Quantification and processing of NMR imaging data through Deep Learning techniques

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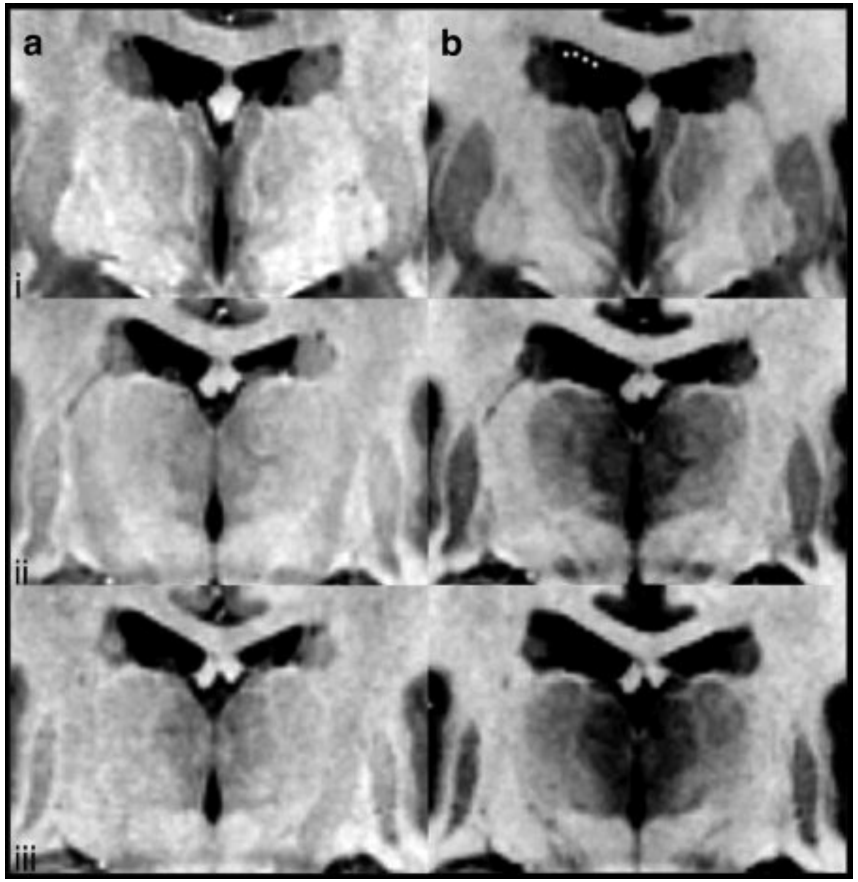
Overview

1. MR Imaging: from qualitative to quantitative imaging.
2. Deep Learning for Magnetic Resonance Fingerprinting
    1. Brief introduction to Magnetic Resonance Fingerprinting.
    2. Change of paradigm in quantitative NMR mapping.
    3. Curse of Dimensionality in Magnetic Resonance Fingerprinting
    4. Deep Learning as a solution.
3. Quantitative Susceptibility Mapping: a deep learning approach
    1. Ill-posed problem in QS Mapping.
    2. Deep Learning to solve QSM preserving accuracy while shortening acquisition time.

Shift of paradigm: from qualitative to quantitative MRI



Comparison of coronal slices through the thalamus from the (**a**) 10× averaged deep brain T_1-weighted image and (**b**) the 10× averaged deep brain T_1 map. Acquisition time:17 min each [1]

Problems of bias, reproducibility and interpretation are substantially reduced.

It opens the way to multi-center studies

Deeper biological knowledge of the disease.

