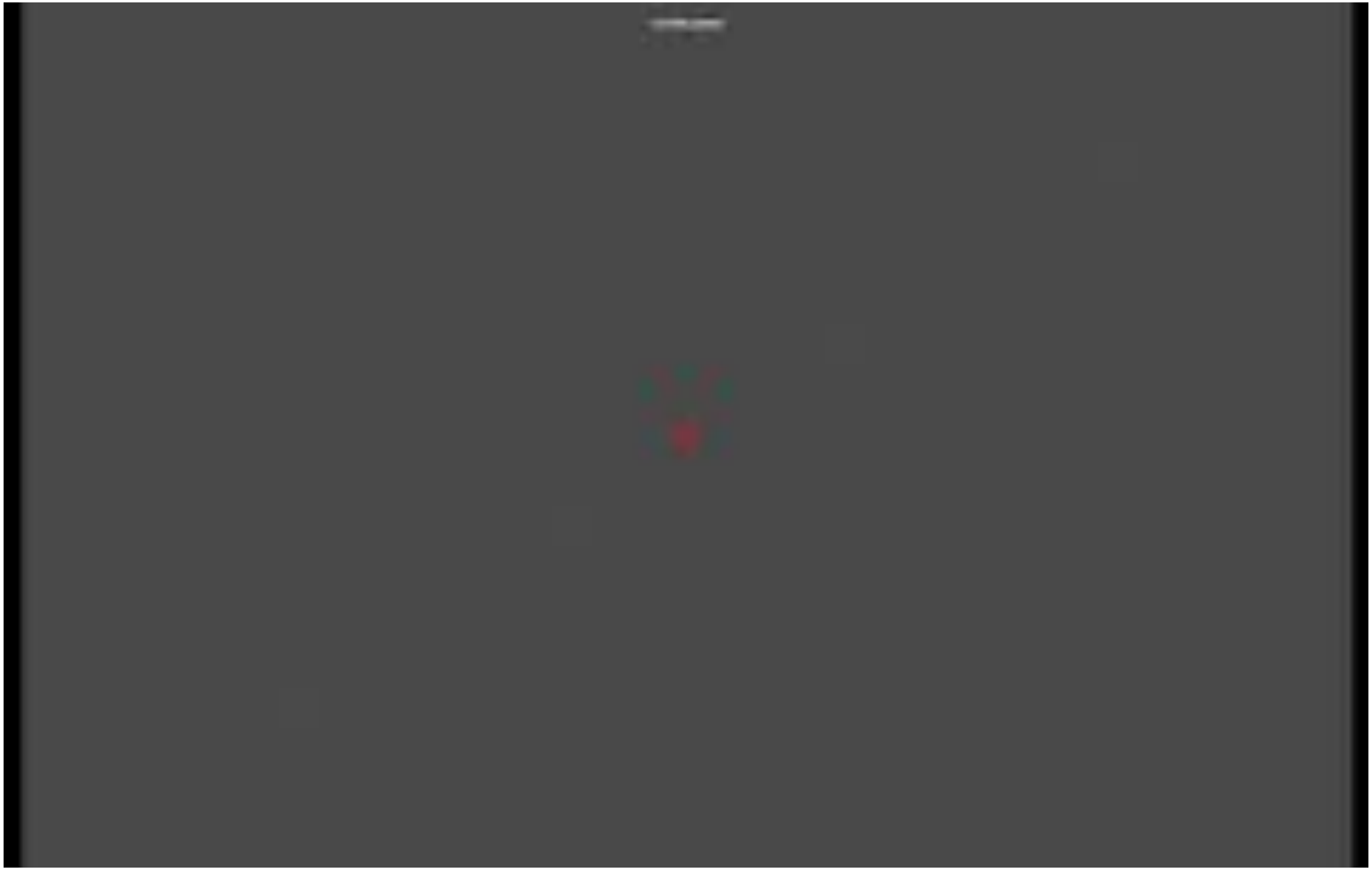
Being able to separate fMRI responses from different columnar-level features and cortical layers opens the possibility to relate cognitive phenomena like attention, expectation, working memory, imagery and awareness to the human mesoscopic scale for the first time providing substantially increased explanatory power for testing and creating detailed cognitive theories of the mind.

Towards Mesoscopic Neural Correlates of Consciousness



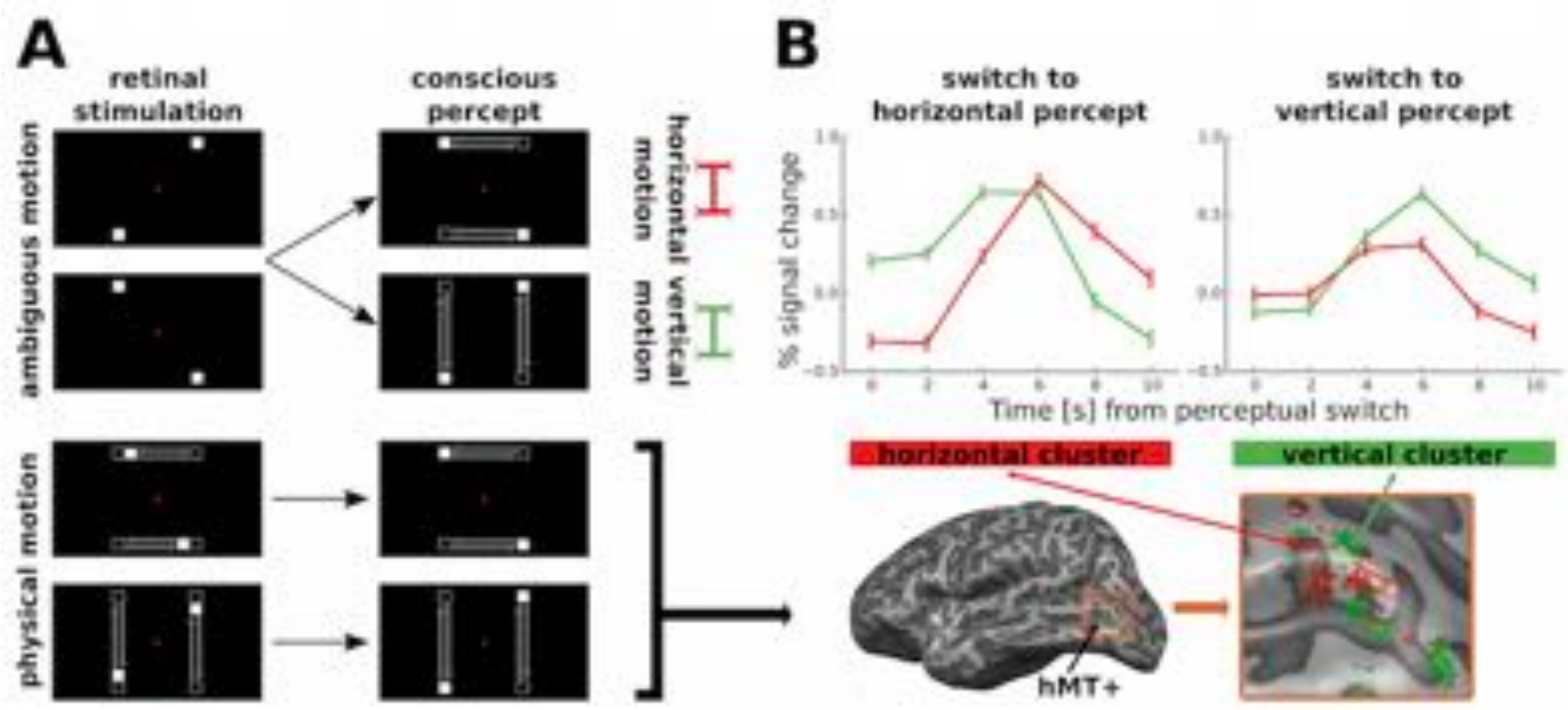
Control Stimulus: Physical horizontal / vertical motion

