





Computational Registration of Biomedical Data towards More Effective Image Analysis

João Manuel R. S. Tavares

tavares@fe.up.pt, www.fe.up.pt/~tavares



UTAustin | Portugal Workshop on Modeling and Simulation of Physiological Systems

December 6-8, 2012, Lisbon, Portugal







Outline

- 1. Introduction
- Methods
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 - b) Spatio & Temporal Registration (registration of 2D image sequences)
- 3. Applications and Results
 - a) Plantar Pressure Images (2D & 2D image sequences)
 - b) Medical Images (2D & 3D)
- 4. Conclusions







Introduction: Matching and Registration of Images

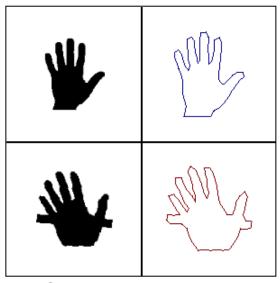




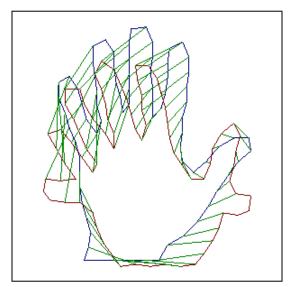


Image Matching

Image matching is the process of establishing correspondences between objects in images



Original images and contours



Some of the correspondences found

Bastos & Tavares (2006) Inverse Problems in Science and Engineering 14(5):529-541 Oliveira, Tavares, Pataky (2009) VipMAGE 2009, pp. 269-274







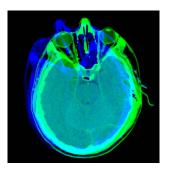
Image registration is the process of searching for the best transformation that change one image in relation to another image in order to correlated features assume similar locations in a common space

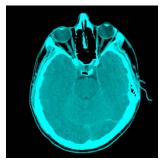
Template (or fixed) image



Source (or moving) image







Overlapped images before and after the registration

Oliveira & Tavares (2012) Computer Methods in Biomechanics and Biomedical Engineering, DOI:10.1080/10255842,2012.670855









Applications

- Facilitate image-based diagnosis
 - Fusion of images from different imaging modalities (CT/PET, MRI/CT, SPECT/CT, MRI/PET, ...)
 - Follow-up of pathologies
- Support surgical interventions (more efficient localization of lesions, find alignments between devices and patients, etc.)
- Optimization of radio-therapeutic treatments
- Automatic recognition of organs/tissues (e.g. support complex tasks of image segmentation and identification)
- Building of Atlas (with well-known cases used for comparison)
- Simplify posterior statistical analysis (e.g. SPM, Z-scores, etc.)

— ...









In the last years, considerable research has been done concerning biomedical data registration. The **methodologies** can be classified based on different criteria:

- Data dimensionality: 2D/2D, 2D/3D, 3D/3D, 2D/3D+Time
- Features used: extrinsic (using features external to the patient) or intrinsic (using information from the patient; e.g. pixel intensity values, relevant points, contours, regions, skeletons, surfaces, ...)
- Interaction: manual, semiautomatic or automatic
- **–** ...





(Cont.)

- Transformation type: rigid, similarity, affine, projective, curved
- Transformation domain: local or global
- Modalities involved: same modality (CT/CT, MRI/MRI, PET/PET, ...), different modalities (CT/MRI, MRI-T1/MRI-T2, PET/CT, ...) or patient/model (e.g. between a patient and an atlas or between a patient and a device)
- Subjects: registration of images from the same subject or from different subjects, or images of a subject with images in an atlas
- Organs/tissues involved: brain, liver, etc.

— ...

Oliveira & Tavares (2012) Computer Methods in Biomechanics and Biomedical Engineering, DOI:10.1080/10255842.2012.670855





In the registration of image data, similarity measures based on pixel intensity values are commonly used; e.g.:

- Cross-Correlation (CC) and related measures

$$CC_{fg} = \sum_{i} f(i)g(i)$$

- Sum of Squared Differences (SSD) and correlated measures, like the Mean Squared Error (MSE)

$$SSD_{fg} = \sum_{i} (f(i) - g(i))^{2} \qquad MSE_{fg} = \frac{1}{N} \sum_{i} (f(i) - g(i))^{2}$$

Mutual Information (MI) and derived measures

$$MI = H(f) + H(g) - H(f, g)$$

where H(f) and H(g) are the Shannon's entropy of f and g images, and H(f,g) the Shannon's entropy of the joint histogram of f and g





In the last years, we have been developing methods for biomedical image data matching and registration based on different techniques and applied them in several applications