New biomarkers

High noise impact

Affects accuracy

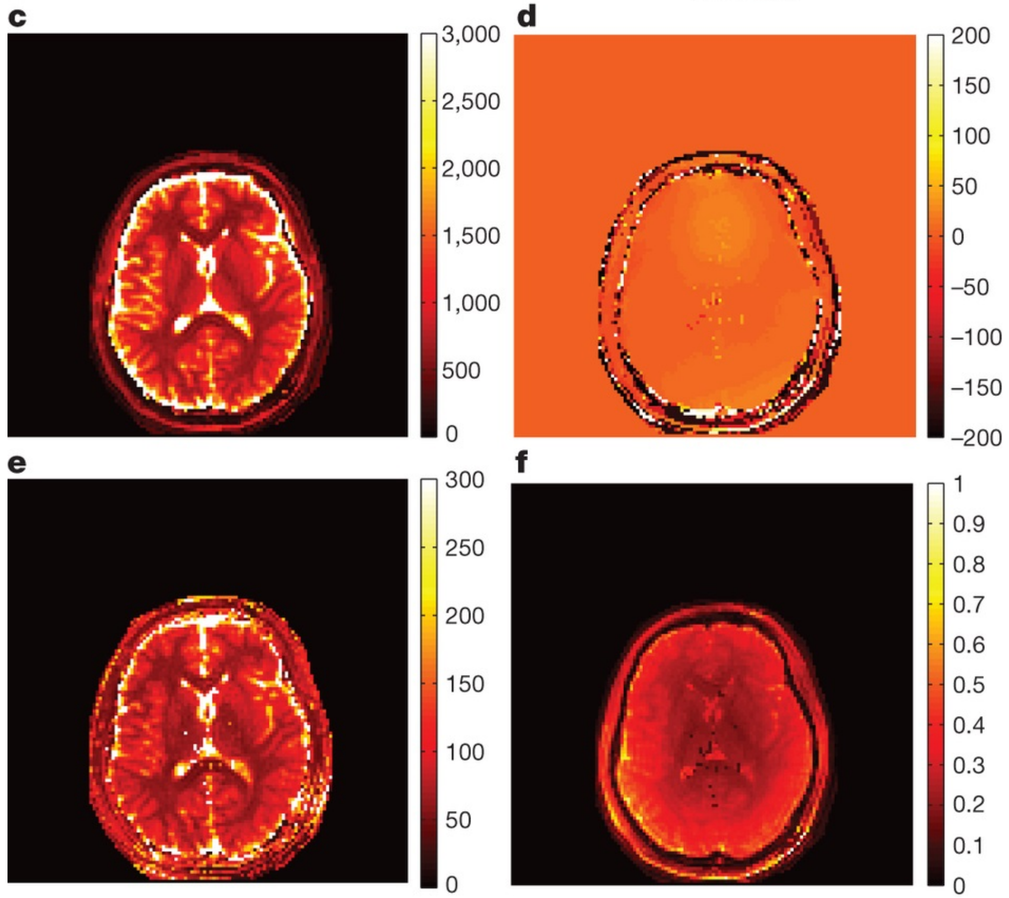
Time consuming

Nowadays, qMRI is not part of routine clinical evaluation.

[1] **Magnetic Resonance in Medicine**
Volume 53, Issue 1, pages 237-241, 22 DEC 2004 DOI: 10.1002/mrm.20314

Magnetic Resonance Fingerprinting (MRF)

A new approach to quantitative MRI



(c) T1 map (ms), (d) Off-resonance frequency (Hz),
(e) T2 map (ms), (f) Proton density (M0) normalized scale.

Magnetic resonance fingerprinting