Towards Mesoscopic Neural Correlates of Consciousness



Ambiguous Motion Quartett Stimulus with two squares alternating same positions:
Switches between horizontal / vertical motion perceived by observer (apparent motion)

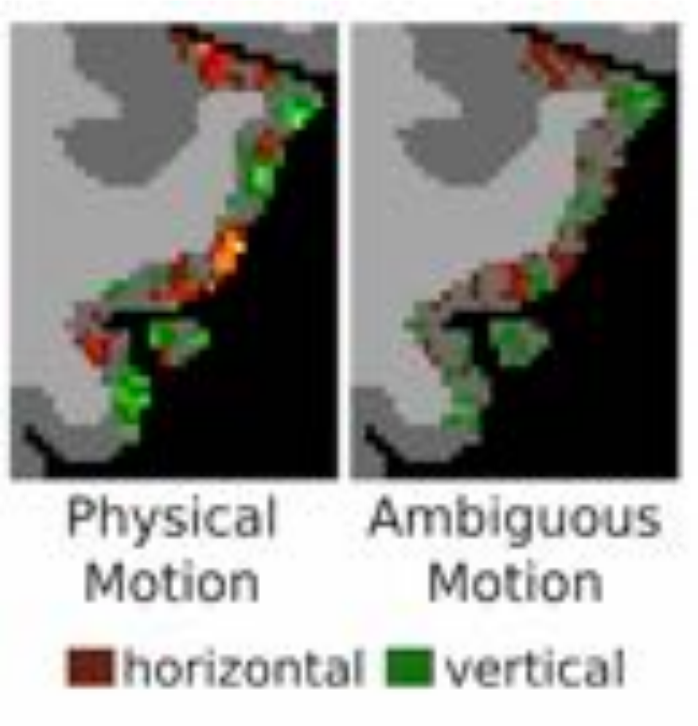
Towards Mesoscopic Neural Correlates of Consciousness

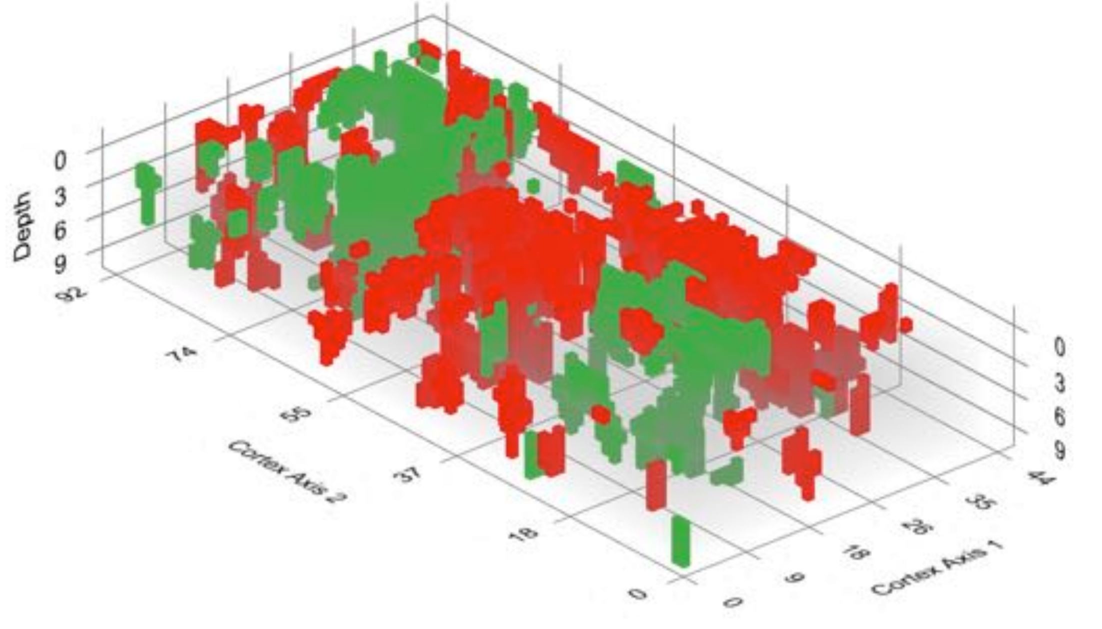


Predicting Perceived Direction of Motion from Activity Dynamics in Direction-of-Motion Selective Columnar-Level 7T fMRI Responses

Schneider M, De Martino F, Goebel R.(2018). in preparation.

