MEDICAL IMAGE COMPUTING (CAP 5937)

LECTURE 4: Pre-Processing Medical Images (II)

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Outline

- Diffusion based Smoothing in Medical Scans
- Intensity inhomogeneity Correction in MRI

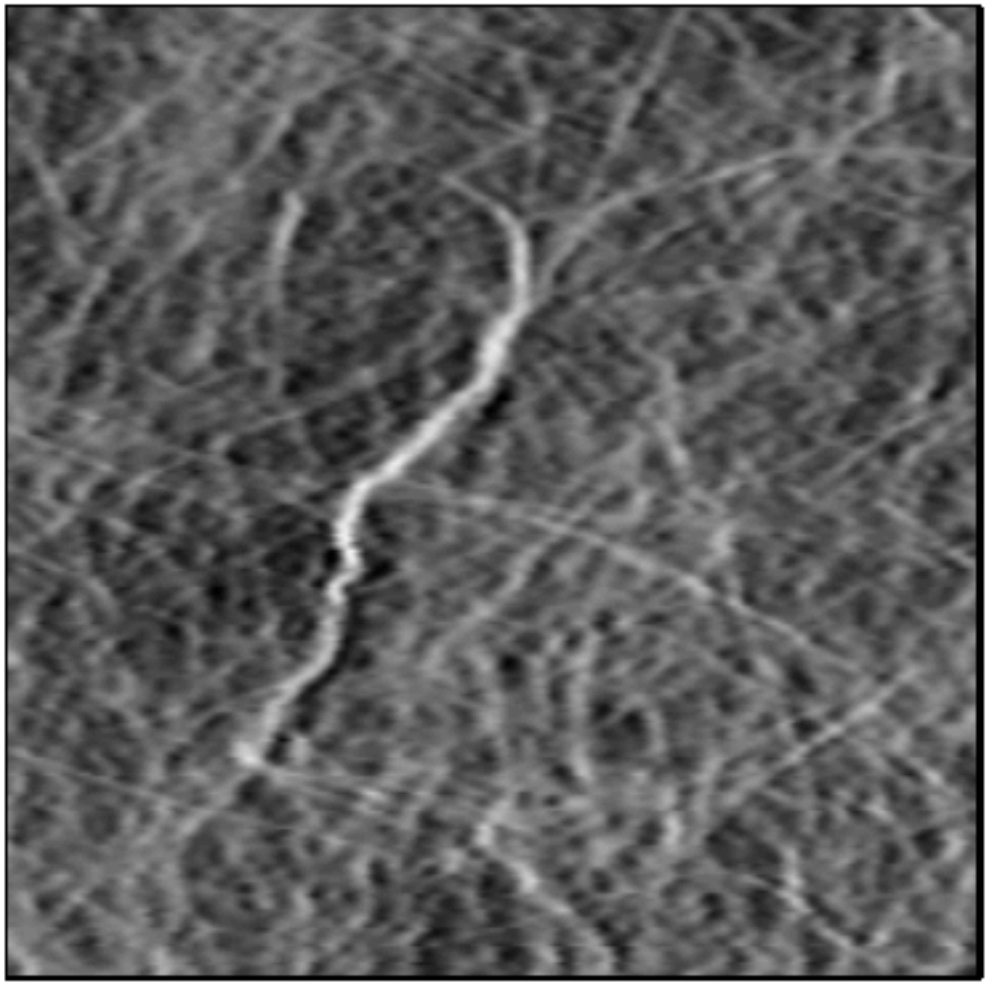
Linear and Non-Linear Filtering (Smoothing)

Linear approach:

Treat every pixel with the exact same convolution.

Non-Linear approach:

Treat a pixel with varying intensity, depending on its neighborhood qualities.



Possible?

Perona-Malik (Anisotropic Diffusion) Filtering

- Perona and Malik propose a nonlinear diffusion method for avoiding the blurring and localization problems of linear diffusion filtering [PAMI 1990].
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$$g(s^2) = \frac{1}{1 + s^2/\lambda^2}$$

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  - approximation $\partial_t u = \nabla u$

General Idea on Anisotropic Diffusivity

- if (x,y) is a part of an edge ➔ apply little smoothing
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- if (x,y) is a part of an edge ➔ apply little smoothing
- Else ➔ apply full smoothing
- Assume, E is edge likelihood (telling you if you are in homogeneous or edge regions)
- CONTROLLING THE BLURRING (SMOOTHING)

$$g(\|E\|) = e^{-((\|E\|/k)^2)}$$

or

$$g(\|E\|) = \frac{1}{1+\left(\frac{\|E\|}{k}\right)^2}$$

General Idea on Anisotropic Diffusivity

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- Define general coefficient (c) for diffusivity:

$$c\,(x,y,t) = g\,(\|\nabla I\,(x,y,t)\|)$$

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$$[I(\mathbf{x})]_{t+1} = \left[I(\mathbf{x}) + (\Delta T) \sum_{d=1}^{\Gamma} c_d(\mathbf{x}) \nabla I_d(\mathbf{x}) \right]_t ,$$

d=1,… direction

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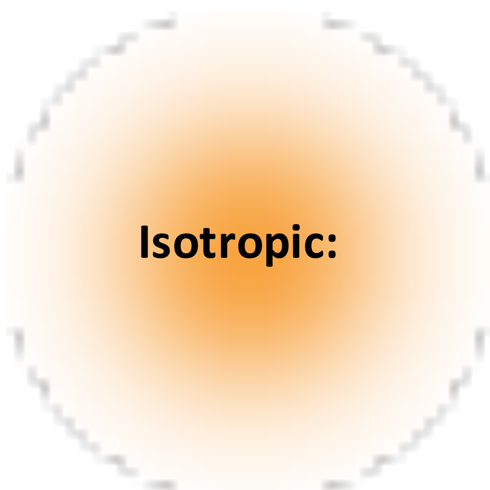
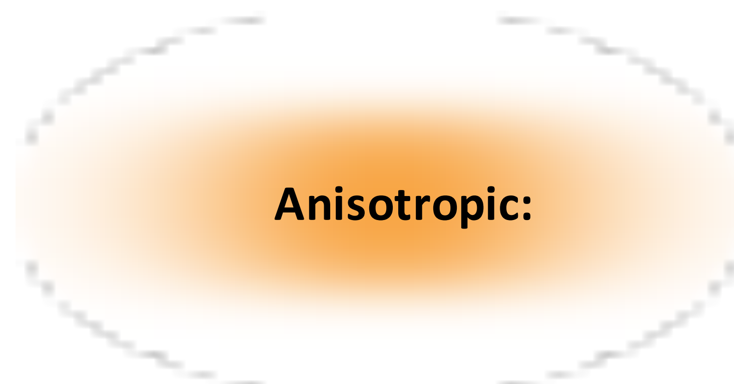
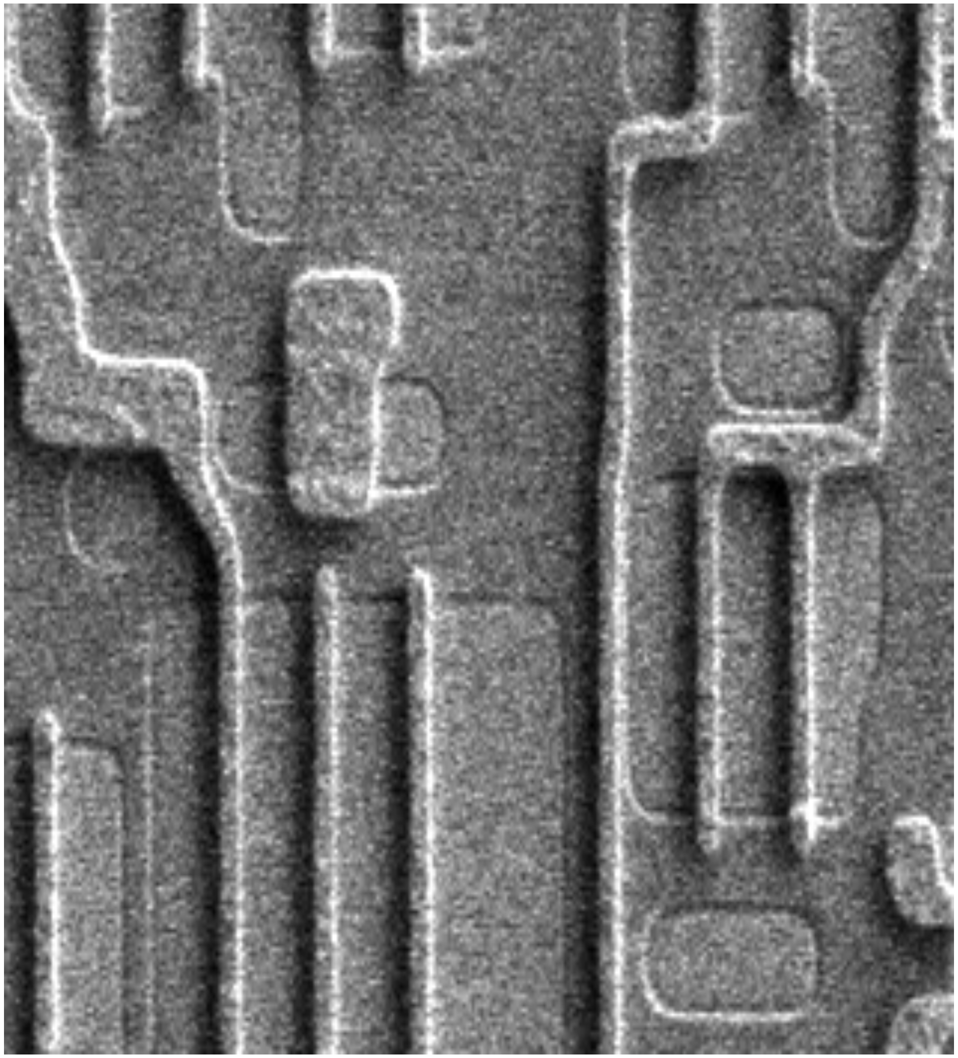