Dan Ma[1], Vikas Gulani[1,2], Nicole Seiberlich[1], Kecheng Liu[3], Jeffrey L. Sunshine[2], Jeffrey L. Duerk[1,2] & Mark A. Griswold[1,2]

14 MARCH 2013 | VOL 495 | NATURE | 187

qMRI multi-parametric acquisition.

T1, T2, PD, Off resonance frequency.

Time saving!
These data required 12.3 s to acquire.

Figure taken from the original article: Dan Ma et al, Nature, March 2013,

Conventional approach to MR parameter mapping

Multi echo pulse sequence

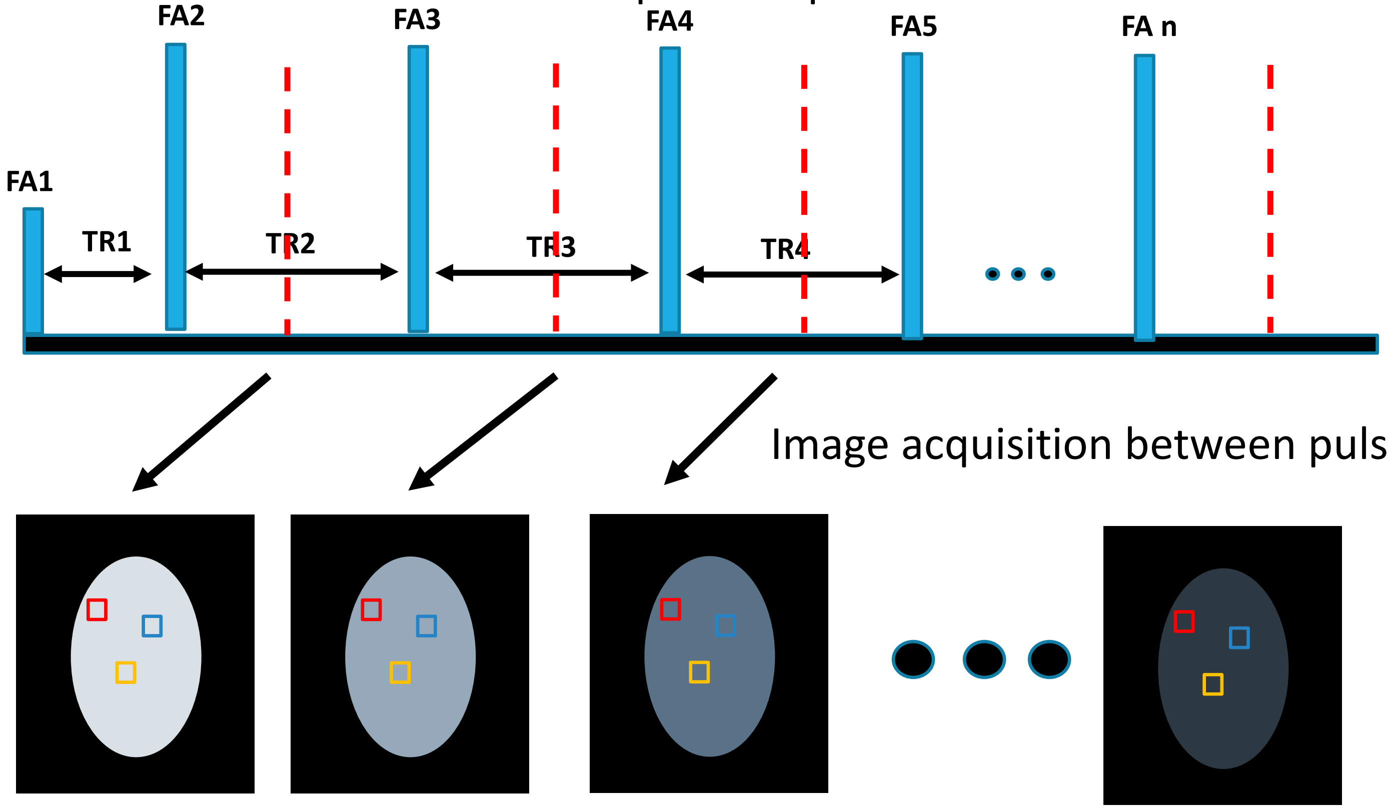
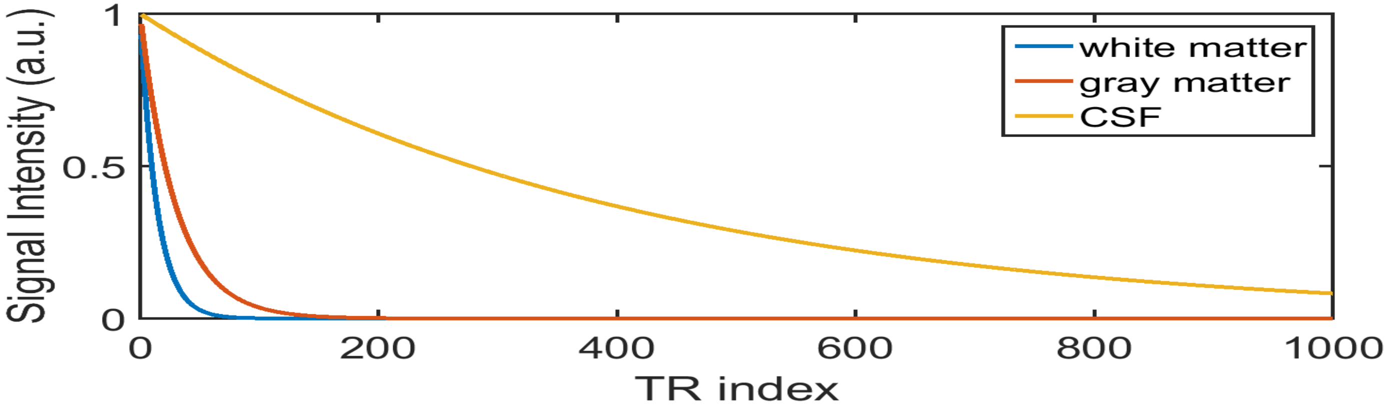


