Medical Image Processing for Diagnostic Applications

Bias and Gain Fields

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Topics

Inhomogeneities in MRI

Mathematical Modeling

Summary

Take Home Messages Further Readings







Causes for Inhomogeneities

Definition

If there are slow and nonanatomic intensity variations present in the image of one and the same tissue class, we talk about the presence of **intensity inhomogeneity** (IIH).

In other words, in an image subject to IIH it can happen, for instance, that water molecules have different intensity values in the image domain.

As a consequence no mapping of intensities to tissue classes is possible.

Major reasons for intensity inhomogeneities in MR imaging are:

- non-uniform radio-frequency,
- inhomogeneity of the static main field,
- patient motion.







Bias and Gain Fields

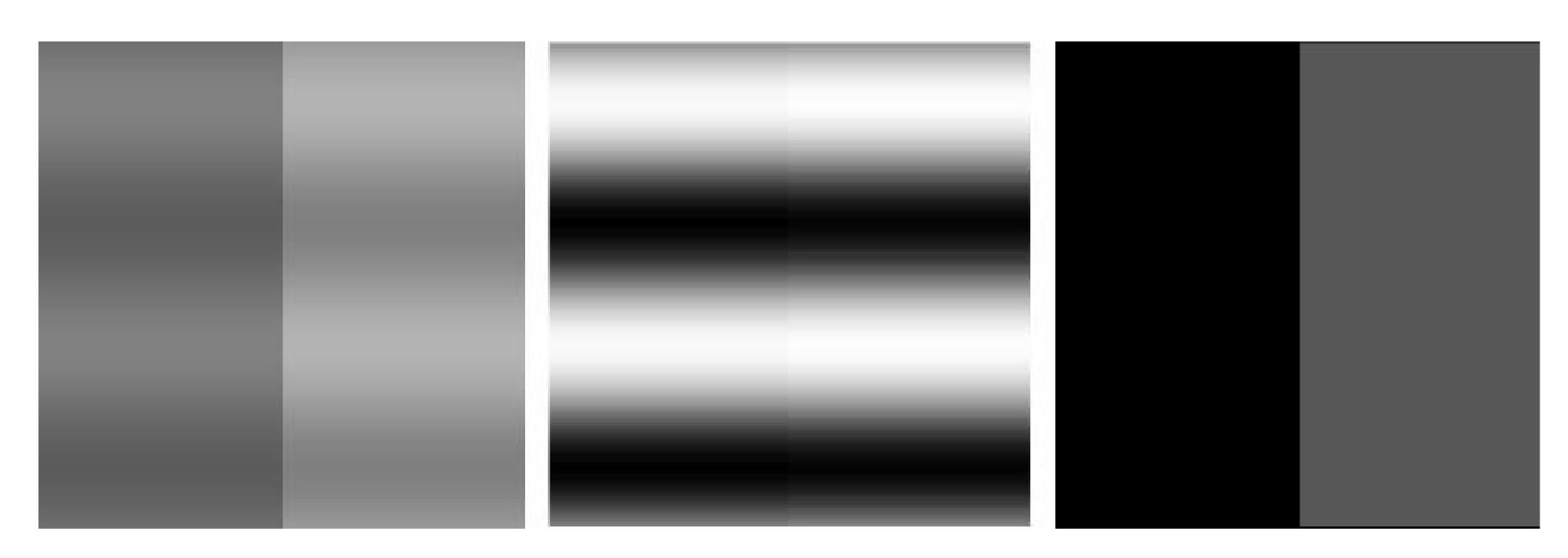


Figure 1: Observed image (left), gain field (middle) and ideal image (right) (image courtesy of W. Wells, Harvard University)

gain field = biast field ??