Towards Columnar-Level Neural Correlates of Consciousness





7T fMRI: Horizontal vs vertical columnar-level responses in area hMT

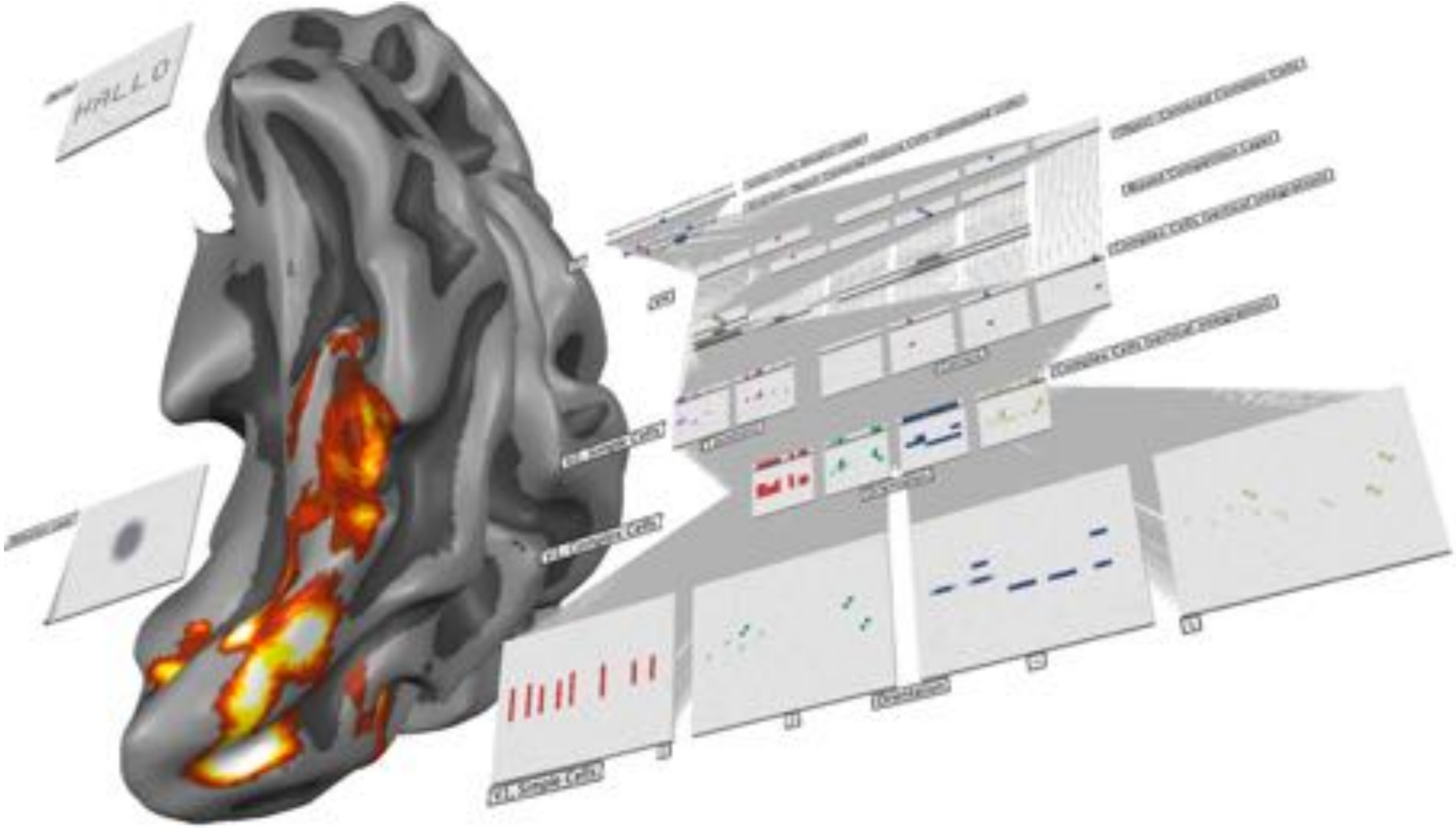
Schneider M, De Martino F, Goebel R.(2018). in preparation.

HBP Co-Design Project “Visuo-Motor Integration”

“In this article, we argue that better understanding biological brains could play a vital role in building intelligent machines.”

Hassabis et al., *Neuron*, 2017

Modeling Neuroimaging Data with Convolutional Deep Neural Networks (DNNs)



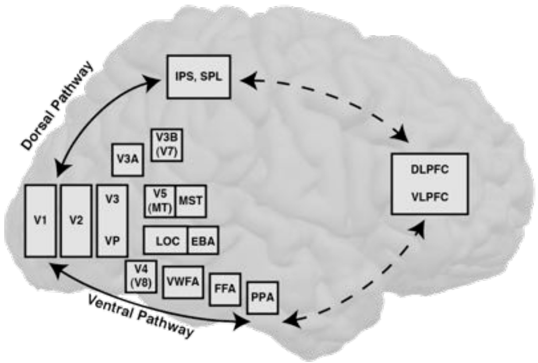
- DNNs are designed with engineering goals, ***not*** to model brain computations.
- DNNs are, however, ***useful tools for neuroscience*** to better understand cognitive functions by constraining ***models based on complex brain data***.
- DNNs may be improved using knowledge from the brain, e.g. *convolutional DNNs* for object recognition emulate basic architecture of visual cortex.

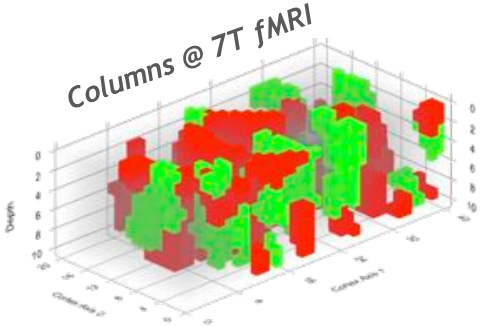
Using Imaging Data as Constraints to Build Embodied Brain Models

- Using a top-down approach, create a **deep, modular, recurrent neural network model** that **performs visuo-motor tasks**.
- Build an embodied comprehensive model by targeting **many visuo-motor tasks** and that can be extended by the community.
- **Derive architecture** (representations and processes) of the model from existing and new **neuroscientific data and theories**.
- **Run on a neurorobotics platform** to **test** predicted human behaviour (eye movement and arm movement control).
- **Validate** architecture and operation of the model with neuroscientific data and **predict new data**.
- Use model to help understand **patient data** (Hemispatial Neglect).