Toy Example

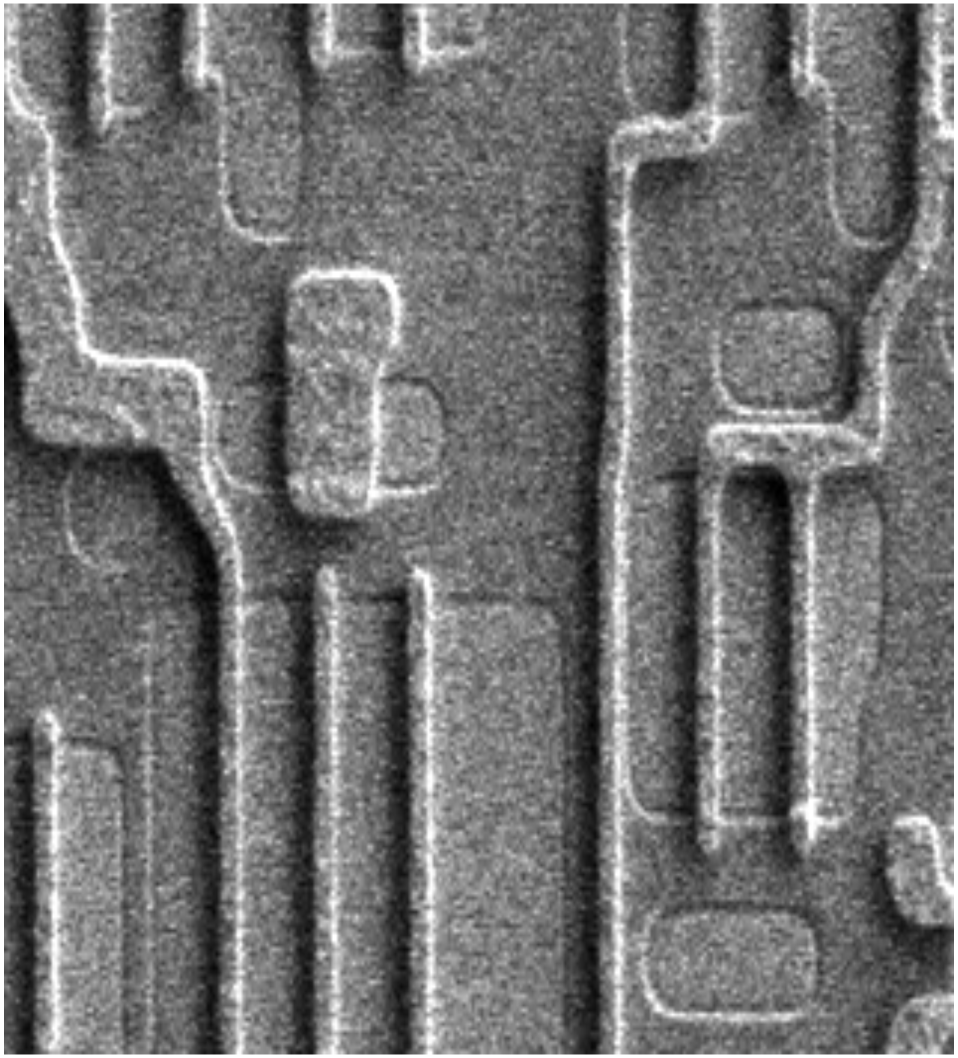
Original



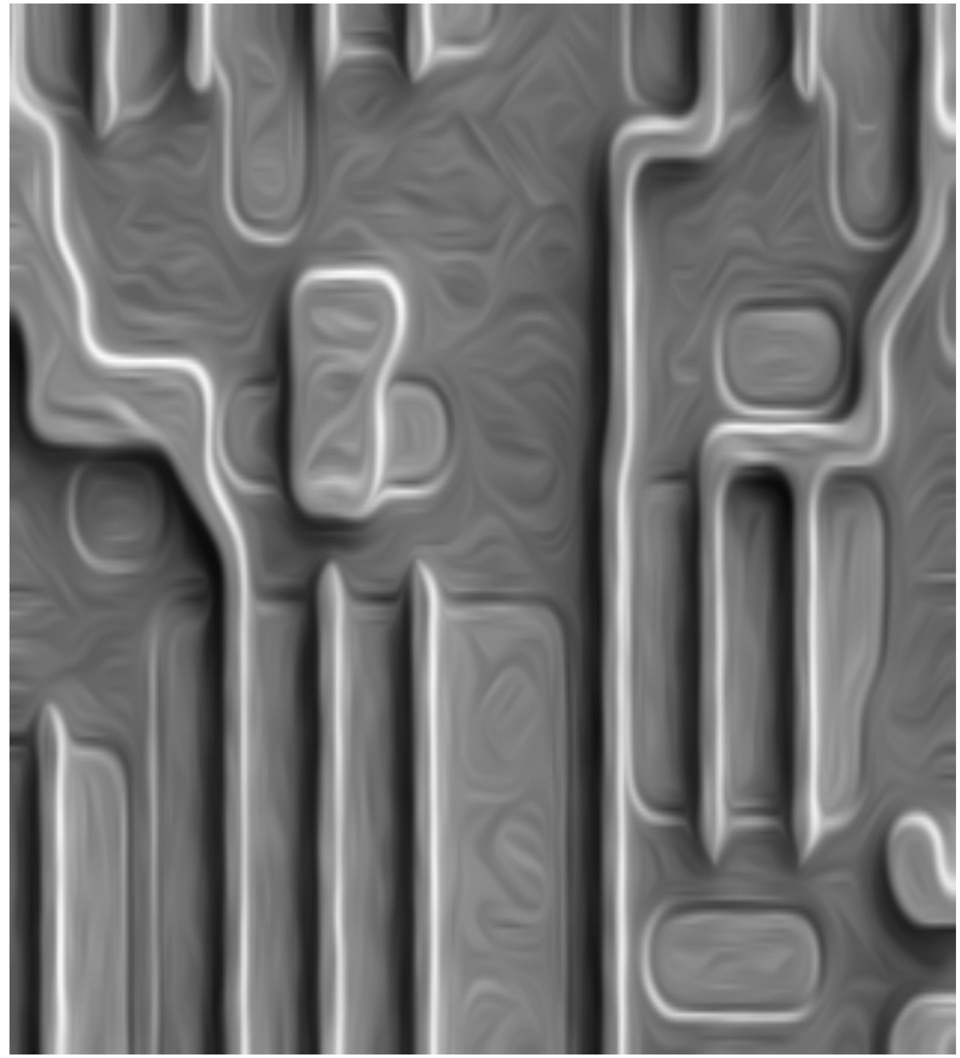
Linear isotropic diffusion (simple Gaussian)