Techniques

- Based on features (points, contours) extracted from the images and based on the intensity of the pixels (or voxels)
- By computing the optimal registration transformation directly or iteratively
- By using different transformation models

Data

- Images from the same patient and from different patients
- Images from the same or different modalities
- Registration of 2D and 3D images, and of 2D image sequences





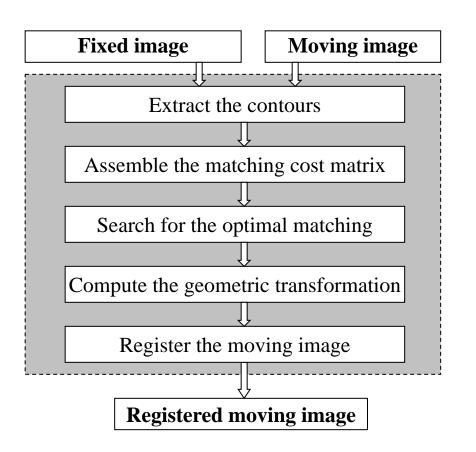
Methods: Spatial Registration of 2D and 3D images







Registration based on Contours Matching



The cost matrix is built based on geometric or physical principles

The matching is found based on the minimization of the sum of the costs associated to the possible correspondences

To search for the best matching is used an optimization assignment algorithm based on the Hungarian method, simplex method, graphs or dynamic programming

Bastos & Tavares (2006) Inverse Problems in Science and Engineering 14(5):529-541 Oliveira & Tavares (2009) Computer Modeling in Engineering & Sciences 43(1):91-110 Oliveira, Tavares, Pataky (2009) Journal of Biomechanics 42(15):2620-2623





Registration based on Direct Maximization of the Cross-Correlation (CC)

Assumption: The higher the cross-correlation between the pixel intensity values of the two images, the better the registration

Cross-correlation between I_0 and I_1 in function of a shift a:

$$CC_{I_0I_1}(a) = \int I_0(x)I_1(x-a)dx$$

It can be written as a convolution:

$$CC_{I_0I_1}(a) = \int I_0(x)\overline{I}_1(a-x)dx = \{I_0 * \overline{I}_1\}(a)$$

And from the convolution Theorem, one have:

$$\mathcal{F}\left\{I_0*\overline{I}_1\right\} = \mathcal{F}\left\{I_0\right\}\mathcal{F}\left\{\overline{I}_1\right\}$$

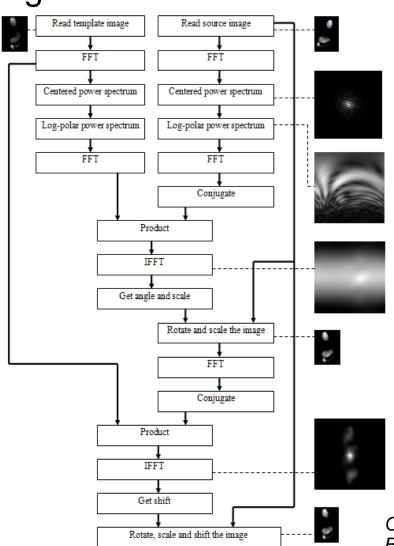
Thus, computing the product of the Fourier transform of I_0 and I_1 and then its inverse Fourier transform, the cross-correlation can be obtained for all shifts

(* represents the convolution operation and \mathcal{F} the Fourier transform)





Registration based on Direct Maximization of the CC



The scaling and rotation are obtained from the spectrum images after their conversion to the log-polar coordinate system

The fundament of this methodology is to search for the geometric transformation involved using the shift, scaling and rotation properties of the Fourier transform

Oliveira, Pataky, Tavares (2010) Computer Methods in Biomechanics and Biomedical Engineering 13(6):731-740





Registration based on Direct Minimization of the Sum of Squared Differences (SSD)

Assumption: The lower the sum of the squared differences between the pixel intensity values of the two images, the better registered the images

Sum of squared differences

between I_0 and I_1 in function of a shift a:

$$SSD_{I_0I_1}(a) = \int (I_0(x) - I_1(x - a))^2 dx$$

This equation can be written as:

$$SSD_{I_0I_1}(a) = \int I_0^2(x)dx + \int I_1^2(x-a)dx$$
$$-2\int I_0(x)I_1(x-a)dx$$

The first two terms can be directly evaluated, and the third term can be transformed into a convolution and then efficiently evaluated using the Fourier transform

The algorithm implemented is quite similar to the Cross-Correlation based algorithm; the main difference is the similarity measure used