An Embodied Large-Scale Architecture of Visuo-Motor Integration

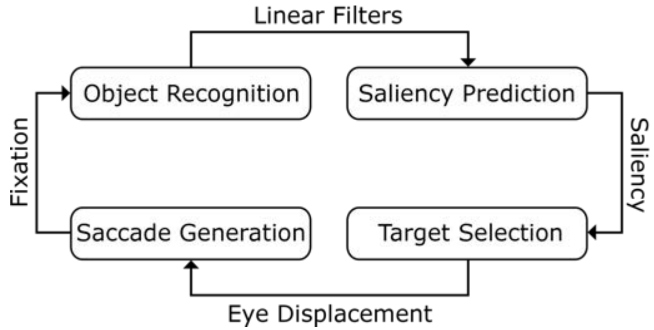
Human Brain Project



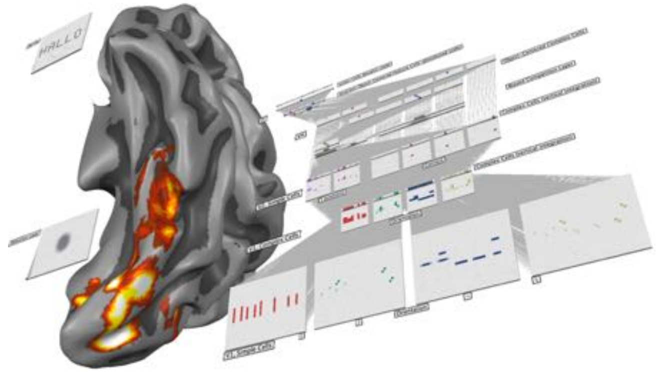


atlas, models, human 7T+ fMRI, iEEG, NHP ephys

Computational architecture

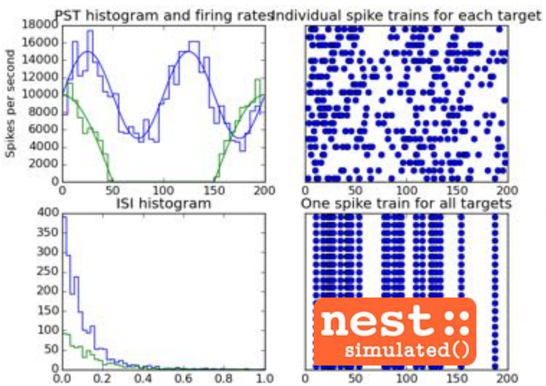


Top-down modelling



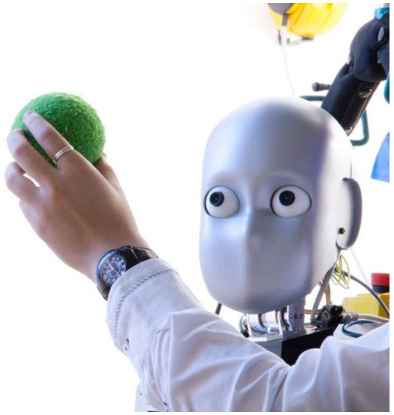
neural population models

Simulation



implement on HPAC platform

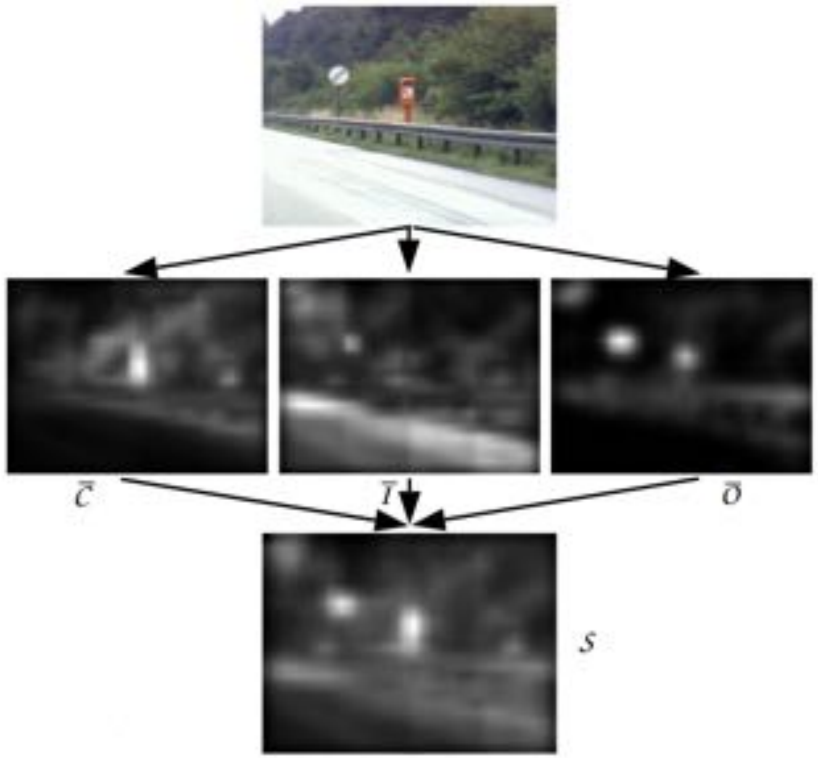
Behaviour



run on neurorobotics platform

Saliency Calculation – Previous Biological Models

- Color, intensity, and orientation filters
- Linear combination into single saliency map
- Contains no semantic information



Adapted from Itti, Koch, & Niebur (1998).

Itti, L., Koch, C., & Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on pattern analysis and machine intelligence*, *20*(11), 1254-1259.