Image acquisition between pulses

Temporal series of voxel intensities

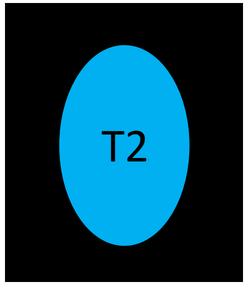


T2 parameter map estimation

Known analytical model for multi echo sequences in function of T2 MR parameter

$$S(t) = S_0 \exp\left(-\frac{t}{T_2}\right)$$

Model fitting per each voxel



Using different pulse sequence to obtain different parameter maps

Time consuming

MRF approach to MR parameter mapping

MRF pulse sequence

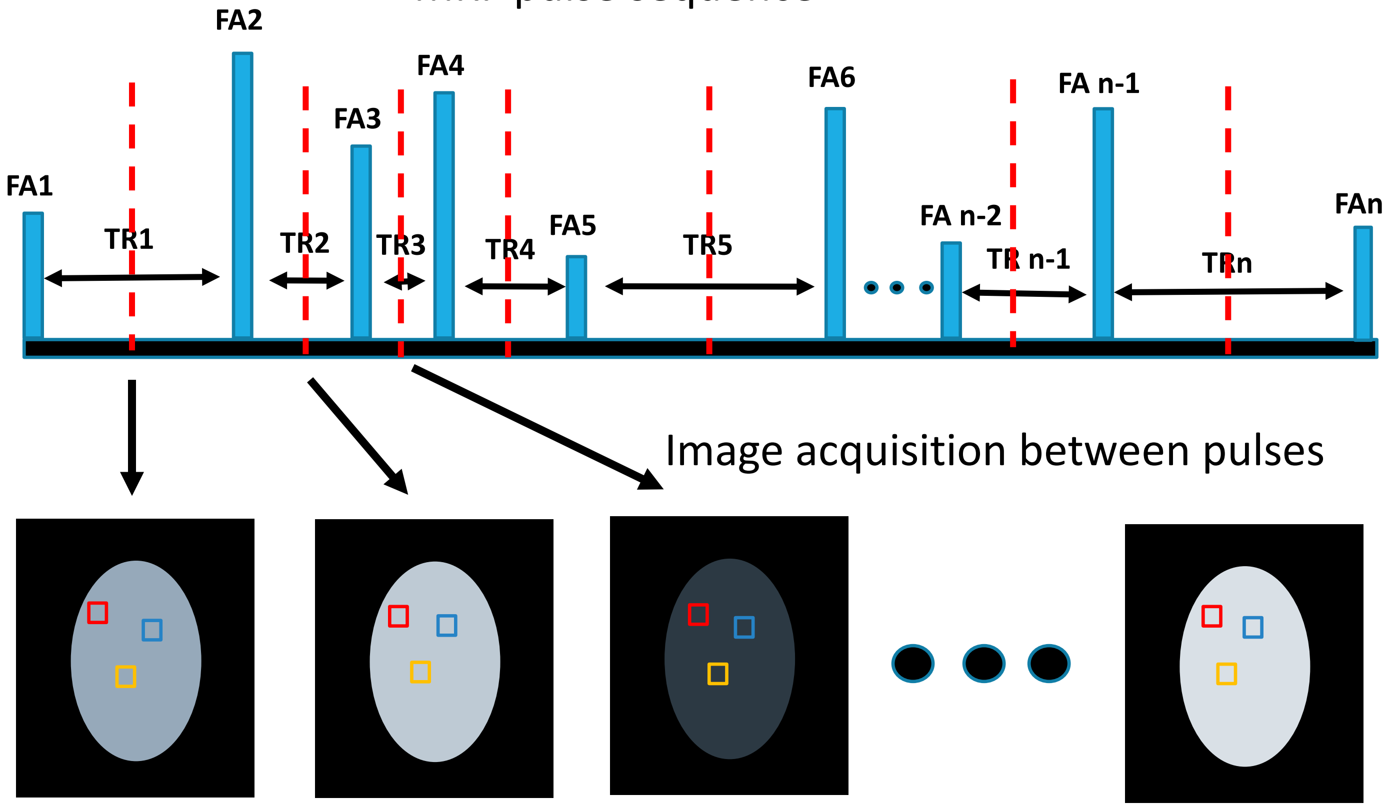
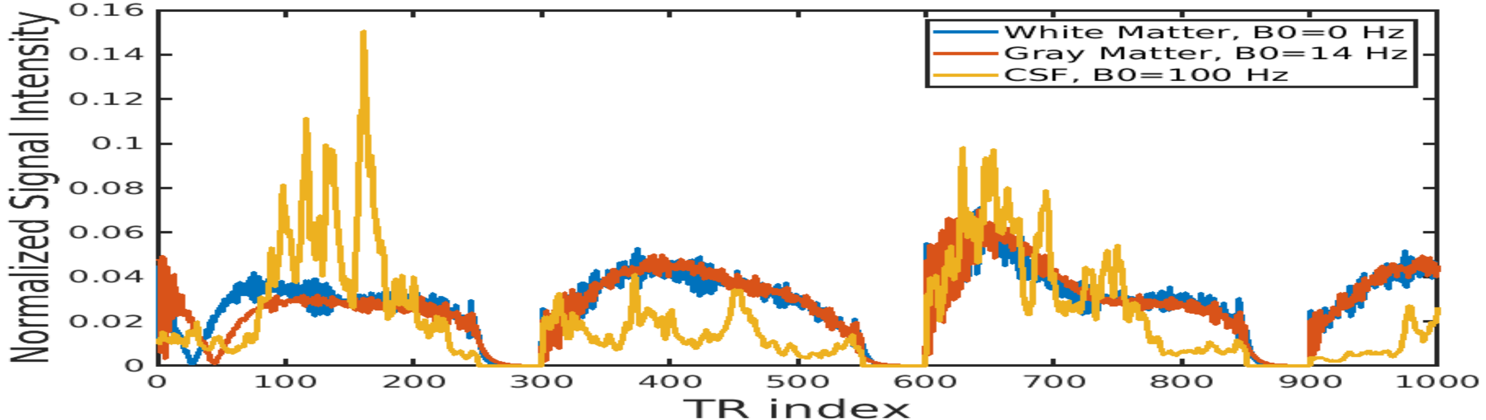
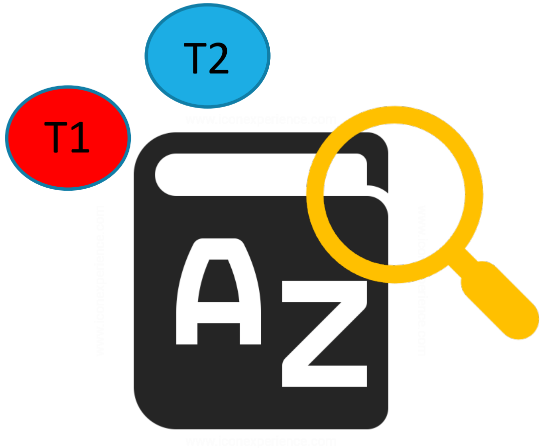