Oliveira, Pataky, Tavares (2010) Computer Methods in Biomechanics and Biomedical Engineering 13(6):731-740





Registration based on the Phase Correlation Technique

This technique is basically based on the shift property of the Fourier transform:

If
$$I_1(x) = I_0(x - x_0)$$

then
$$\mathcal{F}\{I_1(x)\}(u) = e^{-2i\pi u x_0} \mathcal{F}\{I_0(x)\}(u)$$

To estimate the shift between the input images, the inverse of the Fourier transform of the cross-power is computed:

Cross-power:
$$\frac{\mathcal{F}\{I_0\}\,\mathcal{F}^*\{I_1\}}{\left|\mathcal{F}\{I_0\}\,\mathcal{F}^*\{I_1\}\right|} = e^{2i\pi u x_0} \qquad \text{(the * represents the complex conjugate)}$$

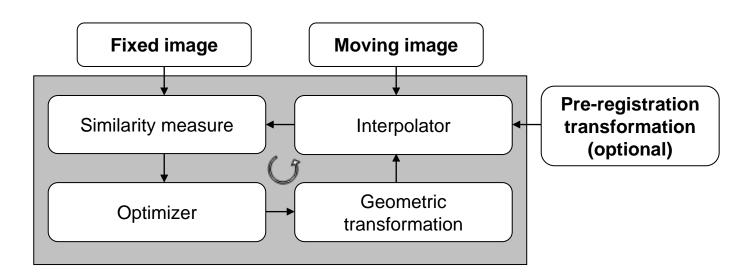
The algorithm implemented is also similar to the cross-correlation based algorithm

Oliveira, Pataky, Tavares (2010) Computer Methods in Biomechanics and Biomedical Engineering 13(6):731-740





Fundaments: This methodology is based on the iterative search for the parameters of the transformation that optimizes a similarity measure between the input images



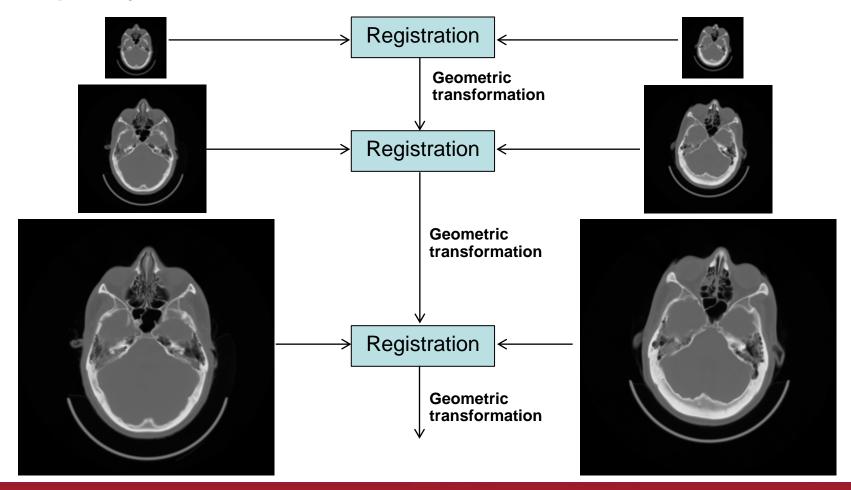
The optimization algorithm stops when a similarity criterion is achieved

Oliveira & Tavares (2012) Computer Methods in Biomechanics and Biomedical Engineering, DOI:10.1080/10255842.2012.670855





To speedup the computational process, the multi-resolution strategy is frequently used

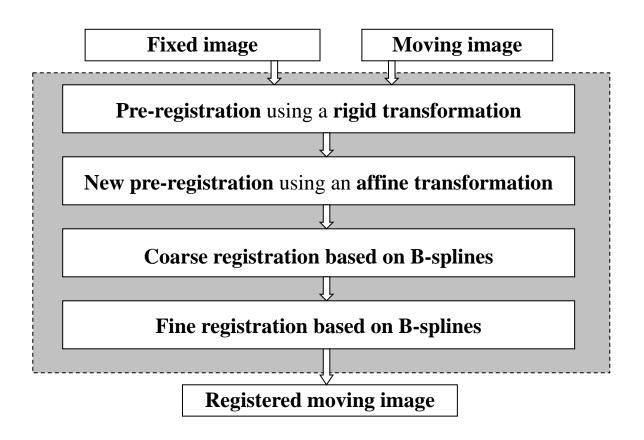








Registration using Iterative Optimization and a curved transformation based on B-splines