Toy Example

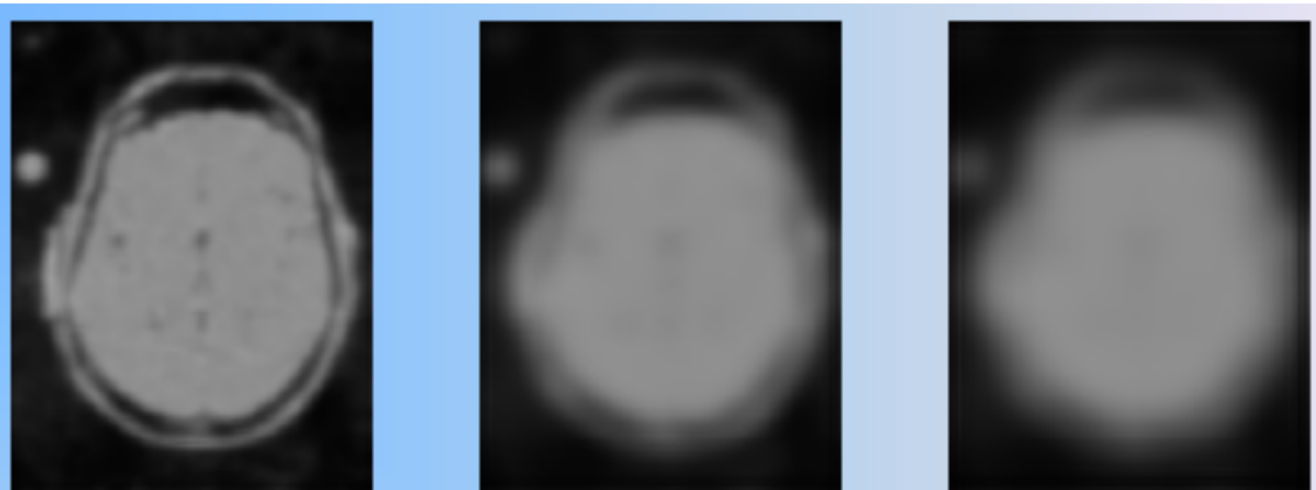
Original



Non-linear anisotropic diffusion

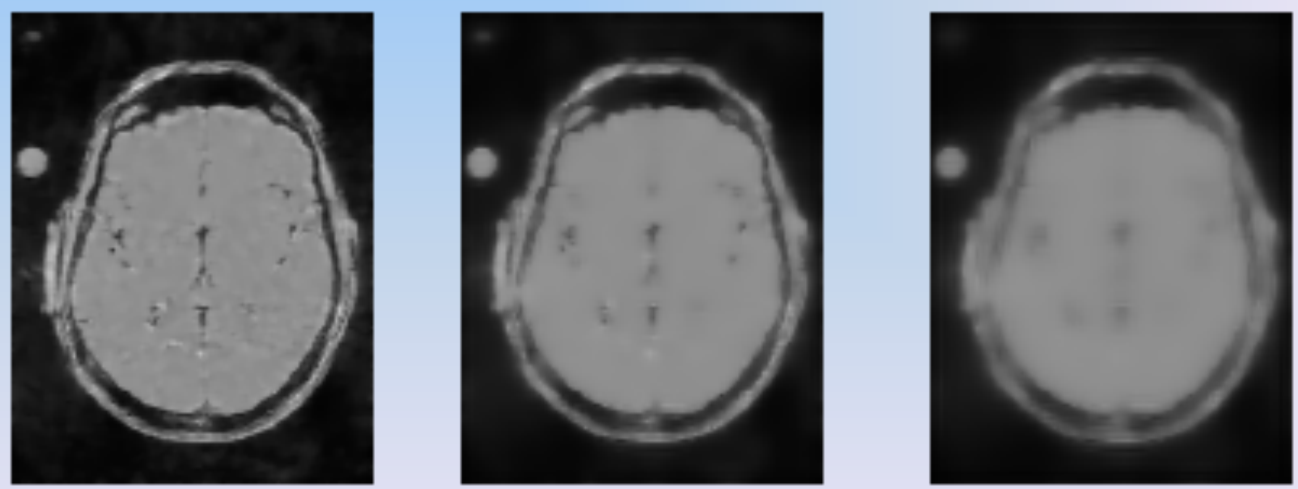


Linear diffusion



t=4 *t=20* *t=40*

Nonlinear diffusion



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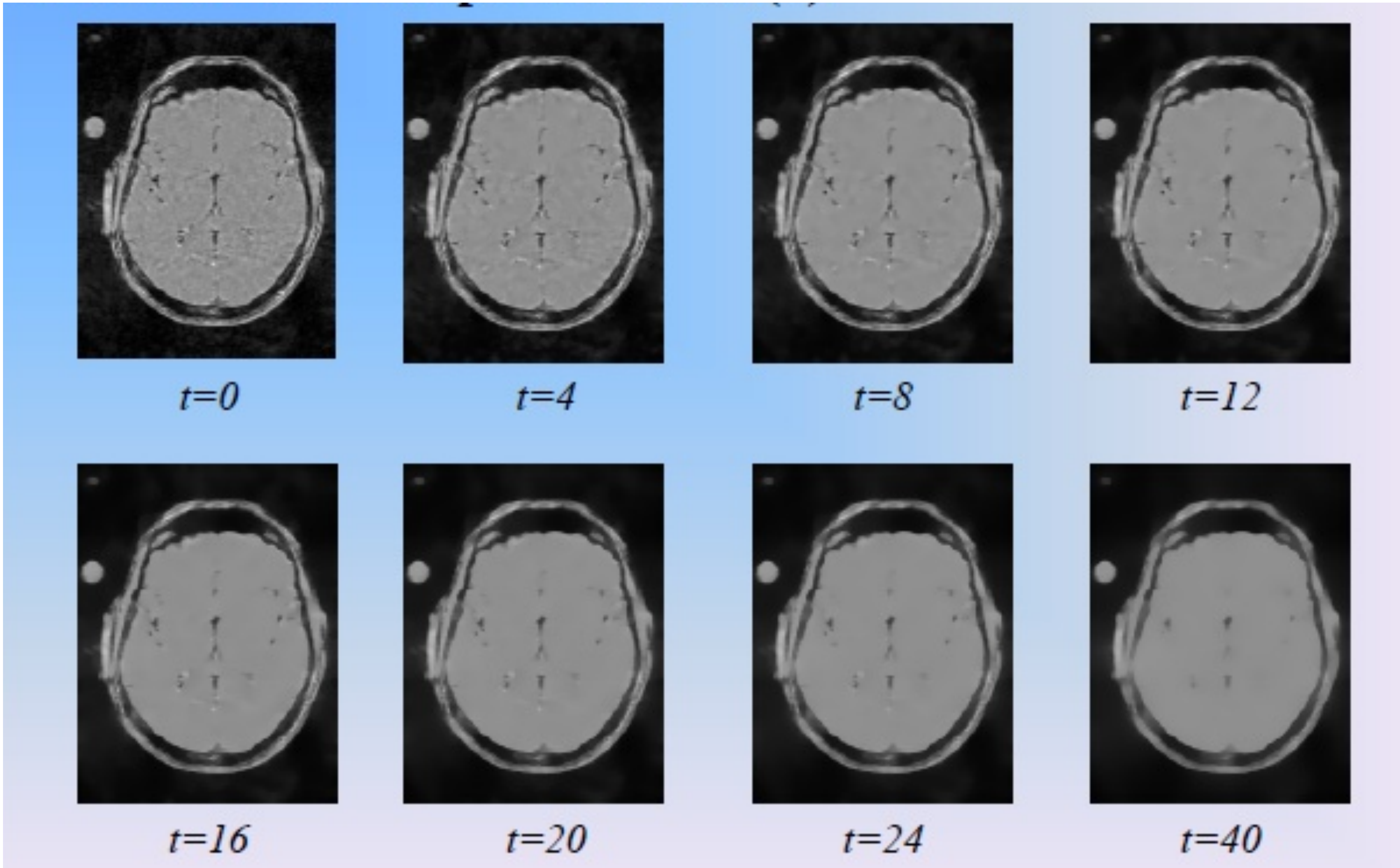
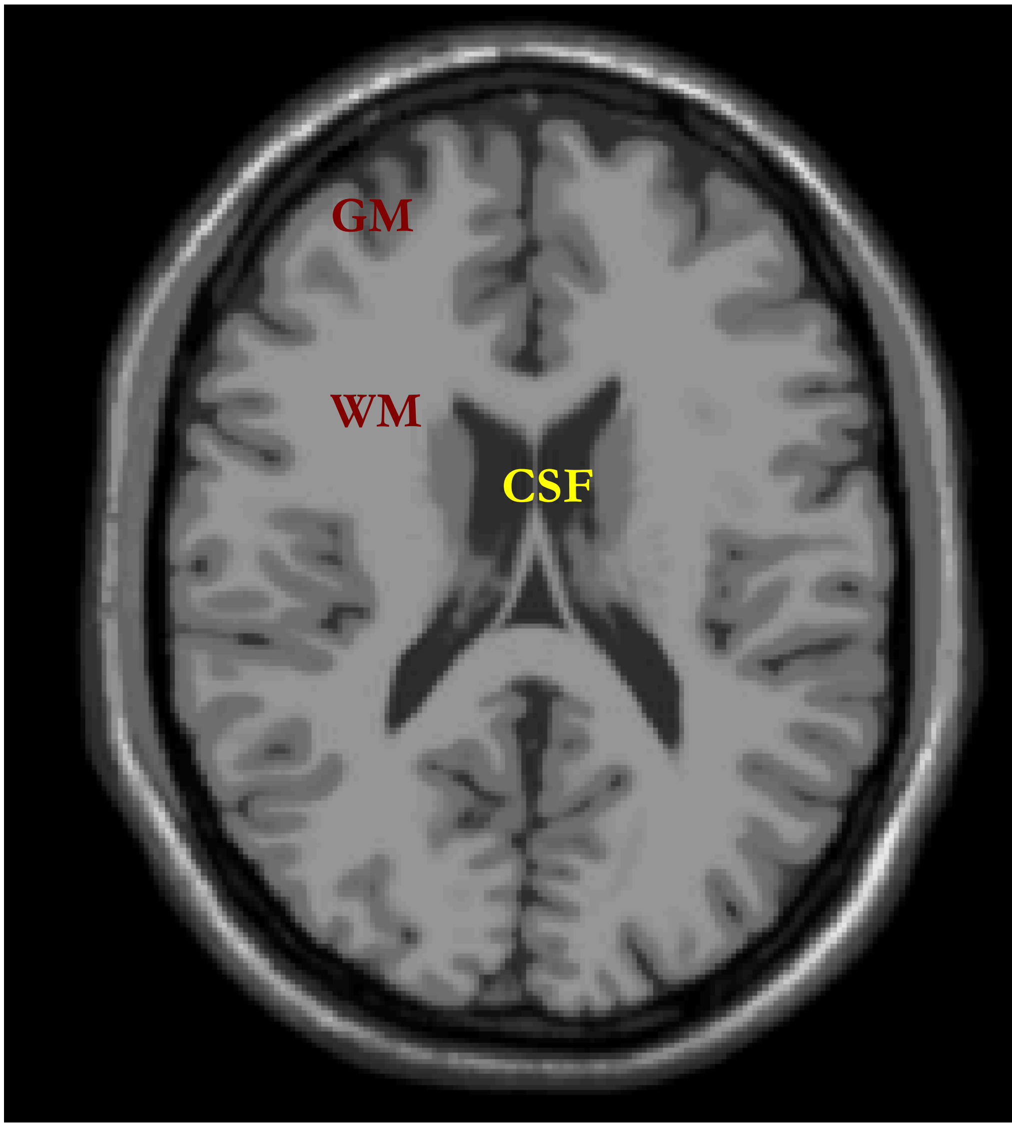
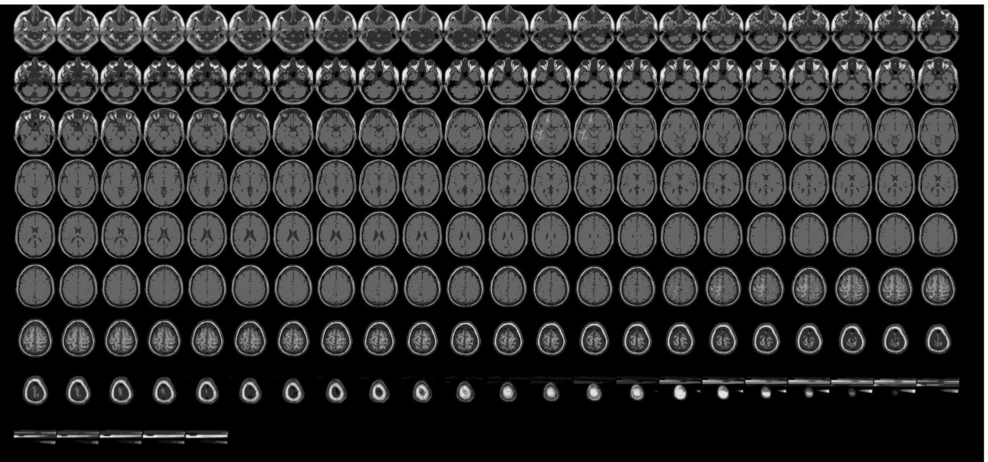
Non-linear Diffusion



Background: *BrainWeb*





MR Brain simulator

Modality: (you can choose one of the following pulse sequences)

T1 ◉ T2 ○ PD ○

Slice thickness: (in-plane pixel size is always 1x1mm)

1mm ◉ 3mm ○ 5mm ○ 7mm ○ 9mm ○

Noise: (calculated relative to the brightest tissue)

0% ○ 1% ○ 3% ◉ 5% ○ 7% ○ 9% ○

Intensity non-uniformity ("RF"):

0% ○ 20% ◉ 40% ○

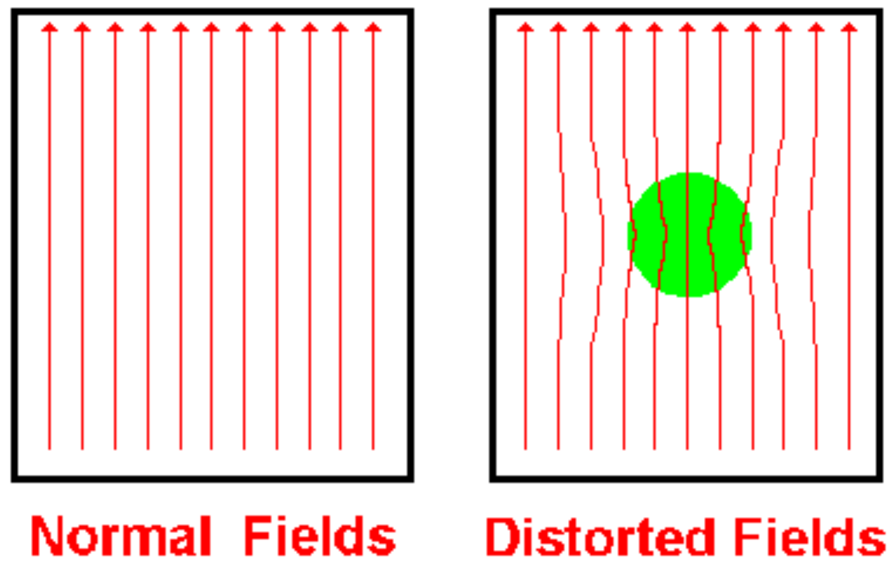
[Reset form] [View] [Download]

Magnetic Field Inhomogeneity

Material	χ (ppm)
Free space	0
Air	0.4
Water	-9.14
Fat	-7.79
Bone	-8.44
Grey Matter	-8.97
White Matter	-8.80

Field *inhomogeneity* is measured in parts per million (ppm)