Image acquisition between pulses

Temporal series of voxel intensities

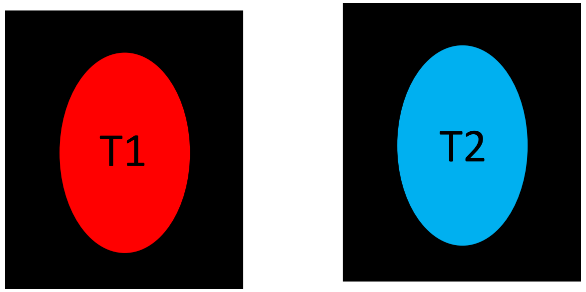


Parameter maps estimation

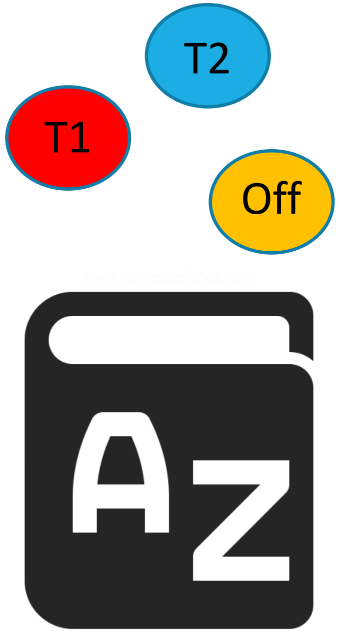


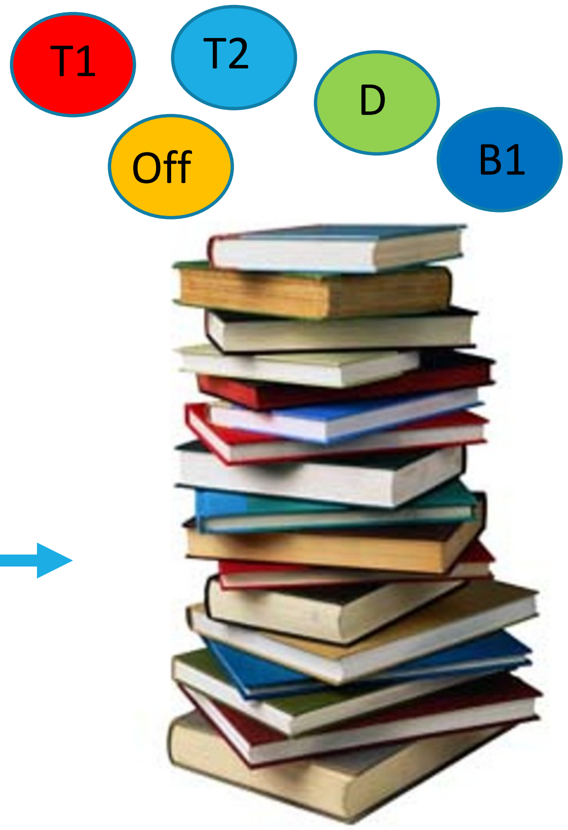
Simulating a dictionary with possible evolutions given a set of NMR parameters

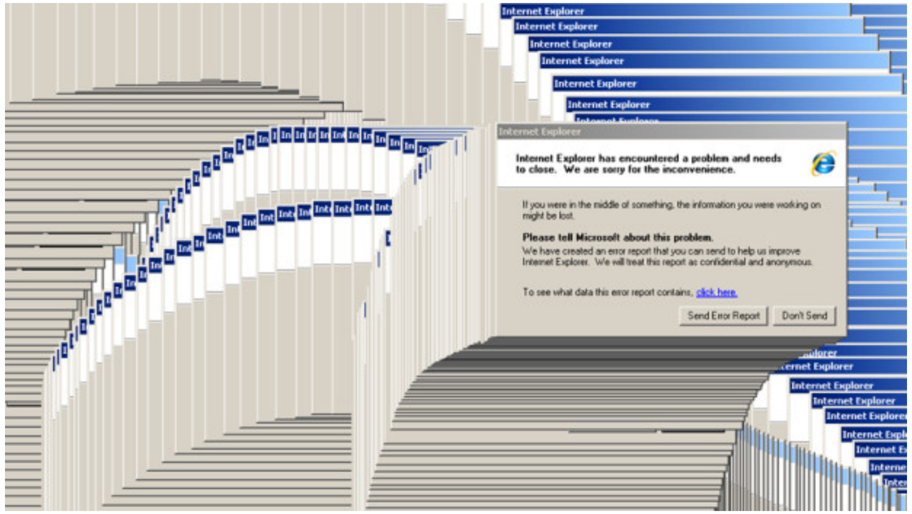
Per each experimental voxel signal performing Nearest Neighbour matching



The Curse of Dimensionality in Dictionary-based MR Fingerprinting







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If you were in the middle of something, the information you were working on might be lost.

Please tell Microsoft about this problem.
We have created an error report that you can send to help us improve Internet Explorer. We will treat this report as confidential and anonymous.

To see what data this error report contains, click here.

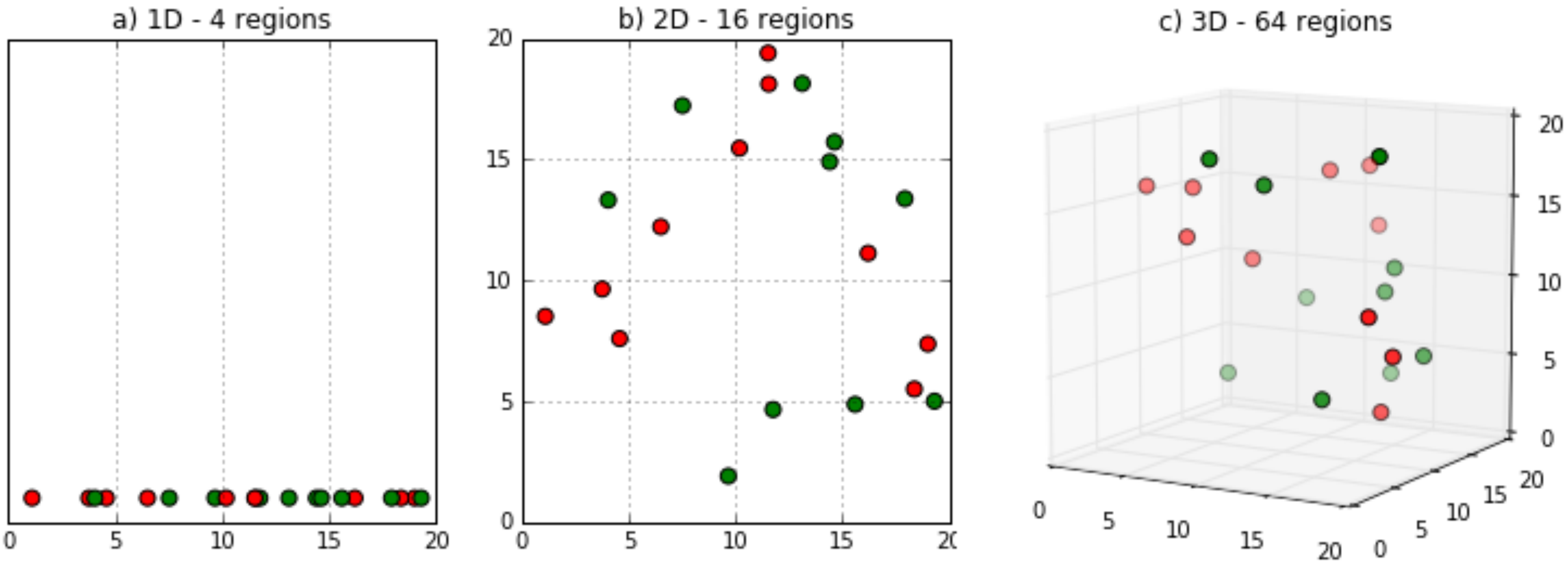
The more parameters the bigger the dictionary, if no drops in accuracy is wanted.