Saliency Calculation – Previous Biological Models

Model predictions from Itti, Koch, & Niebur (1998)
-> selection of low-level contrast

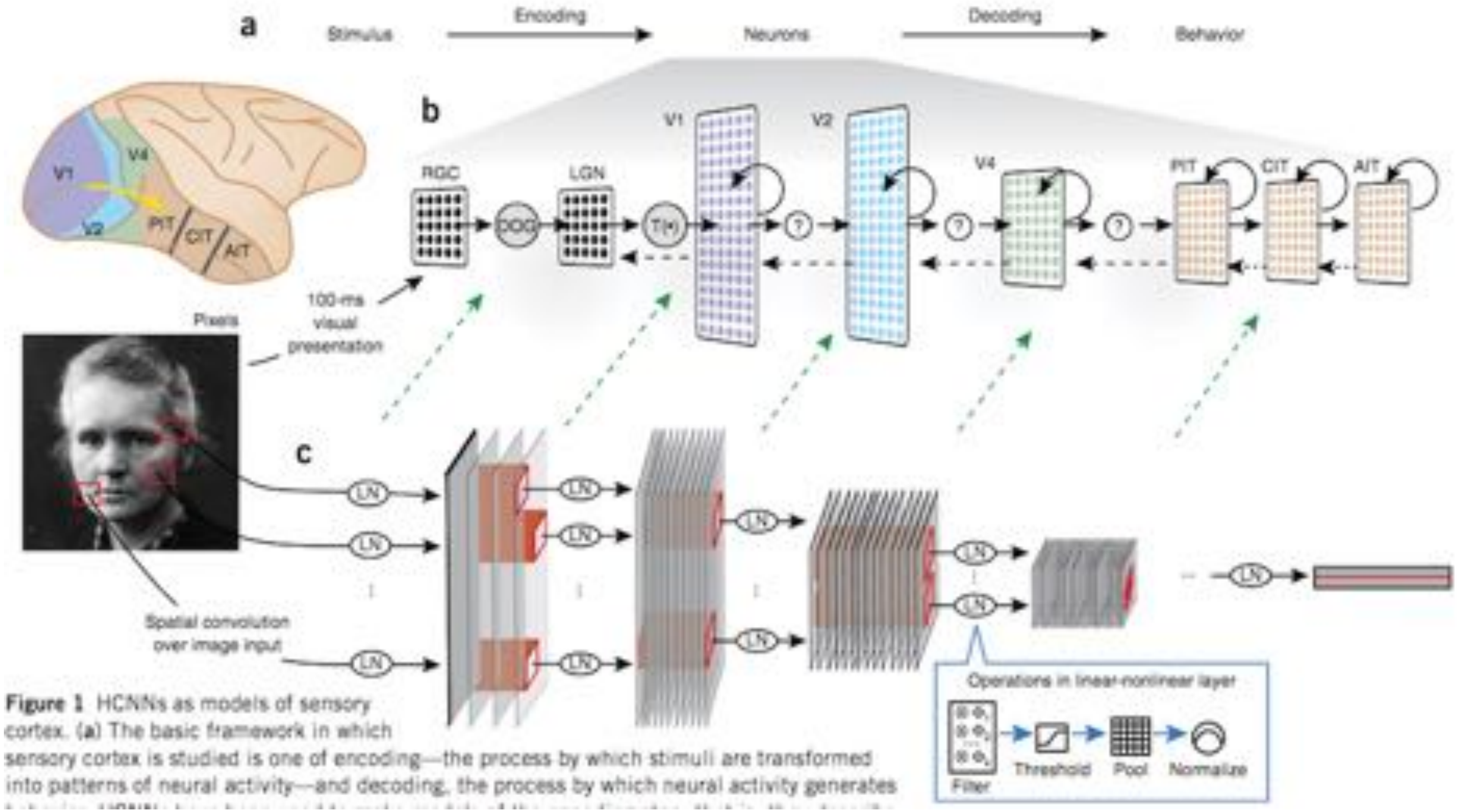
Human Saliency Calculation – Semantics Needed!

Locations humans look at

While brain atlas and fMRI data provides constraints for model architecture (macro-scale, 3T) and representations (meso-scale, 7T), the connection **weights** within and between areas are **largely unknown**!

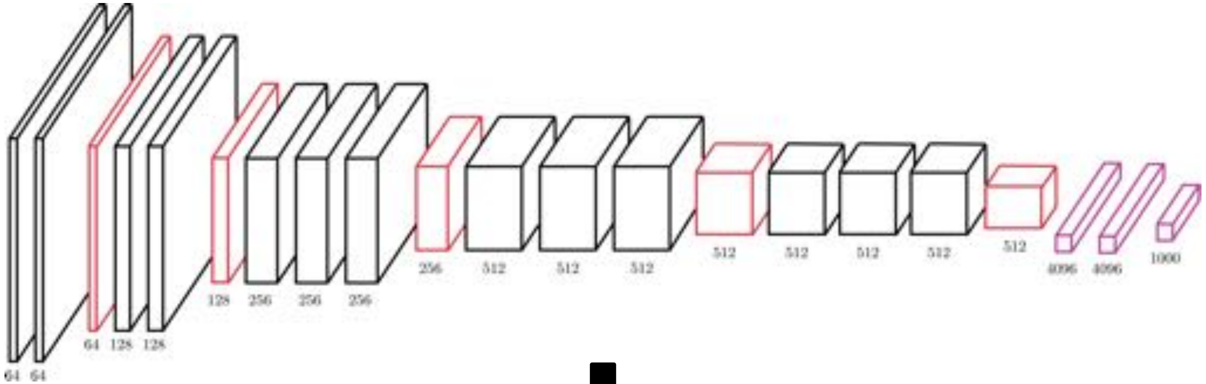
—> Train deep neural networks to fnd connection weights and useful representations in layers
—> Compare learned representations with measured high-resolution columnar representations

Human Saliency Calculation – Semantics Needed!