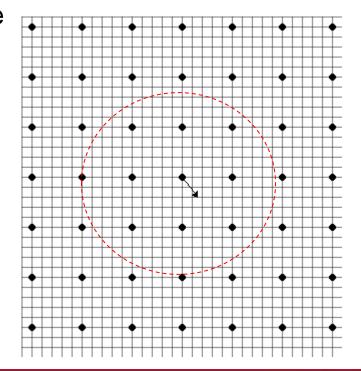


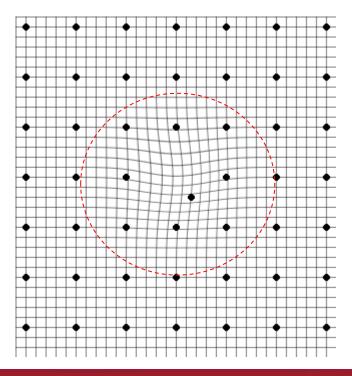


Registration using Iterative Optimization and a curved transformation based on B-splines

The registration based on B-splines is of the free-form deformation type: The deformation is locally defined based on the localization associated to the grid knots; if the localization of a knot changes, then all pixels under its influence are moved accordingly to the B-

spline type







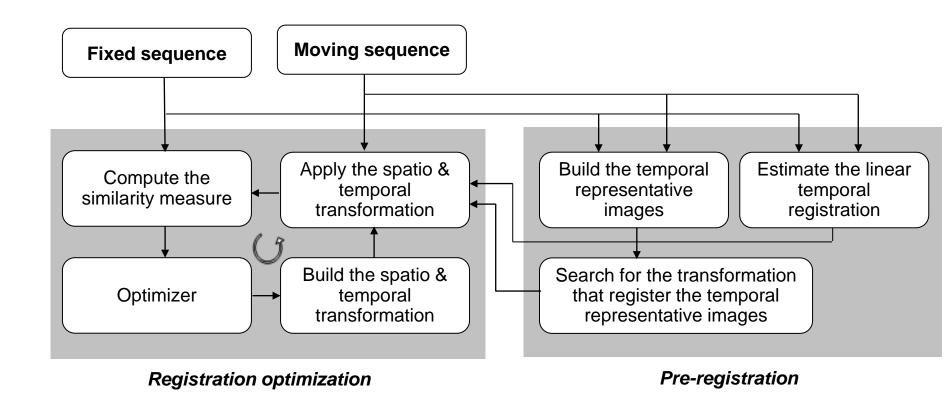


Methods: Spatio & Temporal Registration





Spatio & Temporal registration of image sequences



Oliveira, Sousa, Santos, Tavares (2011) Medical & Biological Engineering & Computing 49(7):843-850

Oliveira & Tavares (2012) Medical & Biological Engineering & Computing DOI:10.1007/s11517-012-0988-3





Applications and Results: Plantar Pressure Images

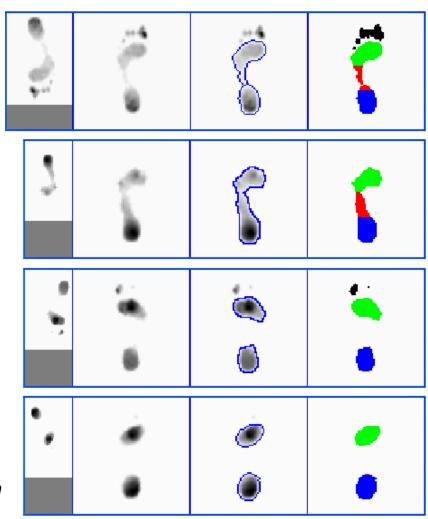




Applications in Plantar Pressure Images Studies

A computational solution, device independent, has been developed to assist studies based on the registration of plantar pressure images:

- Foot segmentation
- Foot classification: left/right, high arched, flat, normal, ...
- Foot axis computation
- Footprint indices computation
- Posterior statistical analysis



Oliveira, Sousa, Santos, Tavares (2012) Computer Methods in Biomechanics and Biomedical Engineering 15(11):1181-1188







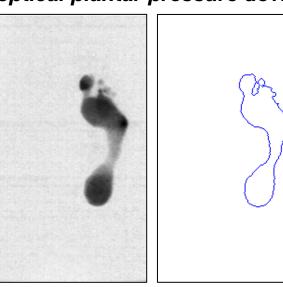
Registration based on Contours Matching

Example 1

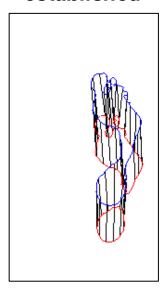
I - Contours extraction and matching

Fixed image and contour (optical plantar pressure device)

Moving image and contour (optical plantar pressure device)



Matching established







Registration based on Contours Matching

Example 1 (cont.)

