Medical Image Analysis

CS 778 / 578

Computer Science and Electrical Engineering Dept.
West Virginia University

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Outline

1. Topic Overview
2. Computational Overview

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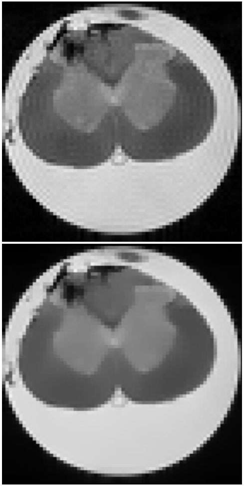
1. **Topic Overview**
   - Image Enhancement and Denoising
   - Segmentation
   - Registration
   - Visualization
2. **Computational Overview**



Problem Statement

Recover an unknown, ideal image given an observed image.

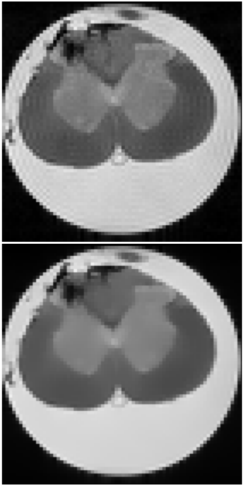
Motivation

The observed image may be degraded during acquisition or transmission. (Thermal noise, quantization)

Challenges

Preserve features which would be destroyed by low-pass filtering.

Image Enhancement and Denoising



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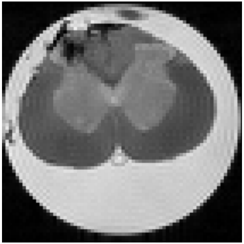

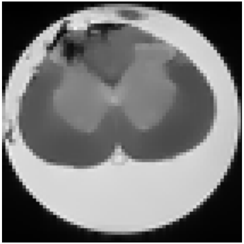

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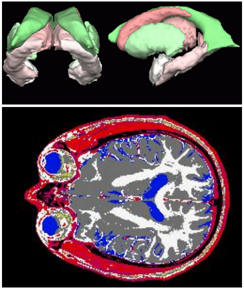

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- Classify (cluster) voxels according to tissue type. hard/soft classification
- Partition image and find boundaries separating tissue classes.

Motivation

Find anatomical structures within images.

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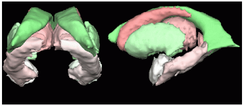
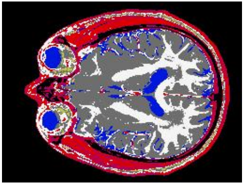
- Partial volume effect.
- Prior knowledge (smoothness, shape representation)





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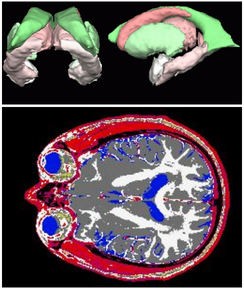

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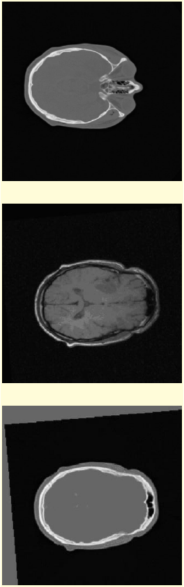

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Determine a coordinate transformation which will align two images.

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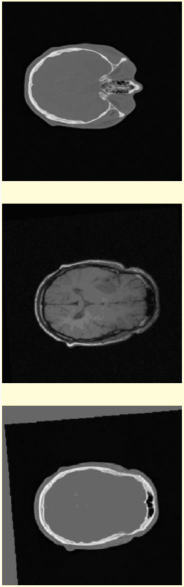
- Compare corresponding voxels from 2 or more images.
- Atlas construction

Challenges

- Different patients.
- Different image modalities.
- Non rigid deformation (pre- and post-surgery).
- Finding an appropriate metric.



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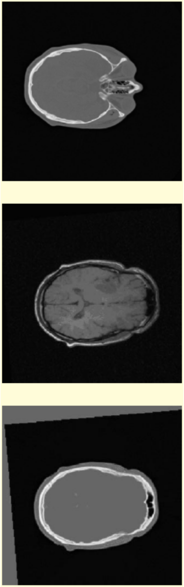

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Produce a rendering which portrays meaningful data features.

Motivation

Clinicians, such as radiologists, may visually interpret images to diagnose injury and disease.

Challenges

- High dimensional data is difficult to inspect visually.
- Extracting (quantifying) the relevant features.
- May require enhancement, segmentation or registration.

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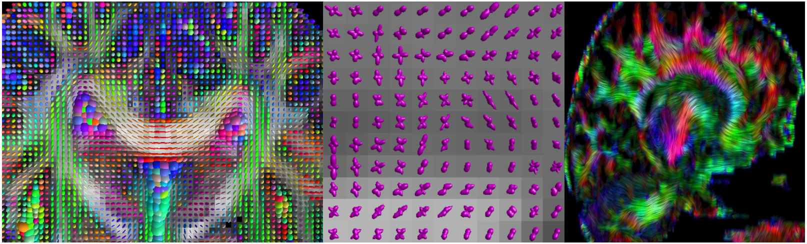
Visualization of high dimensional data



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2. **Computational Overview**
   - Ill-Posed Problems
   - Energy Minimization Methods
   - Numerical Solutions

Energy functionals

Image model

We will consider images, $I(x)$, as surfaces or functions which evolve according to some partial differential equation.

We will apply partial differential equations from other engineering fields.

Example from mechanics

Membrane spline and Thin-plate spline energies model the smooth deformations of materials.

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- does not exist,
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Regularization

Solution of PDEs with noisy initial conditions is generally an ill-posed problem.

Ill-posed problems can be made well-posed by the process of regularization.

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Variational methods

Next, we find the *Euler-Lagrange* conditions which characterize the minimization of $E(I)$.

Variational Calculus is a general technique for minimizing functionals with respect to functions.

This is analogous finding the minimum of $f(x)$ using the conditions $f'(x) = 0$, $f''(x) > 0$.

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Curve / Surface Evolution

Evolve the image in such a way that the steady-state behavior obeys the Euler-Lagrange conditions.

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Numerical Methods

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Next Class

We will apply this framework to the problem of image smoothing.