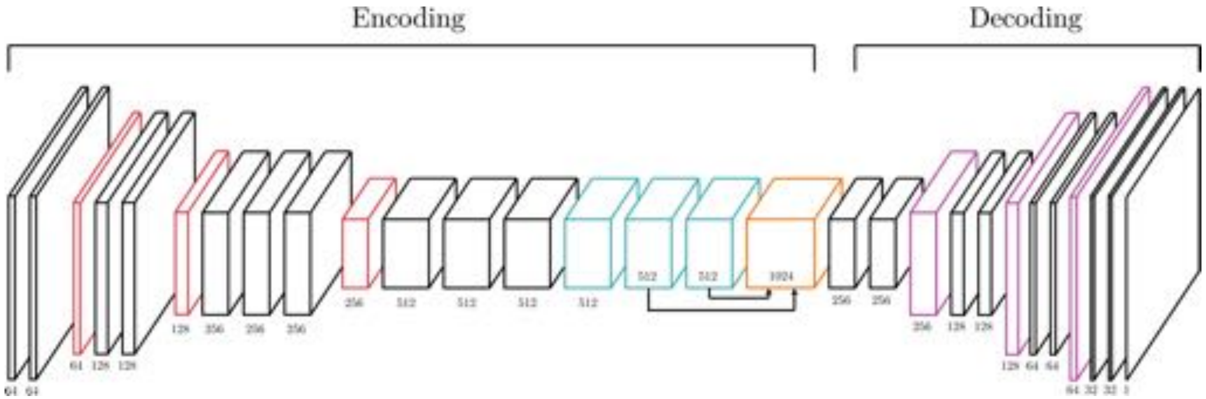


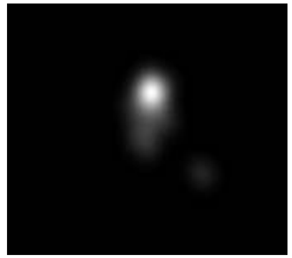
Yamins, DiCarlo (2016). Using goal-driven deep learning models to understand sensory cortex. *Nature Neuroscience*.

New Saliency Model – Adding Object Recognition CNN



"bird"





Neuroscience Perspective:

Adding ventral visual processing stream (1)

Adding semantic saliency based on recognized objects (2)

New Saliency Model – Validation using Human Data

Public saliency data sets

	Images	Participants	Duration	Procedure
MIT1003	1003	15	3s	Eye tracking
CAT2000	2000	24	5s	Eye tracking
SALICON	15000	60	5s	Mouse tracking