Memory usage inefficiency

Exhaustive search can be computationally inefficient.

The Curse of Dimensionality in Dictionary-based MR Fingerprinting

Adding a new dimension to the problem leads to an **exponential growth** in the number of entries to be insert into the box if no degradation in resolution are wanted [1]



This introduce sparsity, which can produce high biases in nearest-neighbour algorithms [2]

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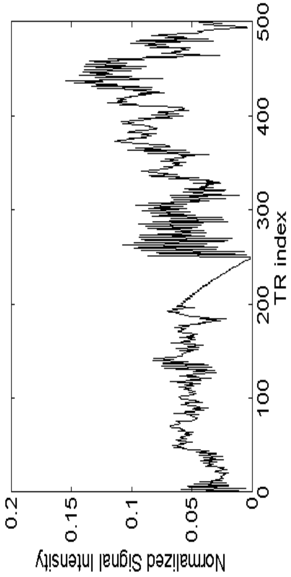
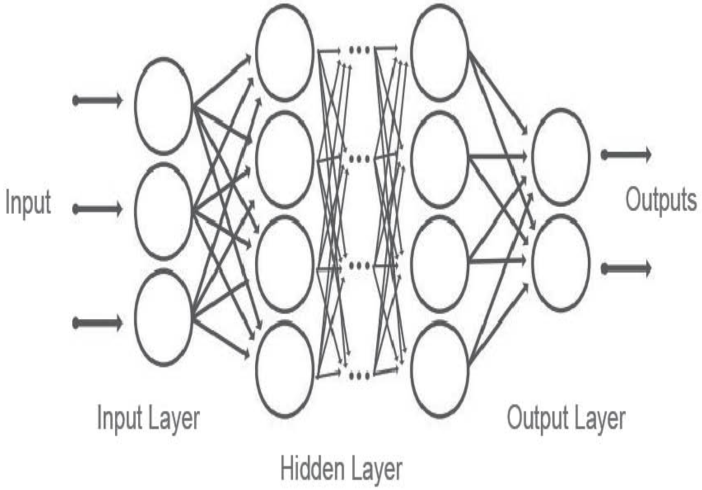
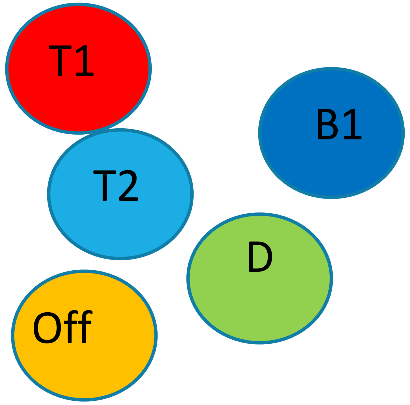
[1] R. Bellman, Adaptive control processes: a guided tour, Princeton University Press, 1961.
[2] J. H. Friedman, On bias, variance, 0/1–loss, and the curse-of-dimensionality, Data Mining and Knowledge Discovery 1 (1) (1997)

Circumventing the Curse of Dimensionality through a Deep Learning Approach







Examples from the signal space

MR parameters that generated the input signal

Learning the Inverse Transfer Function

Once trained, the Neural Network Model allows dictionary free MRF, because the model approximates the inverse transfer function.