with respect to the *external field*



Different tissues have different magnetic susceptibilities

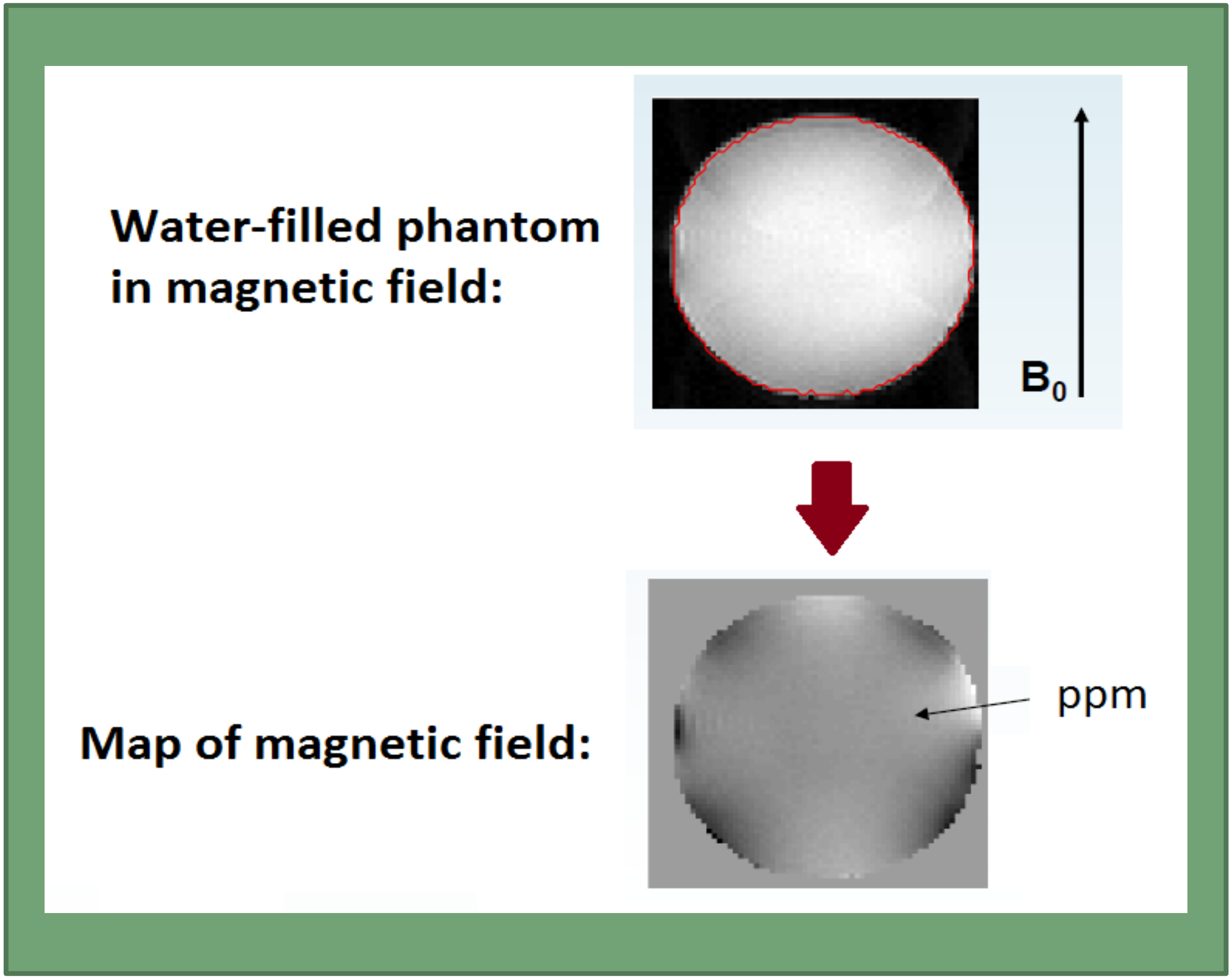
⇨ distortions in magnetic field

distortions are most noticeable near air-tissue interfaces

Credit: K.Friston

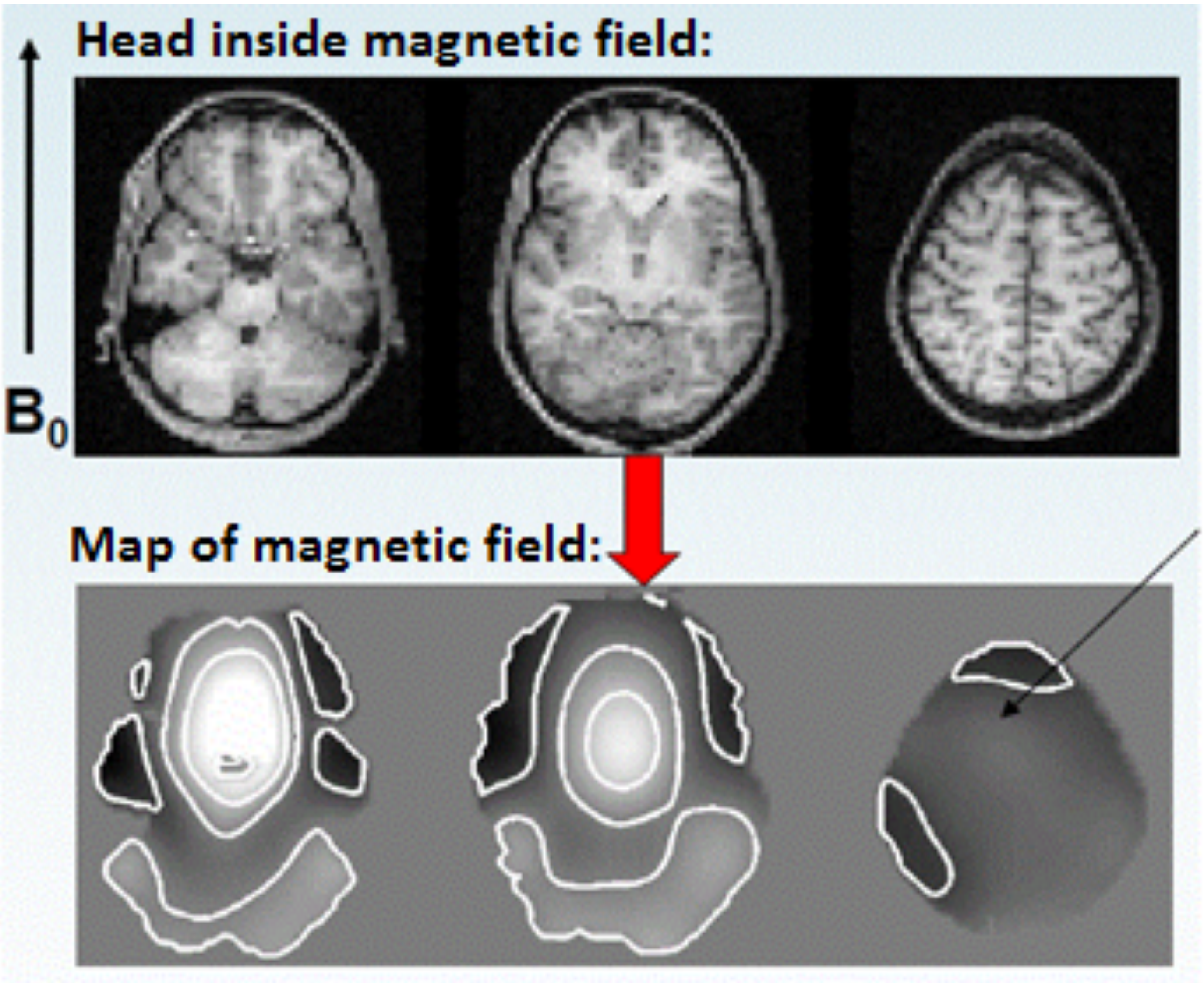
MR Intensity Inhomogeneity

- Often hardly noticeable, but registration, segmentation, and thus quantification processes are significantly affected from inhomogeneity field



(credit: R.Gupta)

MR Intensity Inhomogeneity



Large susceptibility variation in the human brain leads to greater field inhomogeneity and therefore image distortion.

(credit: R.Gupta)

Intensity Inhomogeneity Correction

- Problem:
  - Imperfections in the ***RF* field** cause background variations in *MR* images.
  - Poses challenges in image segmentation and analysis.
- Goal: To develop a general method for correcting the variations that fulfills:
  - (R1) no need for user help per scene
  - (R2) no need for accurate prior segmentation
  - (R3) no need for prior knowledge of tissue intensity distribution

Intensity Inhomogeneity Correction Methods

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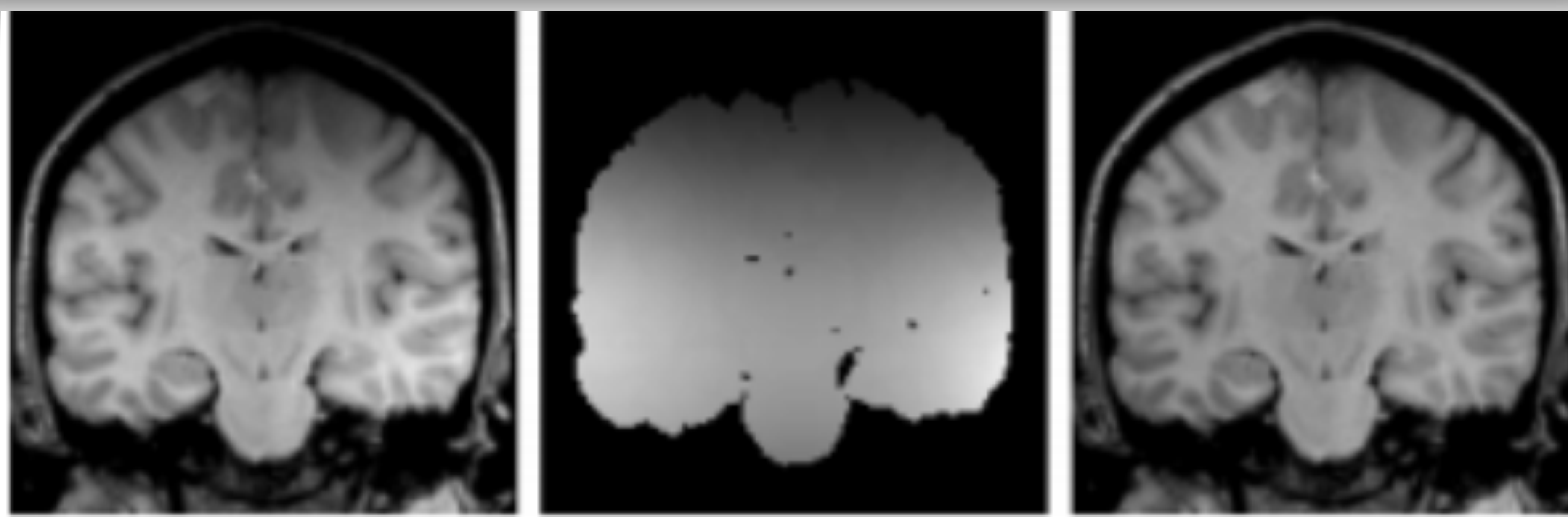
A Review of Methods for Correction of Intensity Inhomogeneity in MRI

Uroš Vovk, Franjo Pernuš, and Boštjan Likar*



Original Image | Inhomogeneity Field | Corrected Image

Bias Correction Approaches

Numerous methods have been published in the last two decades

I. Prospective Approaches
   i. Phantom
   ii. Multicoil
   iii. Special sequence

II. Retrospective Approaches
   i. Filtering
   ii. Surface Fitting (intensity or gradient)
   iii. Segmentation (ML, MAP, FCM, nonparametric,…)
   iv. Histogram
      a. High frequency maximization
      b. Information amximization
      c. Histogram matching

Prospective Approaches-Phantom

- Treat intensity corruption as a systematic error of the MRI acquisition process that can either be minimized by acquiring additional images of a uniform phantom, by acquiring additional images with different coils, or by devising special imaging sequences.

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- Treat intensity corruption as a systematic error of the MRI acquisition process that can either be minimized by acquiring additional images of a uniform phantom, by acquiring additional images with different coils, or by devising special imaging sequences.
- Oil or water is usually used for phantoms and median filtering is applied for image smoothing.

- Warning: The phantom based approach cannot correct for patient-induced inhomogeneity, which is a major drawback of this approach. The remaining intensity inhomogeneity can be as high as 30%

Prospective Approaches-MultiCoil and Special Sequences

- Volume and Surface coils
  - Volume coil: induce less inhomogeneity, poor SNR
  - Surface coil: induce severe inhomogeneity, good SNR
  - **Method:** dividing the filtered surface coil image with the body coil image and smoothing the resulting image
  - **Disadvantage:** prolonged acquisition time

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- Sequence design (pulse design)
  - **Method:** the spatial distribution of the flip angle can be estimated and used to calculate the intensity inhomogeneity.
  - **Disadvantage:** Hardware design

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$$log\ u(x) = log\ v(x) - LPF(log\ v(x)) + C_N$$

- log v(x) is input image, C_N is normalization constant, u(x) corrected image.
- However, this is true only when imaged anatomical structures are relatively small !!!