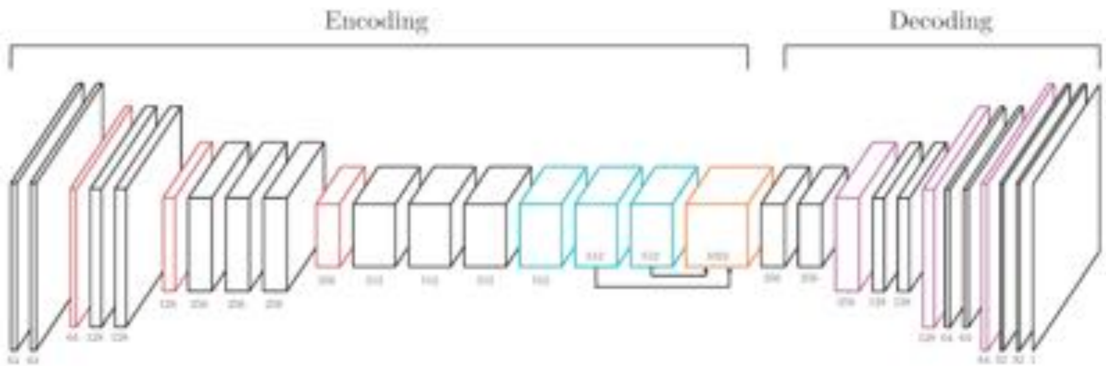
Stimulus

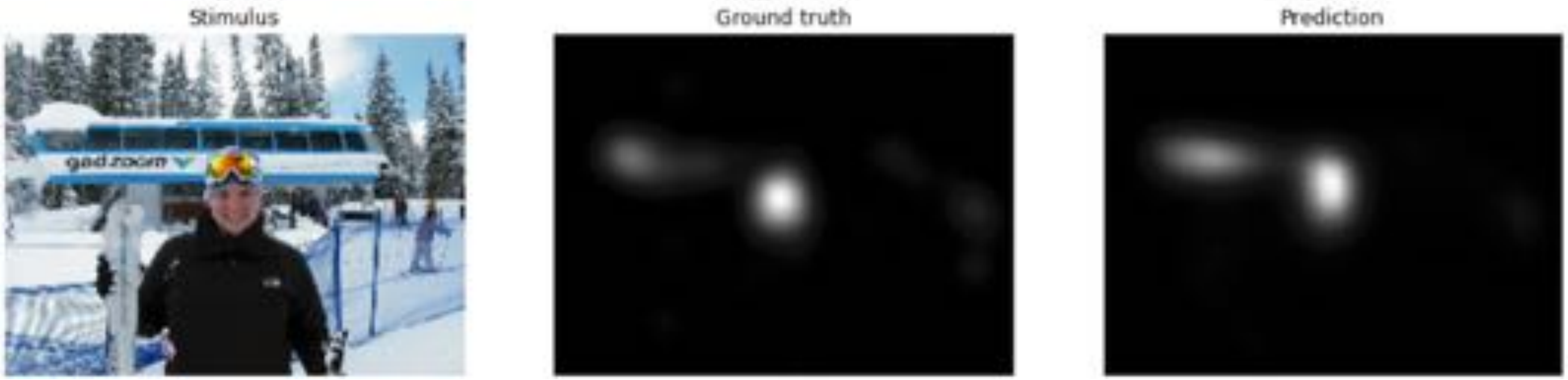

Saliency Map


Fixations

New Saliency Model Produces Human-Level Performance

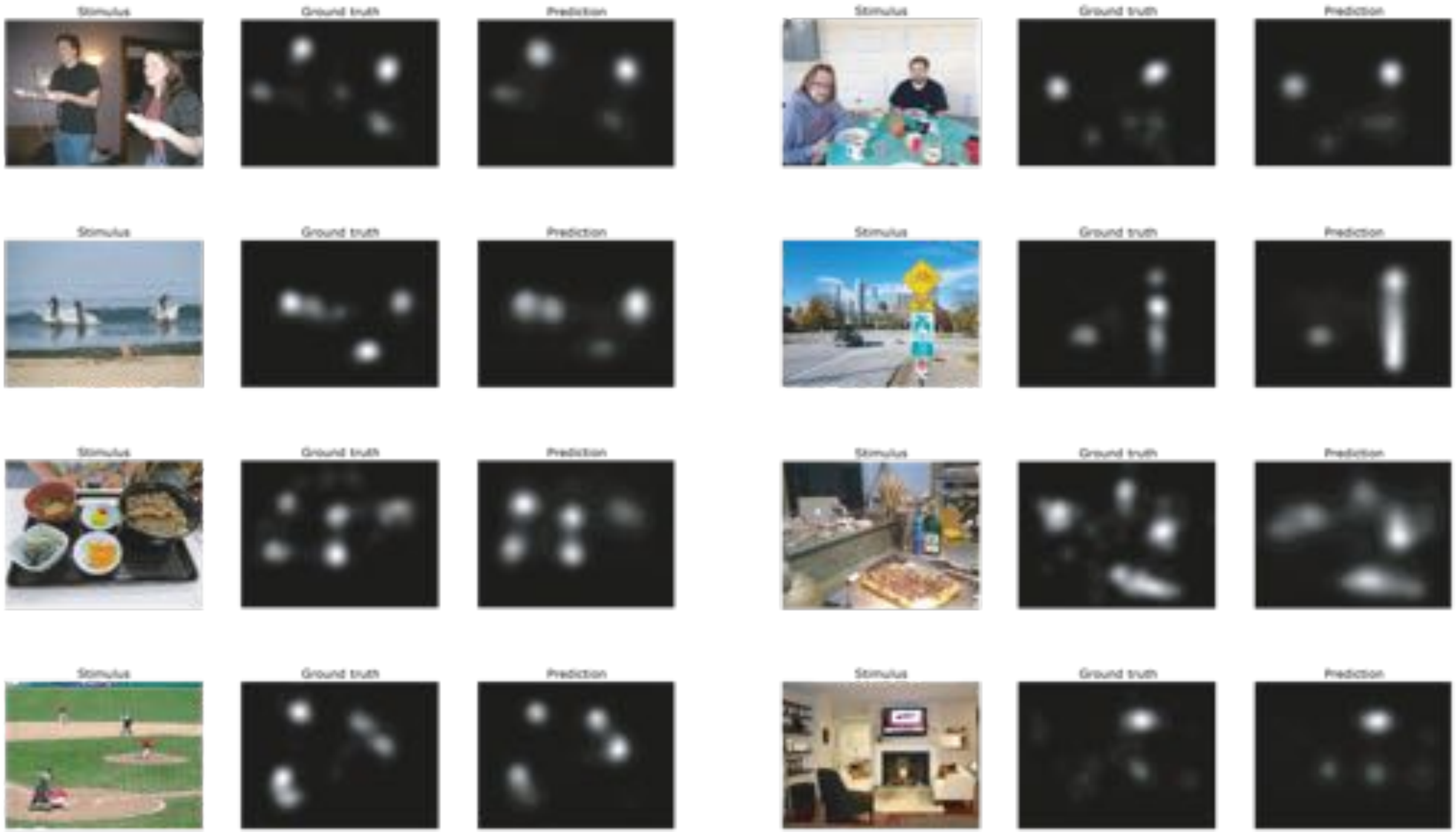
Deep Auto-Encoder predicting human generated saliency map from natural images





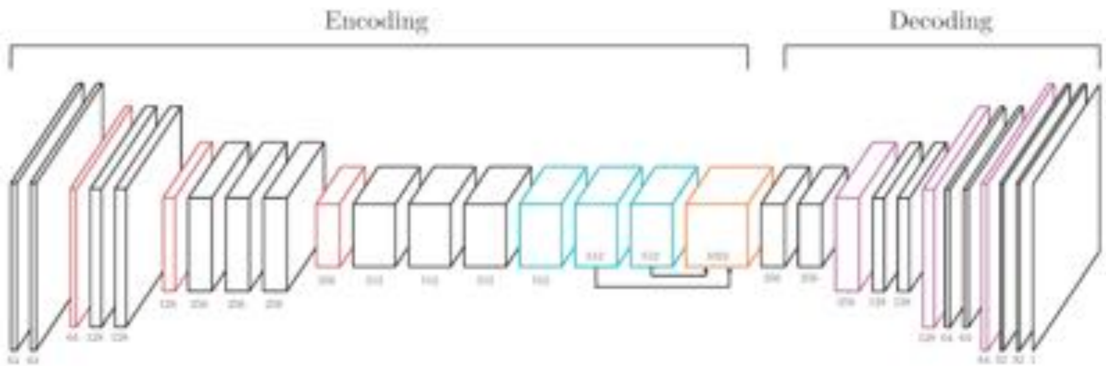
Generalisation to novel images!