Deep Learning for MRF

Our activity

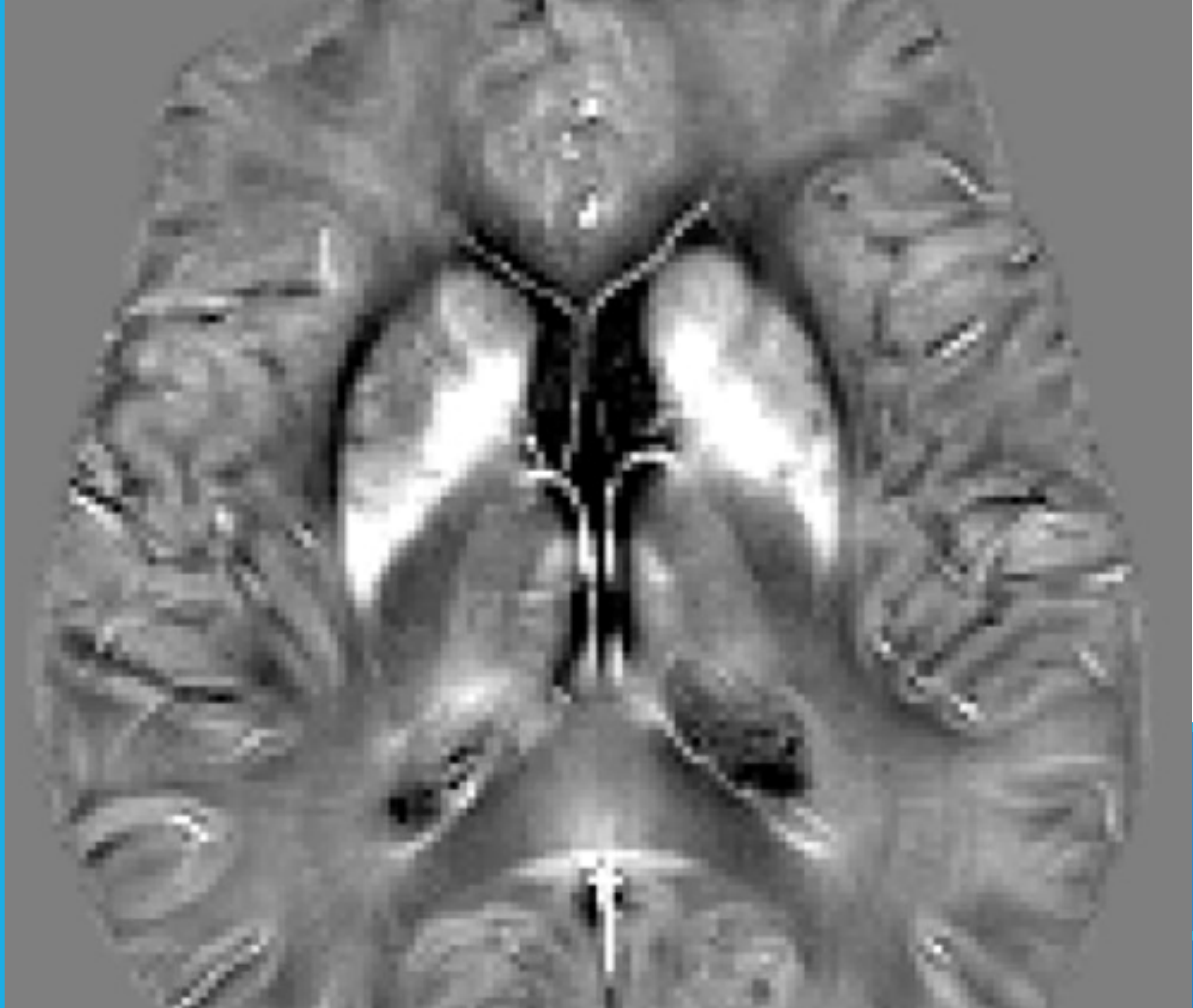
Numerical simulations using different MRF pulse sequences: https://arxiv.org/abs/1811.11477
Deep Learning approach scales really well with number of MR parameters, while dictionary matching approach scales poorly.

Quantitative Susceptibility Mapping

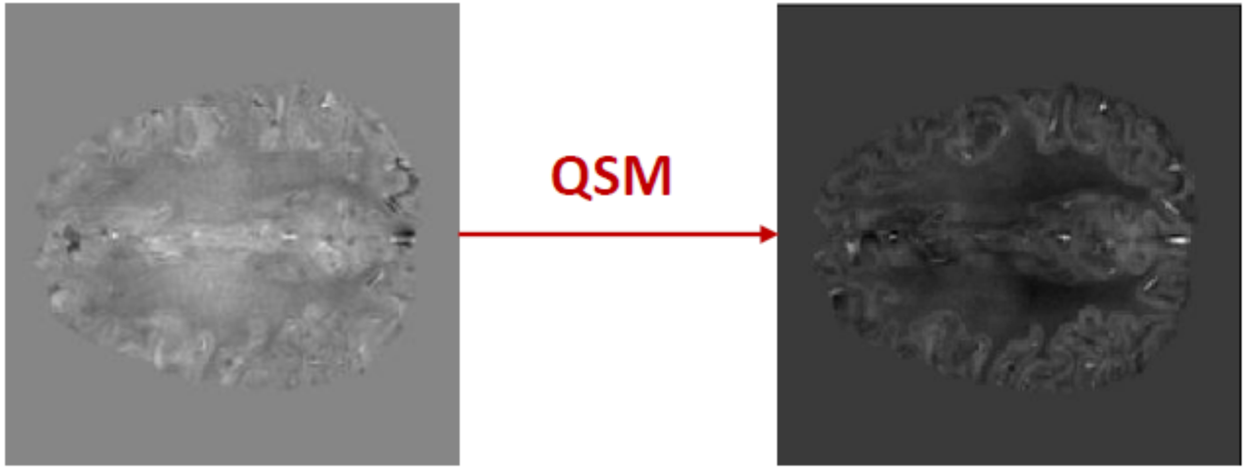
Deep Learning approach

Collaboration with

”Sir Peter Mansfield Institute”Nottingham UK



Quantitative Susceptibility Mapping: using the phase of the signal to retrieve tissue properties



Phase – map

Susceptibility – map

$$\vec{M} = \chi \vec{H}$$

Dimensionless proportionality constant indicating the degree of magnetization of a material in response to an applied magnetic field.