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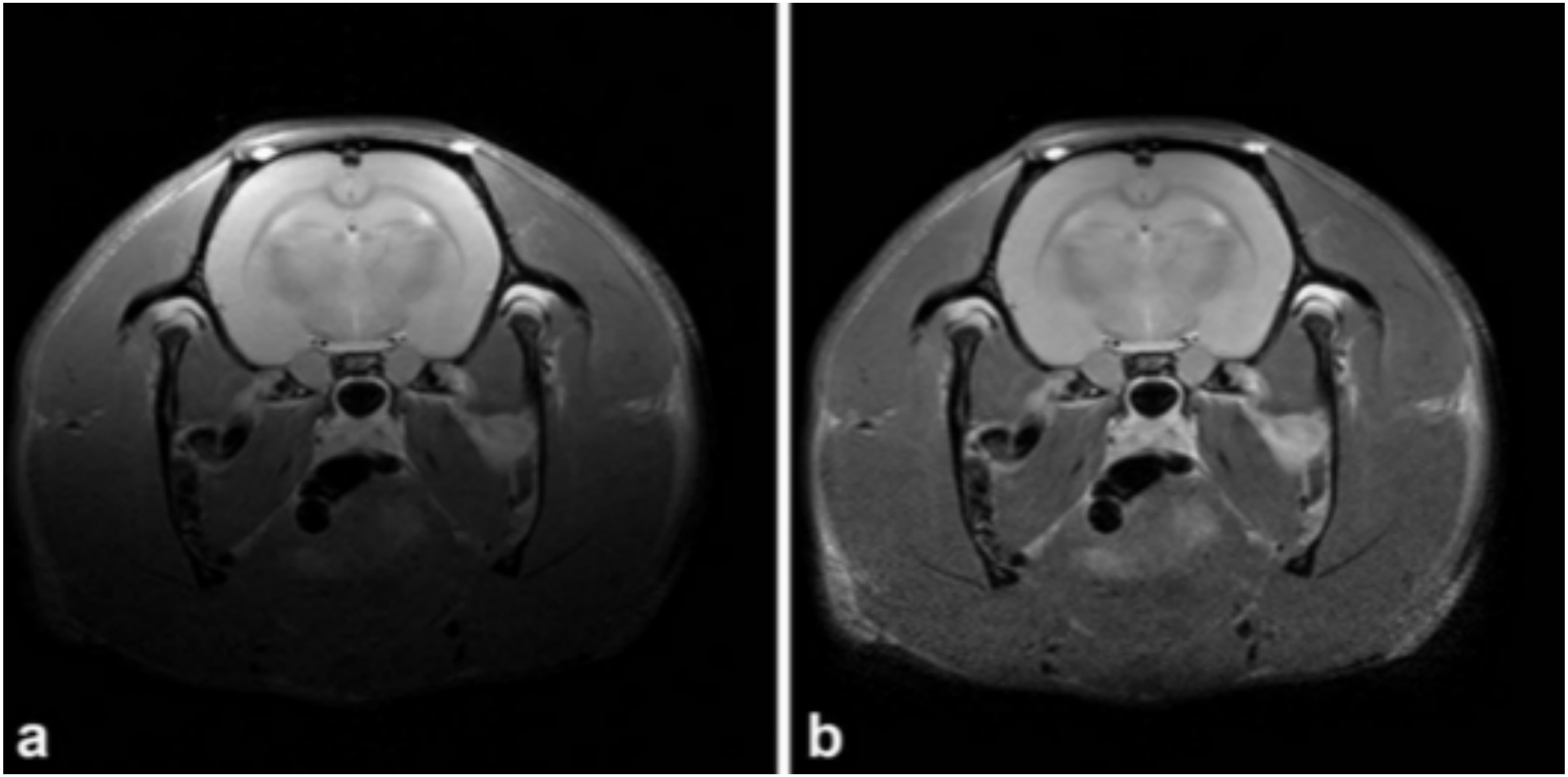
- FILTERING:
  - Homomorphic unsharp masking
  - probably the simplest and one of the most commonly used methods
  - b(x) (bias field) is obtained by low-pass filtering of the input image v(x), divided by the constant C_N to preserve mean or median intensity

$$u(x) = v(x)/b(x) = v(x)C_N/LPF(v(x))$$

Prospective Approaches-Filtering/Surface Fitting



A representative example of a slice from a rat brain. a: Original image. b: after inhomogeneity correction with the phantom based correction algorithm. Credit: Hui et al, JMRI 2010.

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- Segmentation-based approaches:
  - ML (maximum likelihood) or MAP (maximum a posteriori probability) criterion may be used to estimate intensity distribution in MRI
  - FCM (fuzzy c-means) for clustering tissue classes
  - Connectivity criteria is used to enforce smooth labeling

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– Histogram-based approaches:
  - directly on image intensity histograms
  - the inhomogeneity field is slowly varying -> it is natural to assume smooth histogram then!
  - N3 method is widely used, the method is iterative and seeks the smooth multiplicative field that maximizes the high frequency content of the distribution of tissue intensity.

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A Nonparametric Method for Automatic Correction of Intensity Nonuniformity in MRI Data

John G. Sled,* Alex P. Zijdenbos, *Member, IEEE*, and Alan C. Evans

Nonparametric Non-uniform Intensity Normalization (N3-Sled, TMI 1998)

- Consider the following model of image formation in MR:

$$v(x) = u(x)f(x) + n(x)$$

where at location x, v is measured signal, u is true signal, n is noise. f (bias field) is unknown.

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- Let U,V, and F be the probability densities of $\hat{u}, \hat{v}, \text{and } \hat{f}$
- (approx.) if u and f are uncorrelated random variables, then

$$V(\hat{v}) = U(\hat{v}) * F(\hat{v})$$

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- Consider the following model of image formation in MR:

$$v(x) = u(x)f(x) + n(x)$$

if u and f are uncorrelated random variables, the distribution of their sum is found by convolution!

$$\boxed{\hat{v}(x) = \hat{u}(x) + \hat{f}(x)}$$

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\begin{aligned}
E[\hat{u}|\hat{v}] &= \frac{1}{V(\hat{v})}\int_{-\infty}^{\infty} \hat{u}p(\hat{u},\, \hat{v})\, d\hat{u} \\
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\end{aligned}
$$

$$\hat{f}_e(\hat{v}) = E\left[\hat{f}|\hat{v}\right] = \hat{v} - E[\hat{u}|\hat{v}]$$

The method is based on to maximize the frequency content of the image intensity distribution.

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How do we guess f ? (F?)

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How do we guess f ? (F?)

- F is set to be Gaussian field with small variance!

Nonparametric Non-uniform Intensity Normalization (N3-Sled, TMI 1998)

1. Use log domain, and prob. densities of u,v, and f.

The approach is simply to propose a distribution for **U** by sharpening the distribution **V**, and then to estimate a corresponding smooth field **F** which produces a distribution close to the one proposed.

How do we guess f ? (F?)

- F is set to be Gaussian field with small variance!

ITK Implementation of N3

- itkN3MRIBiasFieldCorrectionImageFilterTest

  imageDimension

  inputImage

  outputImage

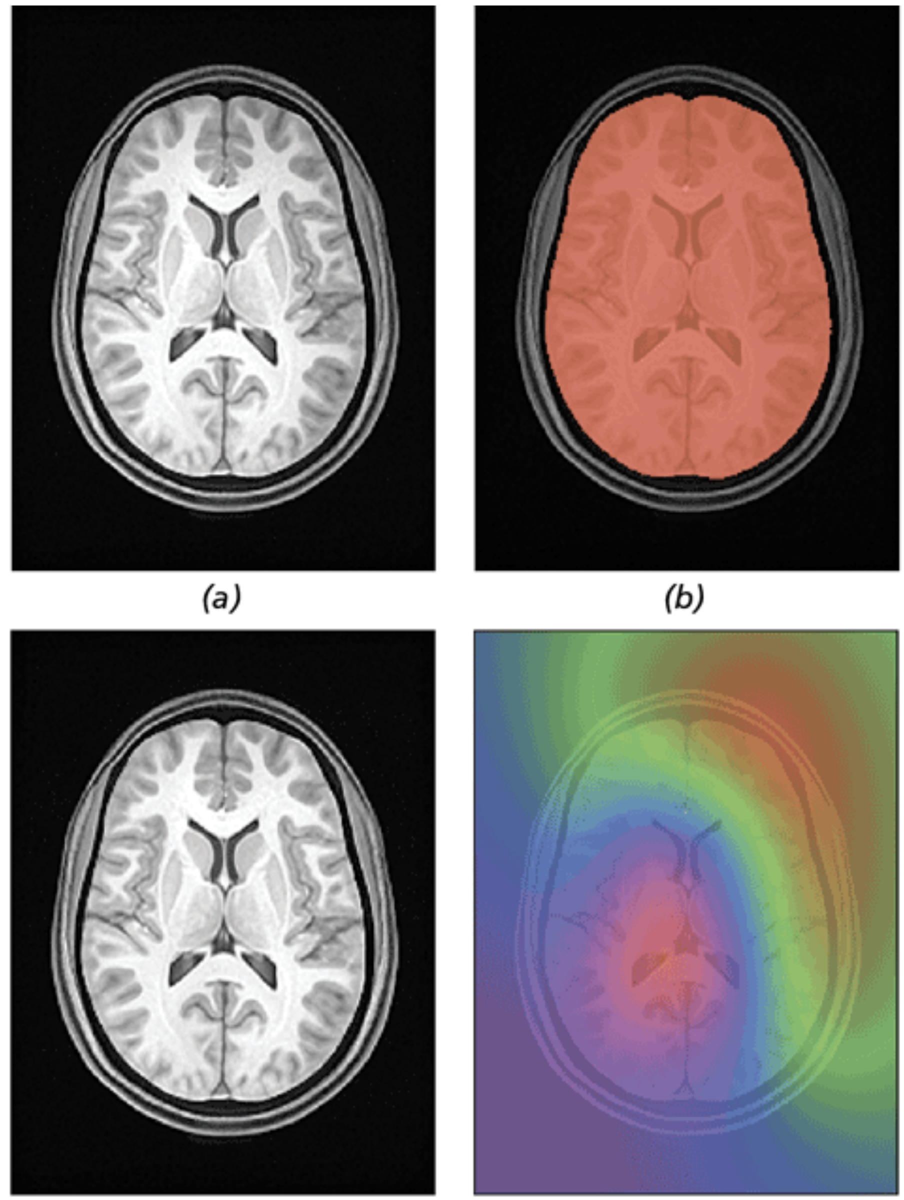
  Input parameters

  [shrinkFactor] [maskImage] [numberOfIterations] [numberOfFittingLevels] [outputBiasField]

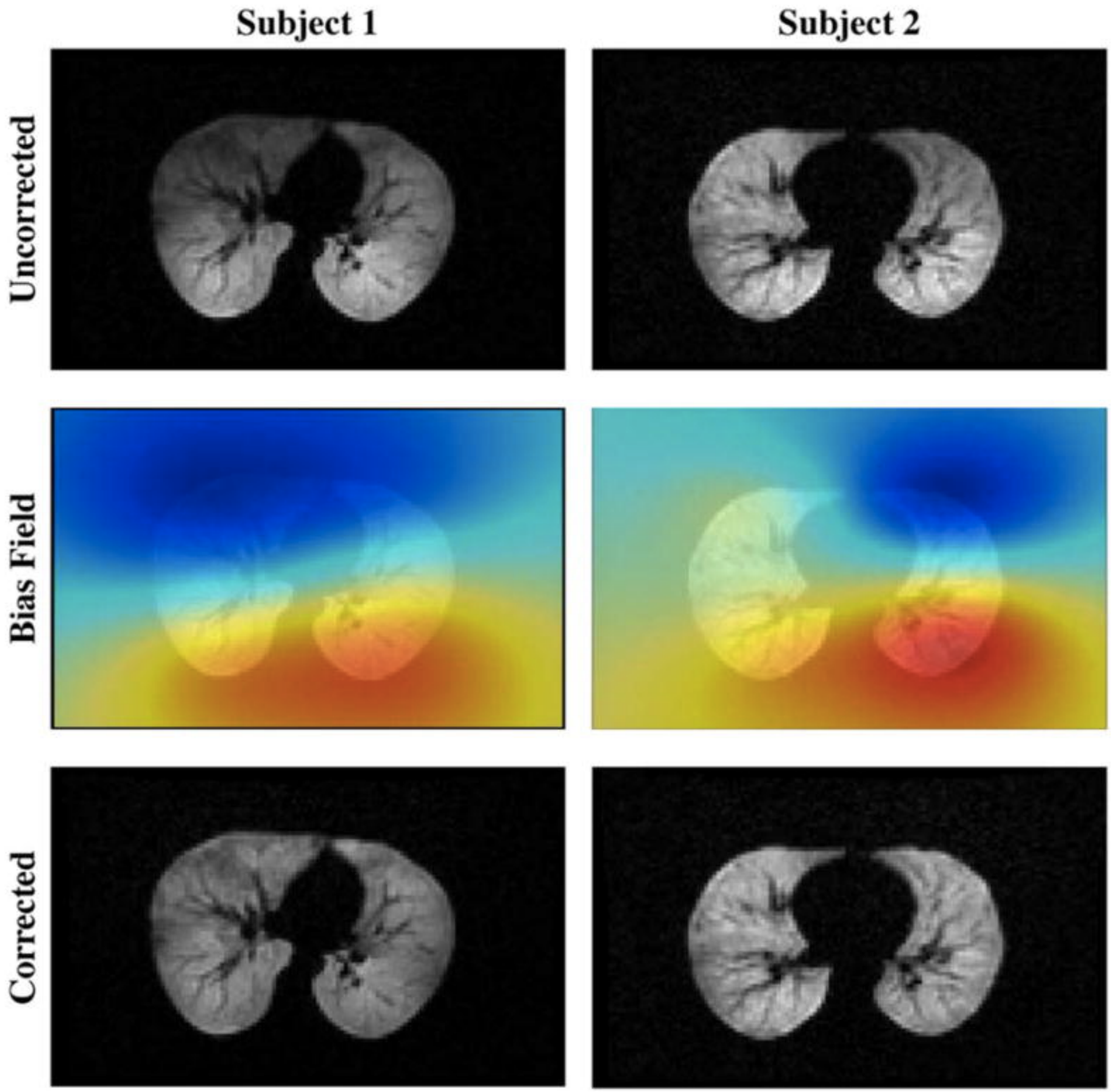
  opt. parameters

ITK Implementation of N3

- itkN3MRIBiasFieldCorrectionIma
  imageDimension
  inputImage
  outputImage
  [shrinkFactor] [maskImage] [numb
  [numberOfFittingLevels] [outputBi



itkN3MRIBiasFieldCorrectionImageFilterTest
2 t81slice.nii.gz t81corrected.nii.gz
2 t81mask.nii.gz 50 4 t81biasfield.nii.gz



(N3 based method)

Local Histogram Based and Standardization Based Correction Methods

- Dividing the image into small subvolumes (via fixed thresholding for instance) in which intensity inhomogeneity was supposed to be relatively constant.