Bias and Gain Fields

different tissues may get the same color:(

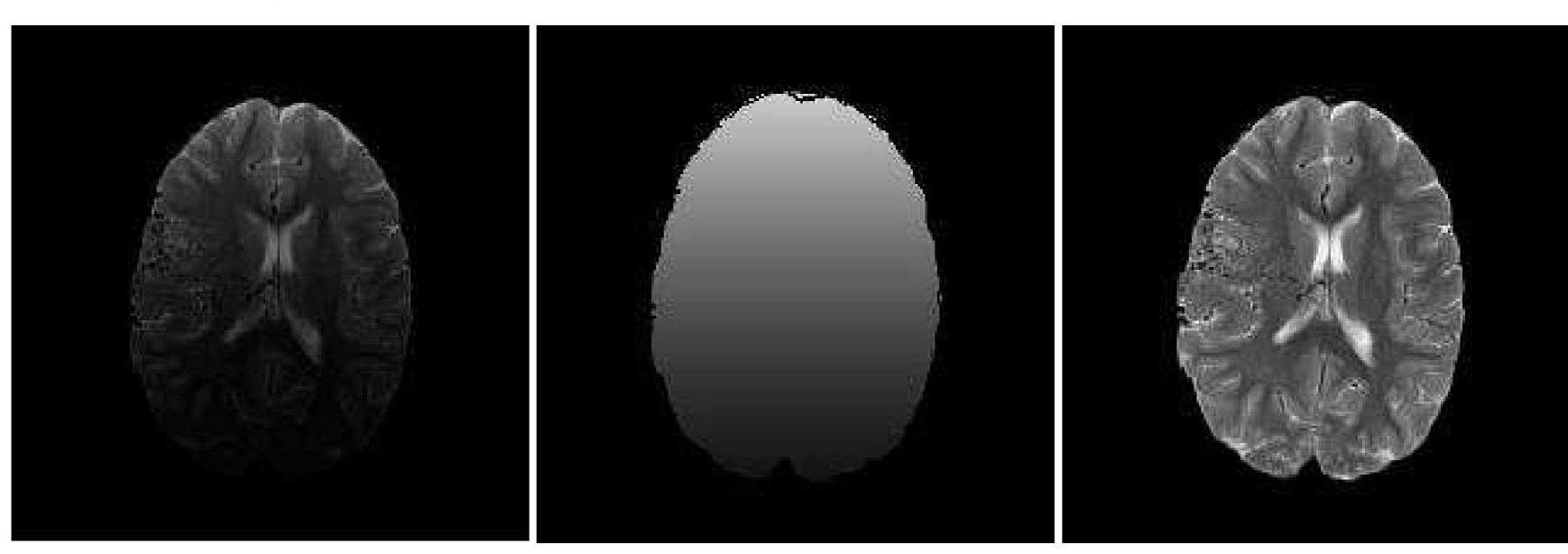


Figure 2: Original MR image (left), gain field (middle) and restored image (right)







Segmentation With and Without Intensity Correction

In this figure the middle image shows that naive segmentation using gradient information can produce inacceptable results. Only appropriate preprocessing implies a segmentation result as shown on the right.

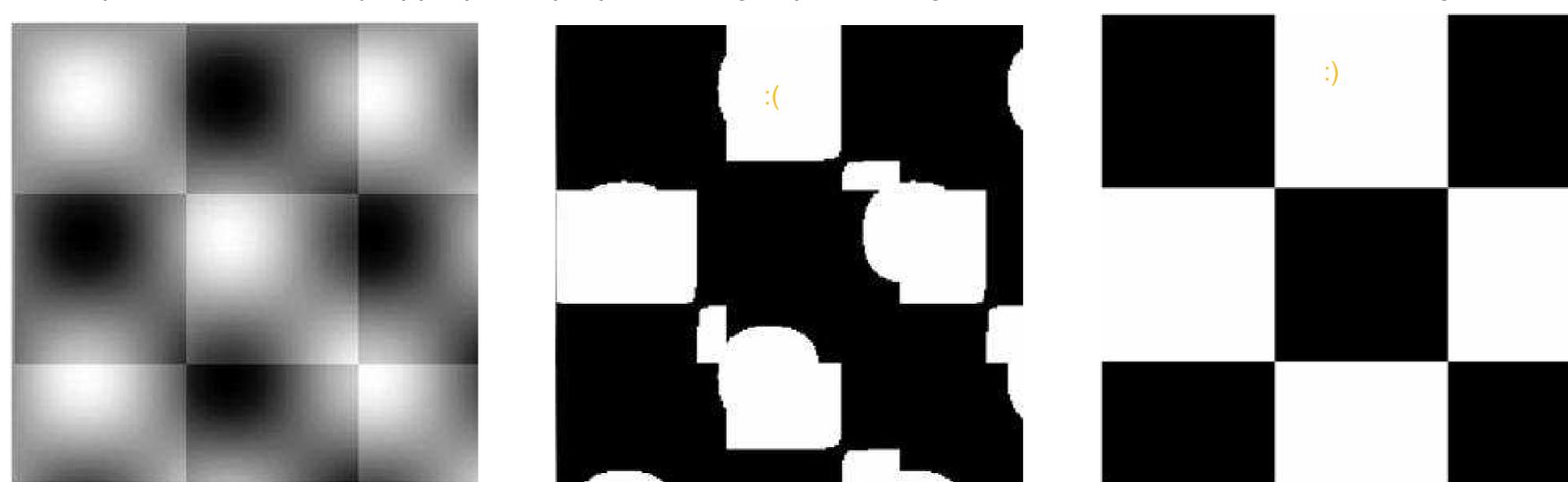


Figure 3: Biased checkerboard (left), segmentation result (middle) and ideal segmentation (right) (image courtesy of W. Wells, Harvard University)







Thresholding and Inhomogeneities

Even simple thresholding ideas fail due to intensity inhomogeneities:

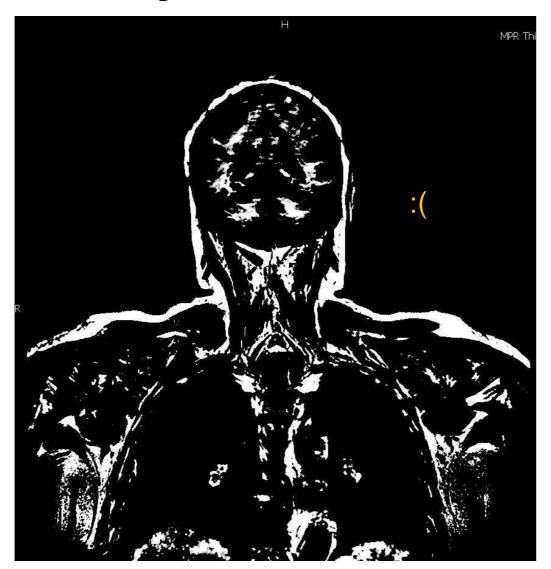




Figure 4: Different MR images are binarized by the same threshold. It is obvious that heterogeneity maps identical tissue classes to different intensities. (Florian Jäger, Pattern Recognition Lab, FAU)

different patients need different threashholds for segmentation







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Categories of Mathematical Models

Mathematical models for IIH are classified in three main categories:

- 1. Low-frequency model: It is assumed that IIH is caused by low-frequency components. The IIH map can be recovered using low-pass filtering. in FD?
- 2. Hypersurface model: The IIH map is represented by a smooth (low-frequency) parametric function. It can be recovered by least-square-fitting (regression). fit a polinomial in normal Domain?
- 3. Statistical model: The IIH map is represented by a stochastic process. Depending on the selected statistical model, the IIH map can be recovered by parametric or non-parametric statistical estimation.







Mathematical Model: Gain Field multiplical distortion -> not realy a biast

Definition

The **gain field** $b = [b_{i,j}]$ is modeled as a multiplicative field which is applied to the ideal image $f = [f_{i,j}]$ pixelwise, i. e., all intensity values $f_{i,j}$ are multiplied by a spatially varying factor $b_{i,j}$:

$$g_{i,j} = f_{i,j}b_{i,j} + n_{i,j}$$
, for $i,j = 0, 1, ..., N-1$,

where $g_{i,j}$ denotes the observed intensity at grid point (i,j), and $n_{i,j}$ is additive Gaussian noise.

Note: IIH correction is mostly applied to the product $b_{i,j}f_{i,j}$. Usually, Gaussian noise is eliminated before by low-pass filtering, smooth model fitting, or regularization.







Mathematical Model: Bias Field

use log to turn multiplication into addition -> now biast field

Definition

The **bias field** $\log b = [\log b_{i,j}] = [\log b_{i,j}]$ results from logarithmizing the gain field. In the absence of additive Gaussian noise this results in an additive model:

$$\log g_{i,j} = \log f_{i,j} + \log b_{i,j}$$
, for $i, j = 0, 1, ..., N - 1$.

we neglegt the gaussian noise?

Some researchers also incorporate additive noise in the above equation with logarithms, but this is not a proper noise model for practical applications.







Mathematical Model: Bias/Gain Correction

calculate ideal image:

• Gain field correction: If the gain field is known, the computation of the ideal image can be done pixelwise by:

$$f_{i,j} = \frac{g_{i,j}}{b_{i,i}}, \text{ for } i,j = 0,1,\ldots,N-1.$$

• Bias field correction: If the bias field is known, the computation of the ideal image can be done pixelwise by:

$$\log f_{i,j} = \log g_{i,j} - \log b_{i,j}$$
, for $i, j = 0, 1, ..., N - 1$.







Multiplicative vs. Log Additive Model

multiplicative closer to reality than additive models

- Early models for image inhomogeneity assumed a pure additive model, but additive effects are rarely observed in MRI.
- Smooth multiplicative inhomogeneity is in accordance to the physics of MRI imaging.
- The log additive model with Gaussian noise is not modeling the MRI acquisition specific noise properly.
- Today multiplicative models are commonly accepted.







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Take Home Messages

quantitative MRI imaging is difficult -> contrast is not absolute like in ct but relative :(

- In MRI intensity inhomogeneties can be present in the acquired images and can make further processing ineffective.
- Gain and bias correction are crucial, not only, but especially in MRI.







Further Readings

The webpage of the National High Magnetic Field Laboratory can be one starting point for more detailed information regarding MRI. For an initial overview of the technology, the following article is worth reading: MRI: A Guided Tour by Kristen Coyne.

If you want to know more about segmentation of MR images, e.g., consult the Google Scholar record of 'Sandy' Wells' publications.

Another article worth reading is this survey paper on algorithms for intensity correction methods: Zujun Hou. "A Review on MR Image Intensity Inhomogeneity Correction". In: *International Journal of Biomedical Imaging* 2006.Article ID 49515 (Feb. 2006), pp. 1–11. DOI: 10.1155/IJBI/2006/49515