Susceptibility map: tissue contrasts in MRI

- 1980s, diseases characterization
- Response to an external magnetic field

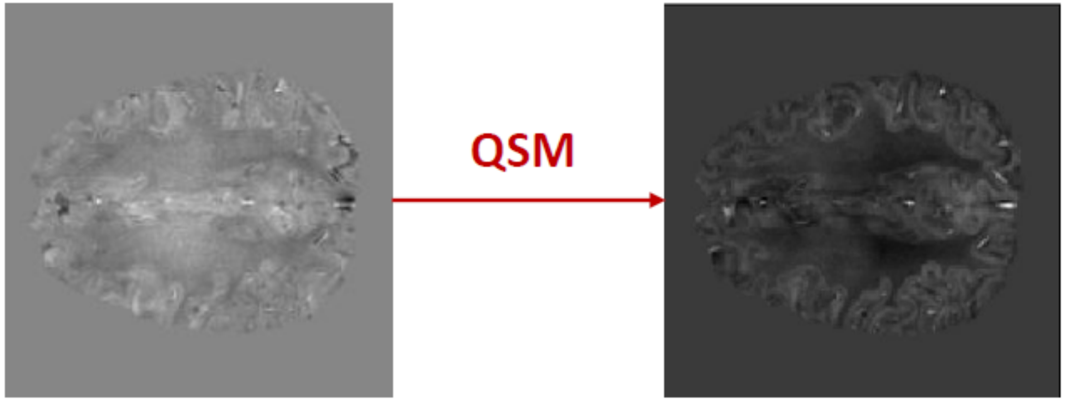
- *In vivo:* water, myelin, iron and calcium

Applications

- Anatomical imaging of human brain
- Lesion classification
- TBI (Traumatic Brain Injury)
- Brain tumours
- Neurodegenerative diseases
- DBS (Deep Brain Stimulation)
- Blood oxygen saturation

- Short relaxation times

Quantitative Susceptibility Mapping: an ill-posed problem



Phase – map

Susceptibility – map

$$\chi(k) = \Delta B(k)/\left(\tfrac{1}{3} - (\hat{\boldsymbol{k}}\cdot\hat{\boldsymbol{z}})^2\right) = \Delta B(k)/D(k)$$

Noise and errors amplification

Inverse Problem: φ(r) → χ(r)

Ill-posed problem: *D(k) = 0* in k-space

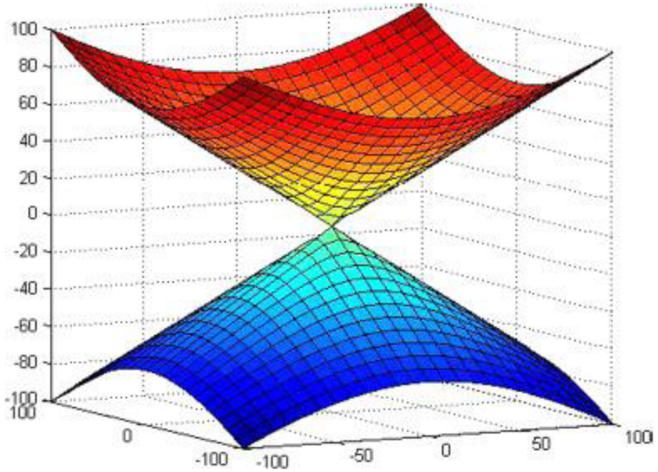
- Different object orientations
- Numerical strategies

TKD:
(Truncated K-space Division)
Faster
Noise and artifacts

COSMOS:
(Calculation Of Susceptibility through Multiple Orientation Sampling)

Long acquisition time
More accuracy

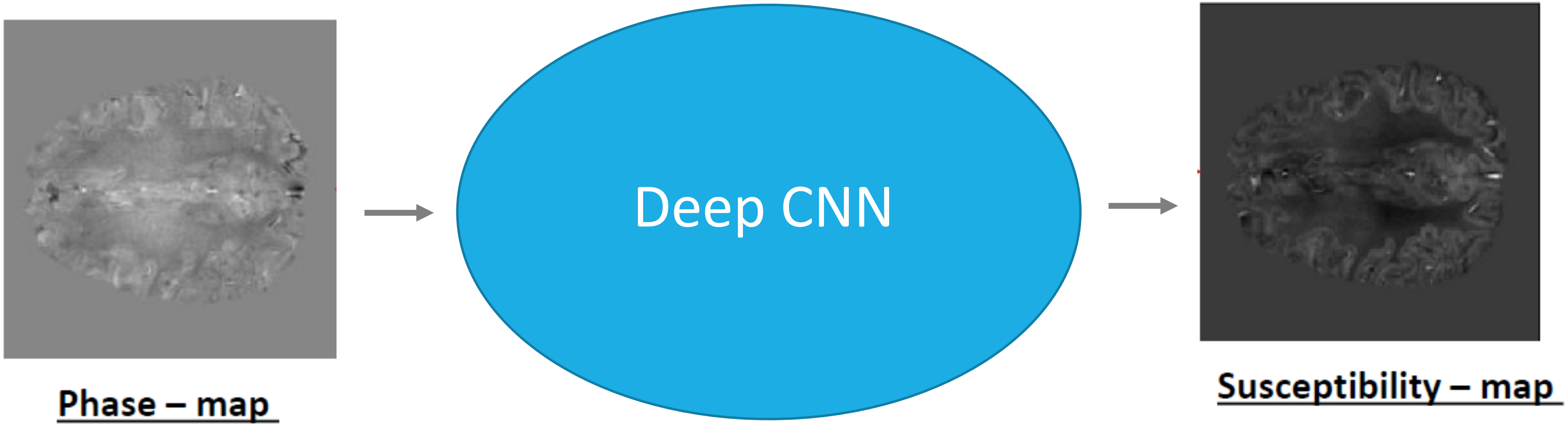
D (k)



Zero-values:

$$(\hat{\boldsymbol{k}}\cdot\hat{\boldsymbol{z}}) = \pm\frac{1}{\sqrt{3}}$$

Quantitative Susceptibility Mapping: Deep Learning approach *(in progress)*



Phase – map

Deep CNN

Susceptibility – map

Train a Deep CNN to retrieve COSMOS output with only one phase map

→ Time efficiency without drops in accuracy;

→ Feasible in clinical protocols.