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- Local intensity inhomogeneity was estimated by least square fitting of the intensity histogram model to the actual histogram of a subvolume
- The applied histogram model was a finite Gaussian mixture with seven parameters, initialized from the global histogram of the image. (B-splines are used to fit parameters)

Better (Simpler) Method – Standardization Based Correction (SBC)

Step 0: Set $S_c = S$, the given scene.

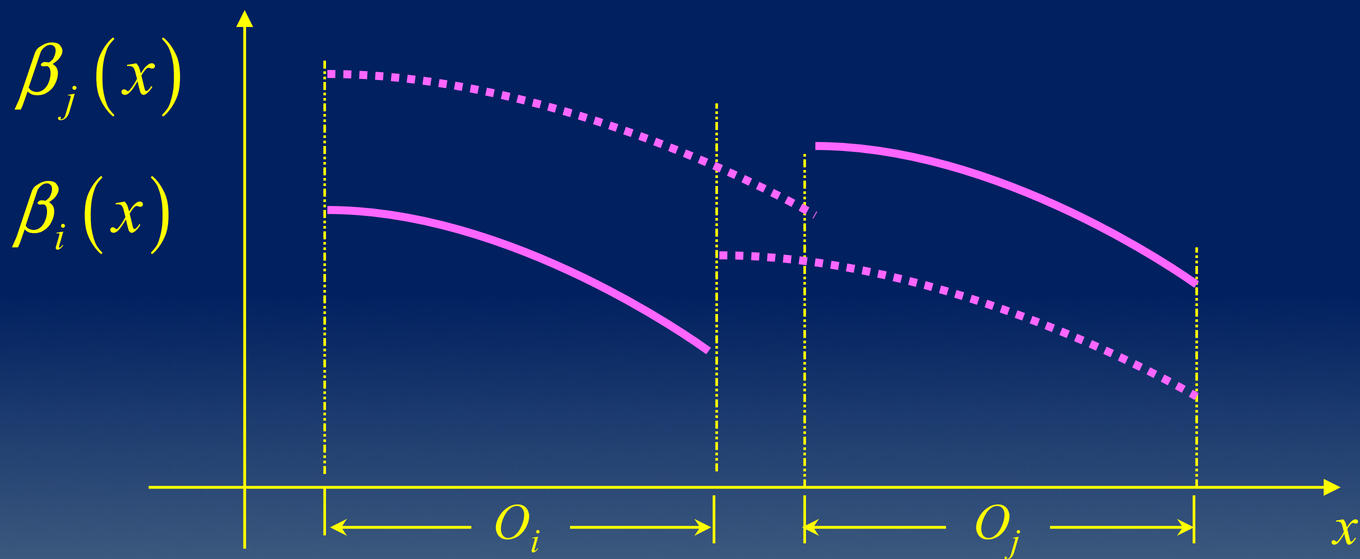
Step 1: Standardize S_c to the standard intensity gray scale for the particular imaging protocol and body region under consideration and output scene S_s;

Step 2: determine m tissue regions S_{B1}, S_{B2}, ..., S_{Bm} by using fixed threshold intervals on S_s;

Step 3: if S_{Bi} determined in the previous iteration are not much (<0.1%) different from the current S_{Bi}, stop;

Step 4: else, estimate background variation in S_s as a scene S_{be}, compute corrected scene S_c, and go to Step 1;

SBC-Intuition



The existence of discontinuity between inhomogeneity maps (continuous lines) estimated independently from different tissue regions O_i and O_j.

We need a single combined inhomogeneity map for correcting the background intensity variation in the whole image.

SBC-Intuition

1. Find a weight factor λ to minimize $\sum_{c \in C} \left[\beta_1(c) - \lambda \beta_2(c) \right]^2$.

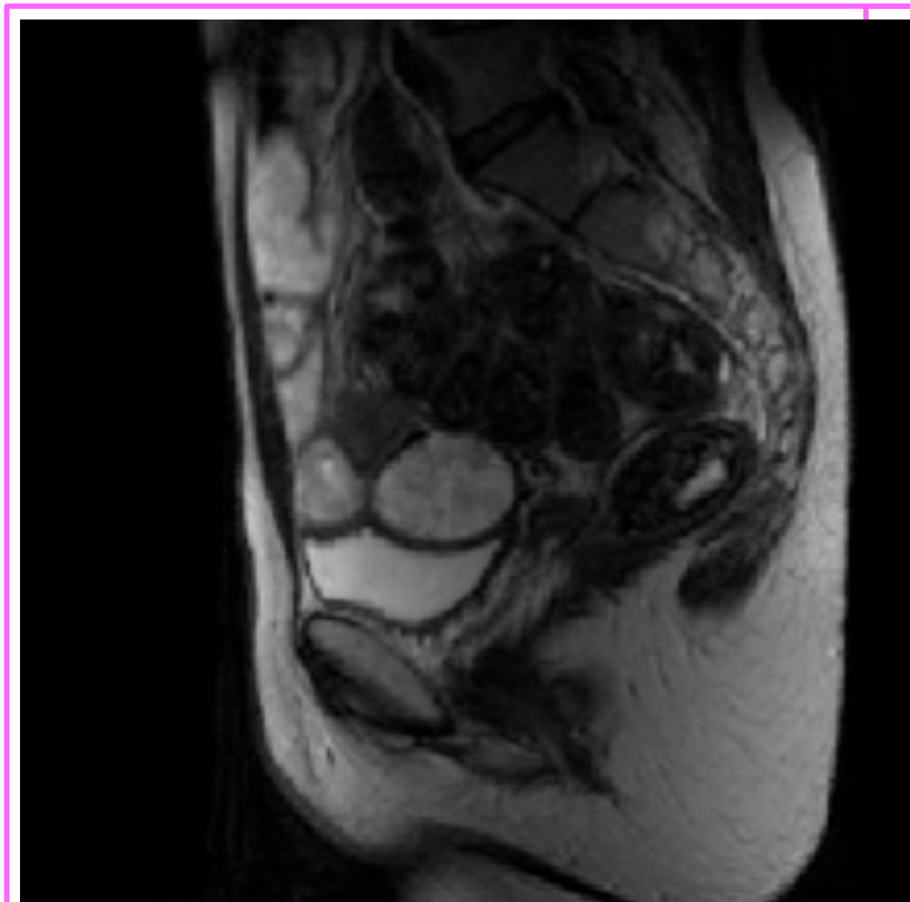
2. Combine the two inhomogeneity maps β_1 and β_2 to obtain a new discrete inhomogeneity map $\beta_d(c)$: $C \rightarrow [0, \infty)$ such that, for any $c \in C$,

$$\beta_d(c) = \frac{\delta(c, O_2)}{\delta(c, O_1) + \delta(c, O_2)} \beta_1(c) + \frac{\delta(c, O_1)}{\delta(c, O_1) + \delta(c, O_2)} \lambda \beta_2(c)$$

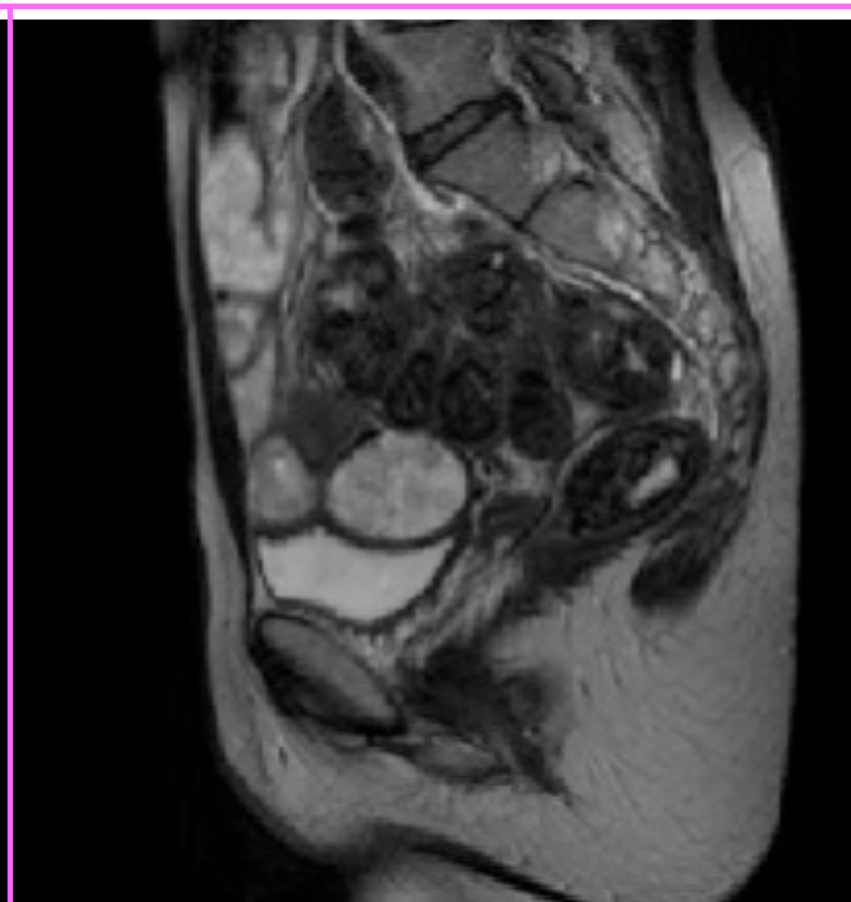
3. Determine a 2nd degree polynomial β that constitutes a *LSE* fit to β_d .

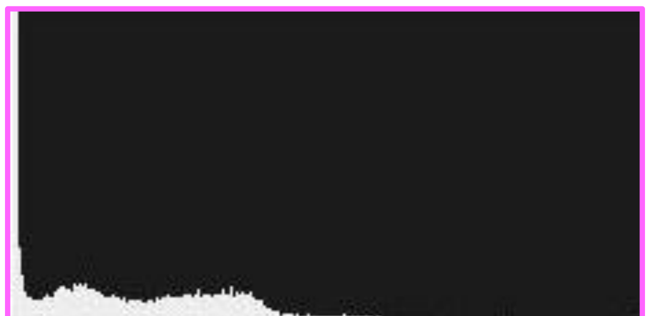
The above steps merge O_1 and O_2 and are then repeated until we have only one region and a single unified inhomogeneity map.

