Non-rigid Slice to Volume Medical Image Registration Using Markov Random Fields

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Motivation
Medical Images

2D Modalities
- Ultrasound (sliced image)
- X-Ray (projective image)

3D Modalities
- CT, MRI
Nowadays: surgery planning with pre-operative images

High definition pre-operative 3D images

Examples: CT, MRI, PET/CT

+ Annotated data

Objects of interest (as organ or tumor) segmentations.

+ Doctor mind

Surgeon experience
Future: surgery planning with pre and intra-operative images

High definition pre-operative 3D images + Annotated data + Intra-operative 2D images = Fused images and plane location

Future: surgery planning with pre and intra-operative images
Non-Rigid Slice to Volume Image registration
Slice to volume image registration

Formal definition

Given a 2D source image \( I \) and a 3D target volume \( J \), we seek the slice from the volume \( J \) that best matches the image \( I \).

It is “non-rigid” because image \( I \) can be deformed.
Slice to Volume image registration
Different approaches

GPS based navigation systems (Electromagnetic sensors)

- Absence of compensation for respiration and patient motion.
- Restrictions in the material of tools that can be used in the surgery.

Image based navigation systems

- It’s possible to deform intra-operative images in order to compensate respiration and patient motion.
- No restrictions about the tools that can be used in the surgery.
Slice to Volume image registration as an optimization problem

\[ \hat{T}_D, \hat{\pi} = \arg\min_{T_D, \pi} \mathcal{M}(I \circ T_D(\mathbf{x}), \pi[J](\mathbf{x})) + \mathcal{R}(T_D) \]

Plane (bi-dimensional slice) \hspace{5cm} Regularization term

Deformation field \hspace{5cm} Data term
\[ MRF(g, f) = \min w_1 \sum_{i \in V} g_i(u_i) + w_2 \sum_{(i,j) \in E} f_{ij}(u_i, u_j) \]

\[ \text{G = } < V, E > \]

\[ V = \text{Set of vertices} \]

\[ E = \text{Set of pairwise cliques} \]

\[ L = \text{Label space} \]
Slice to Volume image registration
5 dimensional label space

\[ \mathbf{u} = (d_x, d_y, d_z, \phi, \theta) \]
Slice to Volume registration
5 dimensional label space

\[ u = (d_x, d_y, d_z, \phi, \theta) \]
Slice to Volume image registration

Data term: Unary potentials

\[ g_i(\mathbf{u}_i) = \int_{\Omega_i} \delta(I(\mathbf{x}), \pi_i[J](\mathbf{x})) \, d\mathbf{x} \]
### Slice to Volume image registration

**Data term: Examples**

| Monomodal registration | \( g_{SAD,i}(u_i) = \int_{\Omega_i} |(I(\mathbf{x}) - \pi_i[J](\mathbf{x})| \, d\mathbf{x} \) |
|------------------------|--------------------------------------------------|
| Multimodal registration | \( g_{MI,i}(u_i) = -\int_{\Omega_i} \log \frac{p(I(\mathbf{x}), \pi_i[J](\mathbf{x}))}{p(I(\mathbf{x}))p(\pi_i[J](\mathbf{x}))} \, d\mathbf{x} \) |
Slice to Volume image registration
Regularization term: Pairwise potentials

\[ f_{ij}(u_i, u_j) = \alpha F_1(u_i, u_j) + (1 - \alpha) F_2(u_i, u_j) \]

Grid regularity
Plane structure
Slice to Volume image registration
Grid regularization: Distance preserving

\[ F_1(u_i, u_j) = 1 - \frac{\| (p_i + d_i) - (p_j + d_j) \|}{\| (p_{o,i}) - (p_{o,j}) \|} \]
Slice to Volume image registration
Plane Structure regularization

\[ F_2(u_i, u_j) = \frac{1}{2} (D_{\pi_j} (p_i + d_i) + D_{\pi_i} (p_j + d_j)) \]
Slice to Volume image registration
Implementation details

• FastPD as optimization algorithm \(^2\)

• Pyramidal approach: from coarse to fine spacing between the control points, refining the label space in every iteration

• Gaussian pyramids to improve the performance

Slice to Volume image registration
Workflow

- Initialization
- Optimization process
- Solution reconstruction
Slice to Volume image registration

Workflow: initialization

\[ T_0 \]
Slice to Volume image registration
Workflow: Optimization process

$T_e$: Estimated Rigid Transformation using Horn's method \[3\]

Slice to Volume image registration
Workflow: Solution reconstruction

Grid projection over regression plane

Final 2D FFD that approximates the Deformation Field
Experiments and Results
Monomodal Dataset
Cardiac Sequence
Monomodal Dataset
Cardiac Sequence
Parameters estimation over 10 temporal series of 20 slices from a beating heart MRI series (total of 200 registration cases) registered with a MRI volume.

The average error is less than 0.013 rad for rotation and less than 1 mm for translation parameters.
Test was performed over 20 manual segmentations of the left endocardium.

Each slice was registered with the initial volume starting from a random position around the ground truth.

The estimated Deformation Field was applied to the initial segmentation.

The average DICE coefficient between the deformed segmentations and the ground truth was 0.93.
Monomodal Dataset
some qualitative results

Six slices from the MRI heart sequence before and after registration
Monomodal Dataset
some qualitative results
Monomodal Dataset
some qualitative results
Multimodal Dataset
Brain Sequence
• DICE increases after registration process an average of 0.05

• CMD decreases an average of 0.4mm.

• Note that average DICE coefficients are always greater than 0.7.
Conclusions

- Image guidance is a fundamental component that has started to be progressively incorporated in surgeries.

- Registration is the key to bring high-resolution pre-operative images into the operating room and improve the accuracy of Image Guided Surgeries.

- We have proposed an image based slice to volume registration algorithm that gives promising results in our experimental dataset.

- Our method is metric free so it can be used to register different types of images.
Future works

Decoupled model
Future works

Learning energy parameters

\[ E(g, f^P, f^I) = \min w_1 \sum_{i \in V} g_i(u_i) + w_2 \sum_{(i,j) \in E} f^P_{ij}(u_i, u_j) + w_3 \sum_{(i,j) \in E} f^I_{ij}(u_i, u_j) \]

- Learning parameters \( \mathbf{w} \) using SSVM

- **Loss function** (that measure the cost of predicting a labeling given GT) must decompose over the random variables.

- **Main limitation**: small dataset and poor ground truth
Related publications

Non-rigid 2D-3D Medical Image Registration using Markov Random Fields
MICCAI 2013, Pages 163-170

Method and device for elastic registration between a two-dimensional digital image and a slice of a three-dimensional volume with overlapping content
N Paragios, E Ferrante, R Marini Silva
US Patent 20,140,192,046
¡Muchas Gracias!