Artificial Intelligence in Medicine



A Machine Learning Approach to Quantitative Susceptibility Mapping

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A Machine Learning Approach to QSM: intro



<u>QSM: $\phi(r) \rightarrow \chi(r)$ </u> <u>Ill-posed problem:</u> singularities in k-space

From<u>Phase – map</u>

To Susceptibility – map



Multiple-orientation approaches

<u>COSMOS</u> (Calculation Of Susceptibility through Multiple Orientation Sampling)

- Multiple head-orientation acquisition
- Long acquisition time
- Uncomfortable for the patient
- Accurate and precise reconstruction



<u>Single-orientation</u> approaches <u>TKD , iLSQR</u> (Truncated K-space Division)

- Single head-orientation acquisition
- Short acquisition time
- Numerical strategies (inverse filtering or iterative methods)
- Noisy reconstruction

QSM with CNNs: first application

For QSM in the clinical area

We need accurate and fast reconstruction

→ Convolutional Neural Networks (CNNs)

Deep learning tool in image processing Image reconstruction task Supervised Learning

INPUT



Database from QSM2016 Challenge

- One subject
- 12 head orientations
- 3D GRE images
- 3T Siemens
- # pixels: (160,160,160)
- Resolution: [1.06, 1.06, 1.07] mm
- FOV : (17, 17, 17) cm
- TE/TR = 25/35 ms

QSM with CNNs: results

- Input data: pre-processed phase data of one volunteer
- Input data with \vec{z} directed along $\vec{B_0}$ direction
- COSMOS map used as label
- Computational details: Keras 2.2.0, Tensorflow 1.9.0 Backend, Python 3.6 GPU nVidia Titanum XP, Cuda 9.0
- Data augmentation: 2D patches, 4 level of depth,15.6 h training time
 <u>TKD (ppm)</u>
 <u>COSMOS (ppm)</u>

NET (ppm)





QSM with CNNs: results

Intensity Histogram and Scatter Plot





QSM with CNNs: second application



To test the generalizability of the model

We applied the 2D-NN for different type of data

The Reference was COSMOS as multiple orientation approach

- Data augmentation: 2D patches; Architecture: 4 level of depth. 8 h training time

Subject database

 $\begin{array}{l} 6 \text{ subjects} \\ \text{Scanner: Achieva, Philips} \\ B_0 = 3T \\ \text{Resolution} = [0.8 \ 0.8 \ 3] \ \text{mm} \\ \text{TE1} = 9.4 \ \text{ms} \\ \text{TE2} = 20 \ \text{ms} \\ \end{array}$

- Subjects 2,4,5,6 were used during the training
- The trained model was tested on subj2 and subj7 (the latter not used during the training)

QSM with CNNs second application: results

2D training, using COSMOS map as label



Subj 2, used during the training

QSM with CNNs second application: results



2D training, using COSMOS map as label COSMOS NET

Subj 7 Not used during the training





QSM with CNNs 2.0

3D training, using COSMOS map as label

- 3D patches
- Data augmentation: 3D patches: Architecture: 4 level of depth. 15 h training time

Subj 2

NET 3D

Larger training size needed:

new GPU TESLA M10 (AIM funding) embedded in a server at the University of Bologna, Department of **Physics**

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UNDER TESTING
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Issues:

- Is COSMOS the right reference? Effect of the registration with non uniform resolution (the coarsest resolution is not always along the same direction with respect to the frame)
- effect of the added thresholding operation in performing the COSMOS algorithm.



Acquisition Details

Scanner: Achieva, Philips B = 3TResolution = [0.8 0.8 3] mm TE1 = 9.4 ms TE2 = 20 ms



Future works:

• 3D training, working with synthetic images

Simulate susceptibility data $\chi(r)$ and reproduce the field perturbation $\Delta B(r)$ ones using: $\frac{\Delta B(r)}{B_0} = F^{-1}(\chi(k) \cdot K(k))$

Simulated data:

20 images with size [288 288 288]. Each of them was filled with 100 spheres and 100 rectangles. To each sphere and rectangle, a uniform values of susceptibility is assigned

Once trained the NNs we will test the net first on other synthetic data and then on in vivo data

SIMULATED SUSCEPTIBILITY MAP $\chi(r)$





EVALUATED FIELD PERTURBATION MAP

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