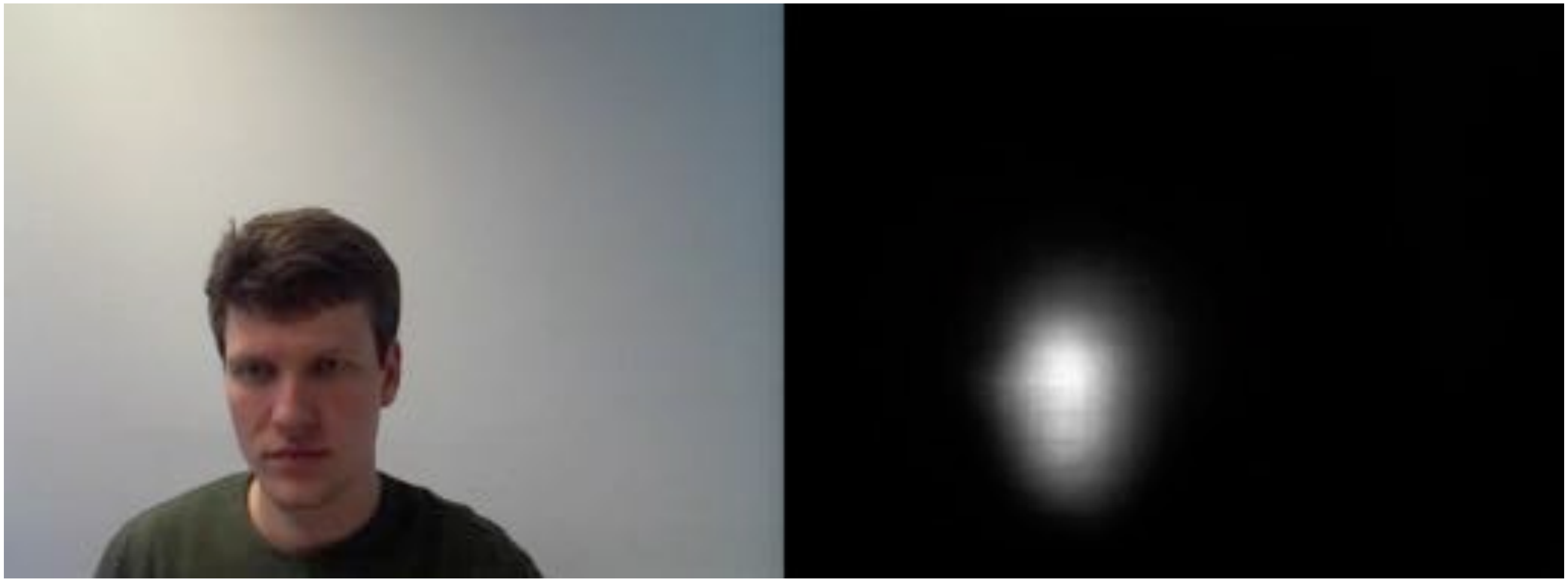
New Saliency Model – Basic Results



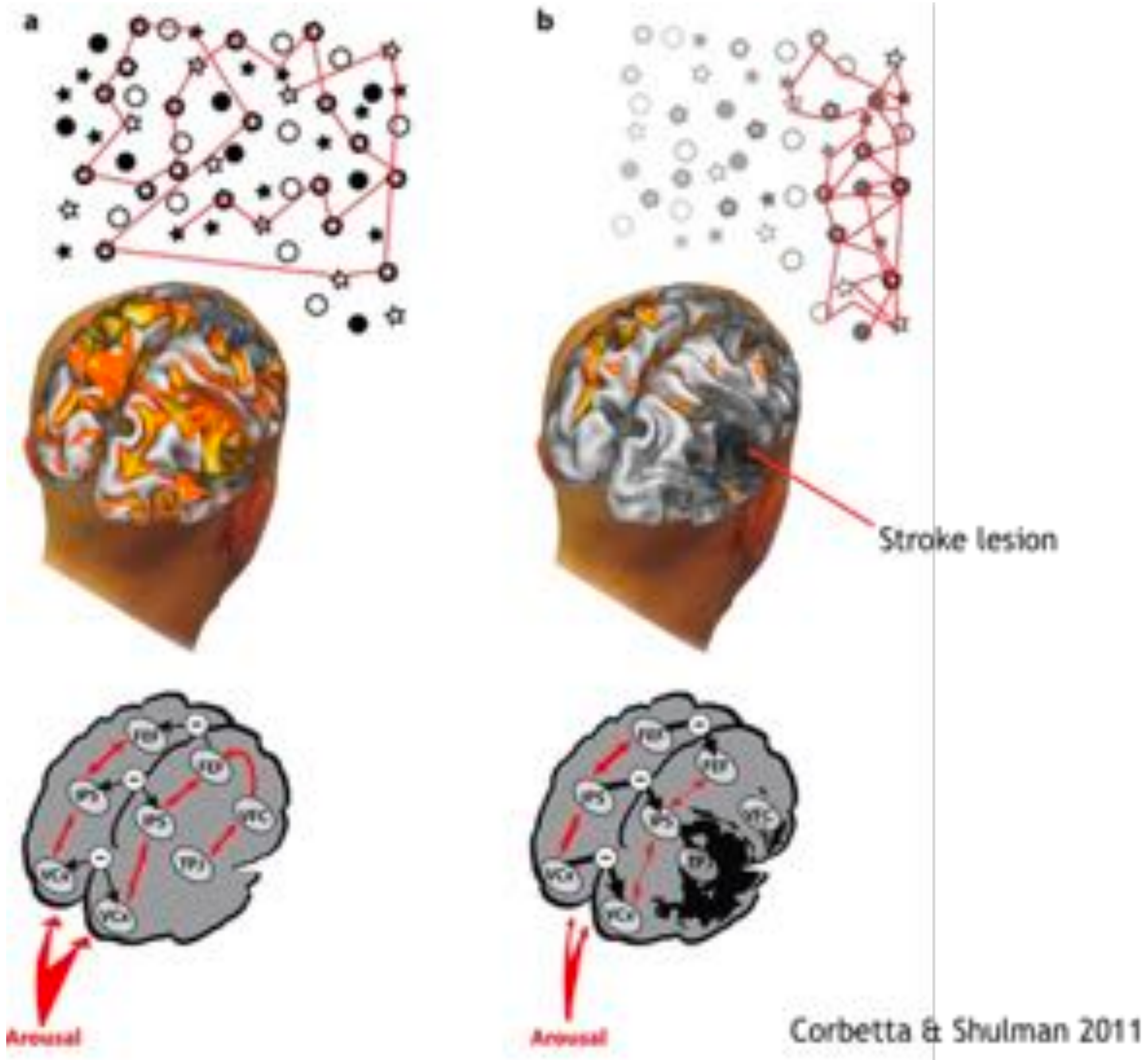
New Saliency Model – Basic Results

Deep Auto-Encoder predicting human generated saliency map from natural images





Understanding Stroke Data Using Model: Unilateral Spatial Neglect



Collaboration with FLAG ERA “Brainsynch-Hit” Project, Lead PI: Maurizio Corbetta

Summary and Conclusions

- To better understand the neural basis of (visual) cognitive functions, **multiple levels of brain organization** need to be integrated.
- Sub-millimeter **ultra-high field (f)MRI** is an important tool helping to **bridge macro- and mesoscopic scales**.
- Recent fMRI experiments show that it is possible to map **known** columnar-level representations in specialised brain areas (V1, A1, hMT, STS/STG).
- Revealing **feature codes** in specialized brain areas at mesoscopic scale has the potential to provide important new insights in the neural substrate of human perception and cognition.
- It is possible to **read out the content of conscious percepts of ambiguous stimuli** from dynamic activation changes in axes-of-motion selective voxels in area hMT+.
- **Top-down modulation** show effects either in superficial or deep layers. Future studies need to investigate whether this is due to paradigm or analyses differences.
- Neural deep network simulations constraint by **feature codes** and **laminar profiles** from multiple brain areas will lead to a deeper understanding of how **visual perception and cognition emerge in the human brain.**

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