Original



Corrected

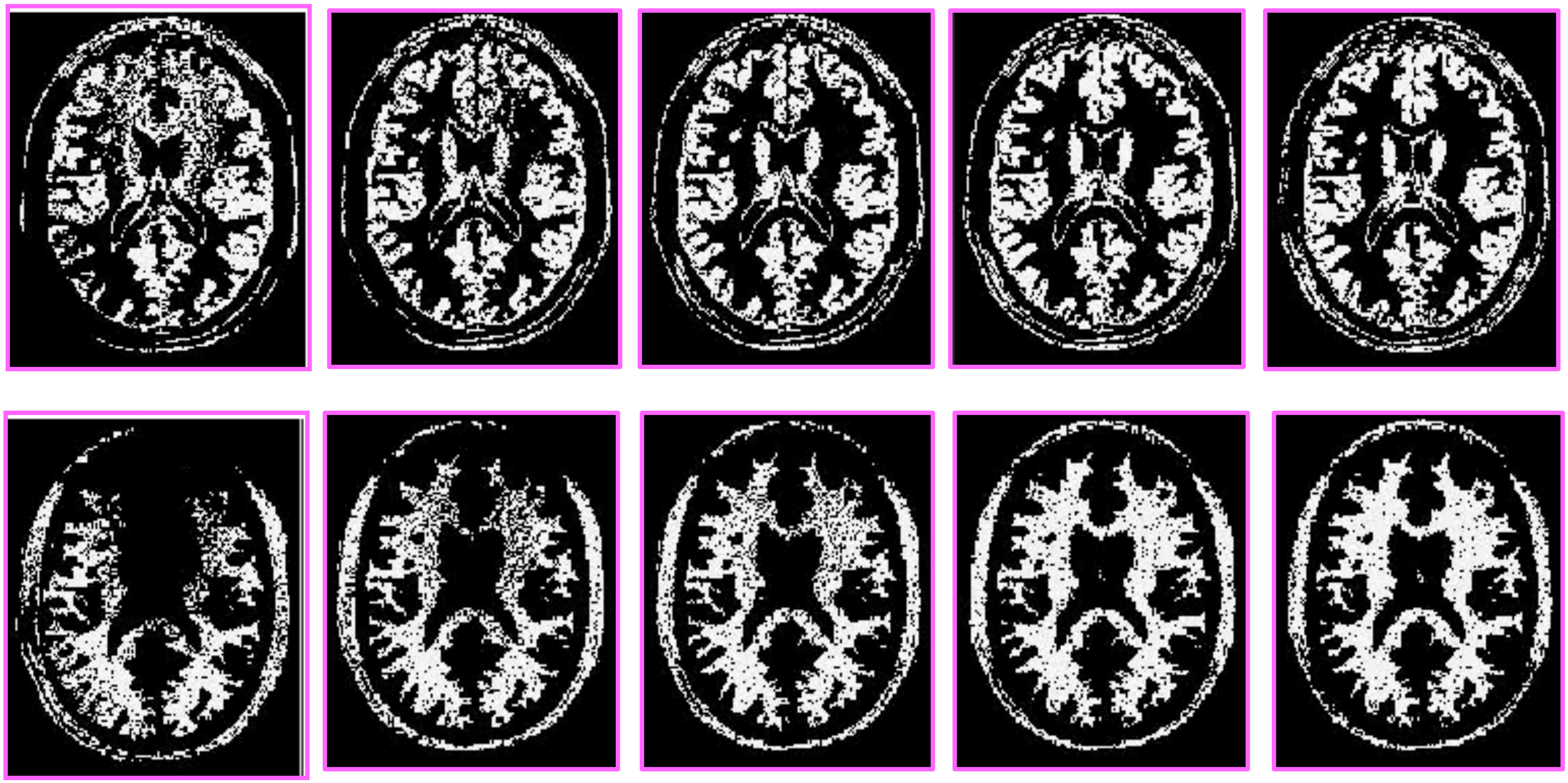




Standardization Based Correction (SBC) Method

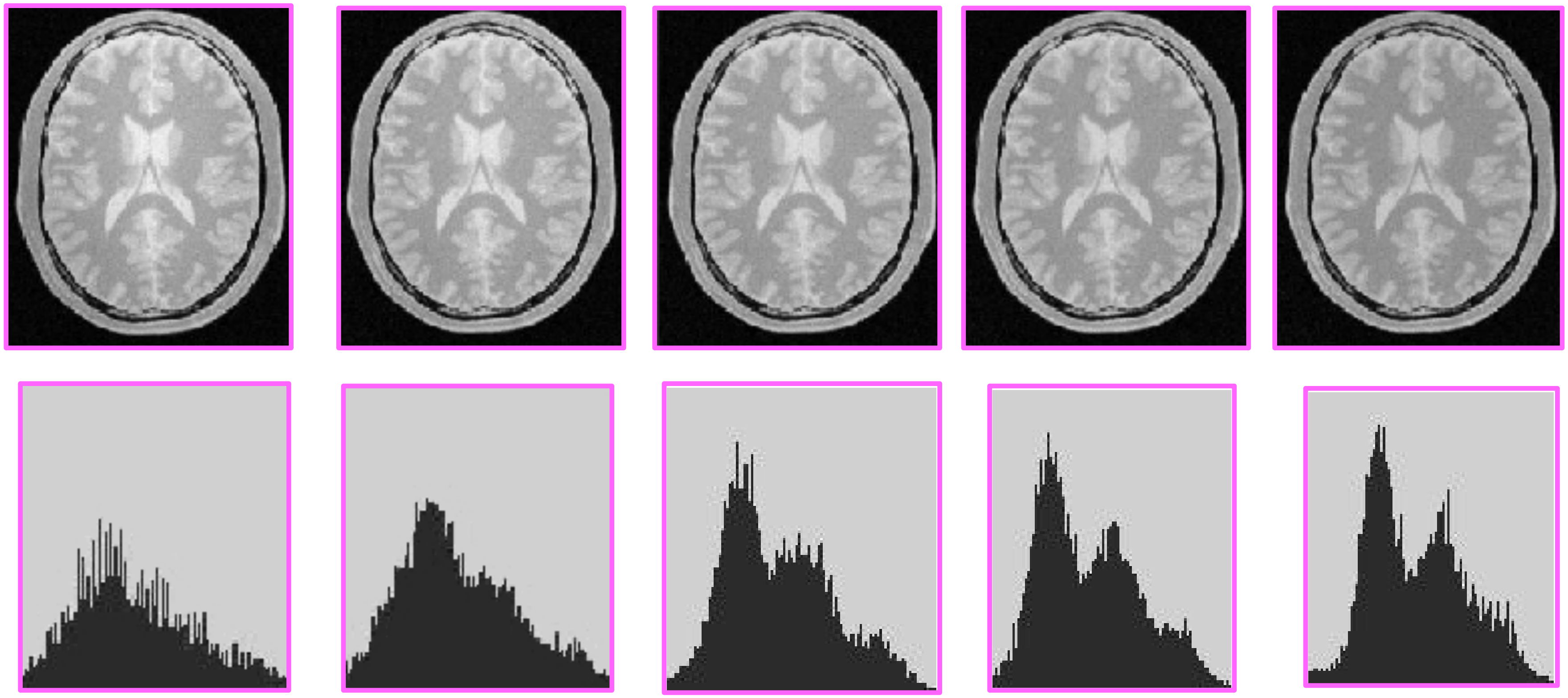
GM

WM



Iteration 1 3 5 10 20

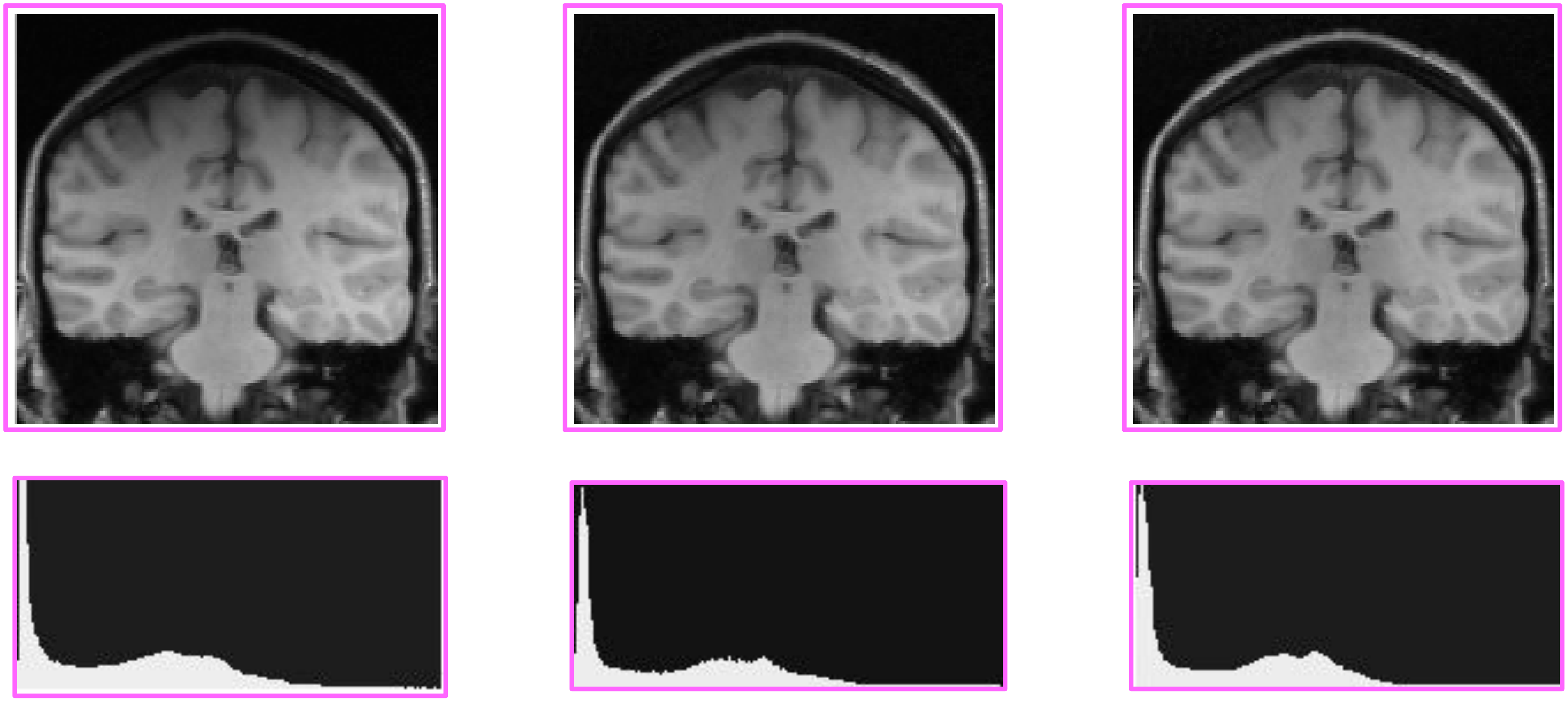
SBC Method



Iteration 1 3 5 10 20

The improvement in correction with increasing number of iterations. Examine the two modes corresponding to *WM* (large mode) and *GM*.

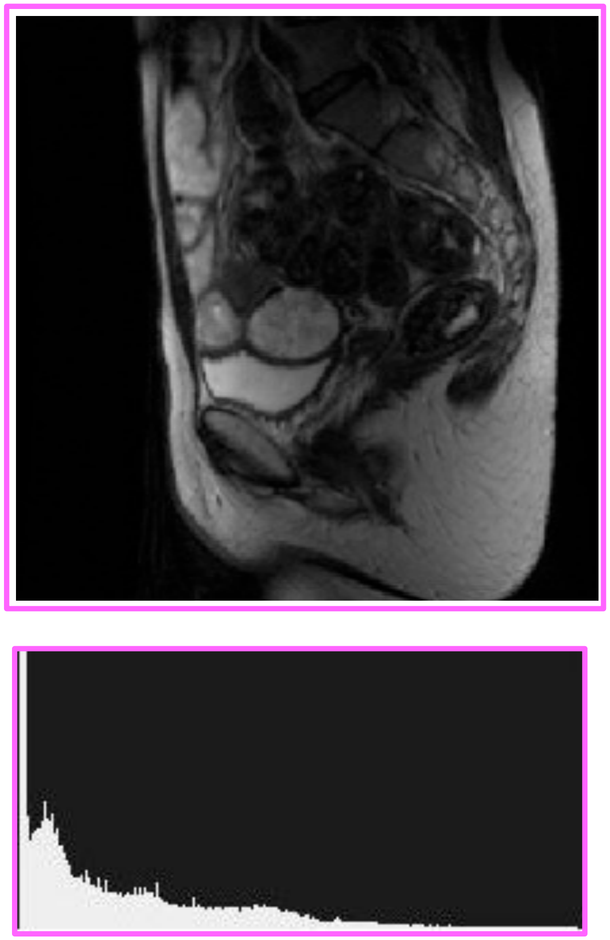
SBC Method-Comparison



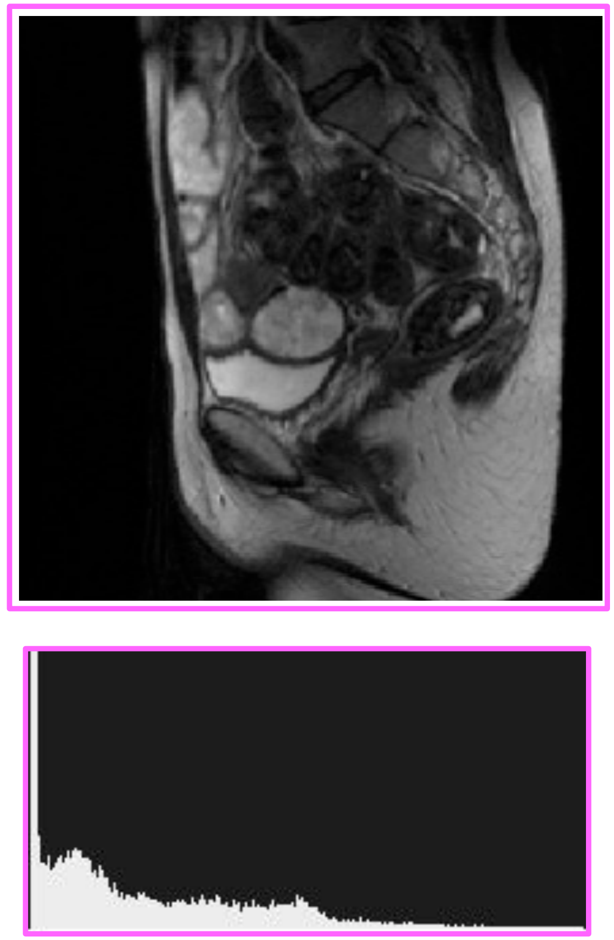
Original | *N*3 (Sled *et al.*) | *SBC*

A slice of *T*1-weighted brain *MR* image. *SBC* shows some improvement over *N*3 particularly as seen in the histogram.

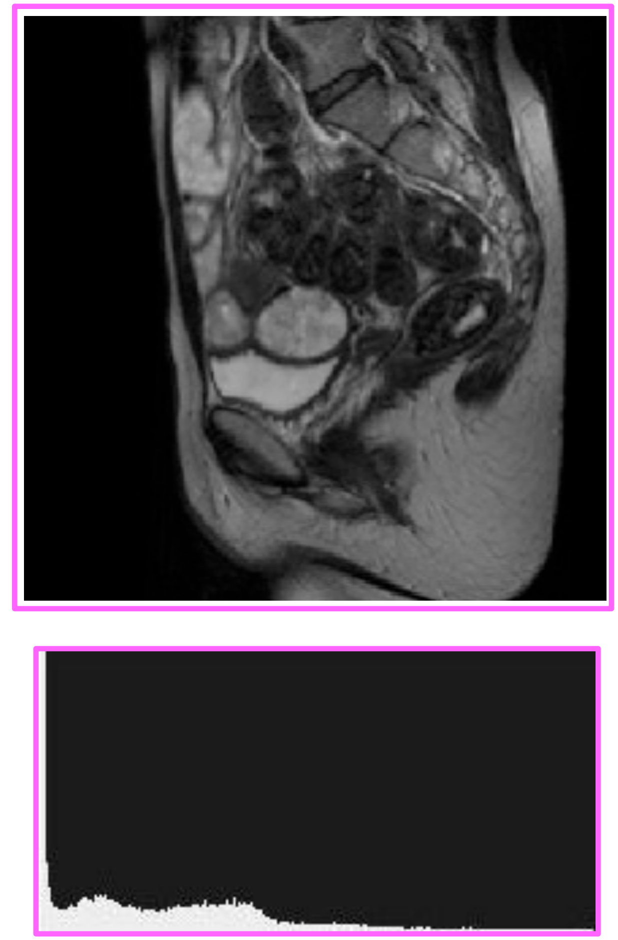
SBC Method-Comparison



Original



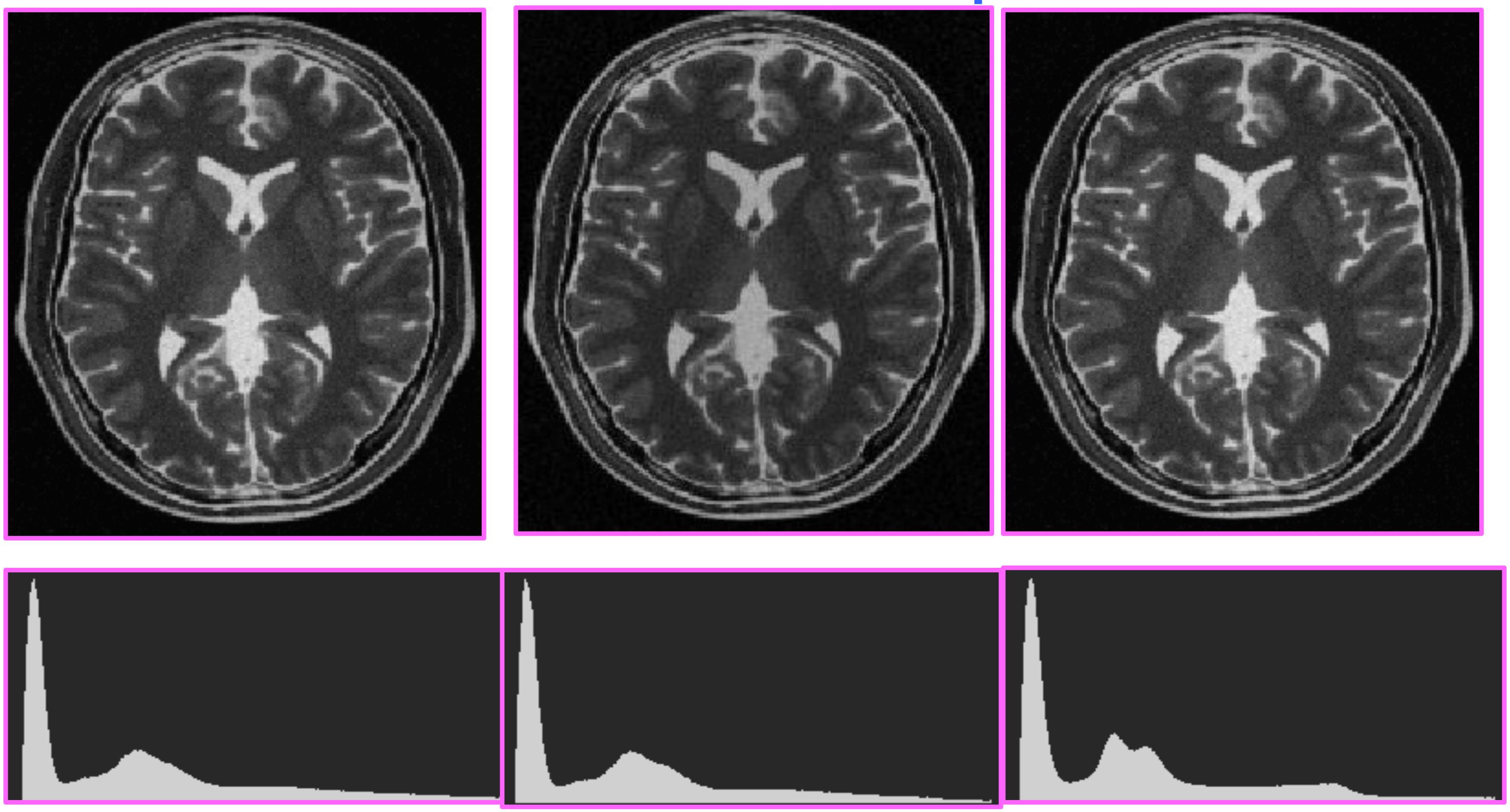
*N*3 (Sled *et al.*)



SBC

A slice of an abdominal *MR* image. *SBC* shows some improvement over *N*3 particularly as seen in the histogram.

SBC Method-Comparison



Original   *N*3 (Sled *et al.*)   *SBC*

*Brainweb T*2-weighted *MR* image. *SBC* shows some improvement over *N*3 particularly as seen in the histogram.

Coefficient of Variation as a quantitative evaluation metric

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  - …

SBC Method Quantitative Comparison

			%cv (GM)			%cv (WM)		
Set	**Modality**	**Inhomo.**	**Original**	***N3***	***SBC***	**Original**	***N3***	***SBC***
Normal	*T1*	20%	11.0	9.9	9.9	6.7	5.1	5.1
		40%	13.5	10.0	9.9	9.2	5.2	5.2
	T2	20%	18.4	18.0	17.9	12.0	11.8	11.7
		40%	20.3	20.0	17.9	13.3	13.0	11.8
	PD	20%	6.3	4.6	4.5	5.5	4.7	4.7
		40%	9.7	4.6	4.5	7.5	4.6	4.6
Ms Lesions	*T1*	20%	11.2	10.1	10.1	6.9	5.3	5.3
		40%	13.7	10.2	10.1	9.3	5.3	5.4
	T2	20%	10.9	10.0	9.8	8.7	8.3	8.1
		40%	13.7	10.1	9.8	10.6	8.2	8.2
	PD	20%	5.8	3.9	3.8	5.3	4.4	4.3
		40%	9.4	4.9	3.9	7.4	4.3	4.3

% *cv* of tissue intensities in segmented *GM* and *WM* regions for twelve simulated *MRI* scenes from ***Brainweb*** before and after correction by *N3 SBC*.

SBC Method Quantitative Comparison

Modality	% *cv* (*GM*)			% *cv* (*WM*)		
	Original	*N3*	*SBC*	Original	*N3*	*SBC*
T2	16.7(1.61)	14.9(1.18)	14.7(1.23)	12.9(1.12)	11.5(1.07)	11.2(0.98)
PD	7.1(0.32	5.9(0.20)	5.6(0.19)	7.8(0.72)	6.6(0.62)	6.2(0.51)

The mean and standard deviation of % *cv* of tissue intensities in segmented *GM* and *WM* regions for ten clinical *T*2- and *PD*-weighted *MRI* scenes of *MS* patients before and after correction by the *N*3 and *SBC* methods.

$SBC > N3$; $p < 0.001$.

References and Slide Credits

- Jayaram K. Udupa, MIPG of University of Pennsylvania, PA.
- P. Suetens, Fundamentals of Medical Imaging, Cambridge Univ. Press.
- N. Bryan, Intro. to the science of medical imaging, Cambridge Univ. Press.
- N. Agam (toy examples)

- Next Lecture (Preprocessing of Medical Images III)
  - Intensity Standardization in MR Images
  - PET/SPECT Image Denoising (multiplicative noise)