II - Registration

Moving image

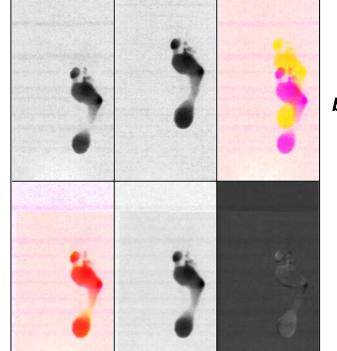
Registration: 2D, monomodal, intrasubject

Processing time: 0.125 s (AMD Turion64, 2.0 GHz, 1.0 GB of RAM)

Images dimensions: 160x288 pixels

Fixed image

Overlapped images after registration



Sum of the images after the registration

Overlapped images before the registration

Difference of the images after the registration







Registration based on Direct Maximization of the CC

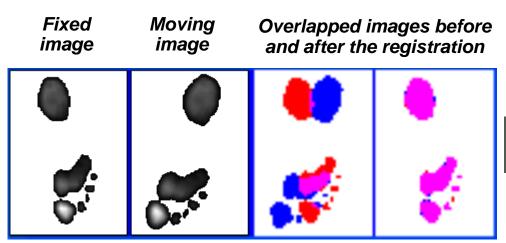
Examples 2 & 3

Image acquisition device: Footscan

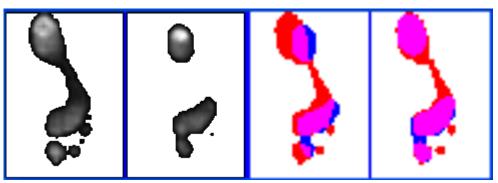
Registration: 2D, monomodal, intrasubject (on the top) and intersubject (on the bottom)

Processing time: 0.04 s (AMD Turion64, 2.0 GHz, 1.0 GB of RAM)

Images dimensions: 45x63 pixels



Images from the same foot



Images from different feet

Using a rigid transformation

Using a

similarity

transformation





Spatio & Temporal registration of Plantar Pressure Image Sequences

Example 1

Device: EMED (25 fps, resolution: 2 pixels/cm², images dimensions: 32x55x13; 32x55x18)

Registration: rigid (spatial), polynomial (temporal); similarity measure: MSE

Processing time: 4 s - AMD Turion64, 2.0 GHz, 1.0 GB of RAM



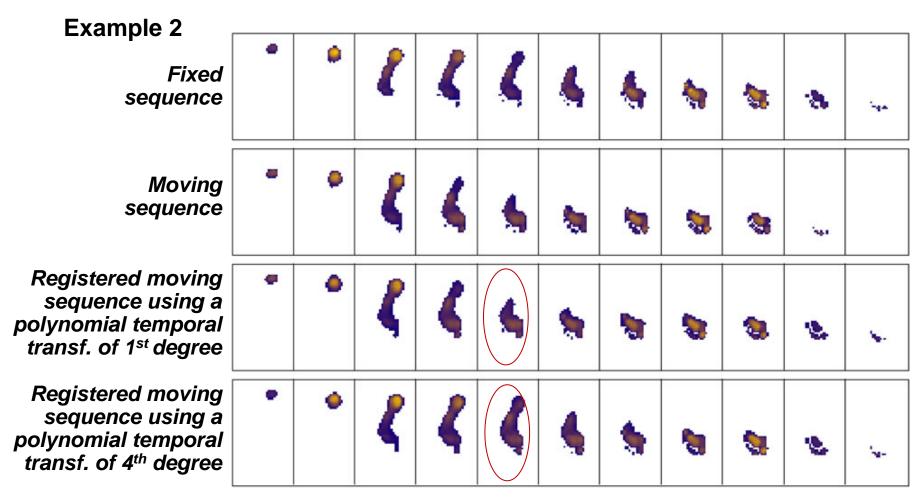


Fixed sequence	Moving sequence	Overlapped sequences	٦
			Before the registration
			After the registration





Spatio & Temporal registration of Plantar Pressure Image Sequences









Applications and Results: Medical Images







Registration based on Contours Matching

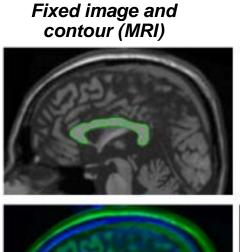
Example 1

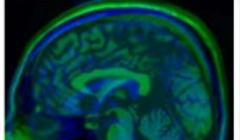
Registration based on the matching of the Corpus Callosum contours

Registration: 2D, monomodal, intrasubject

Processing time: 0.5 s (AMD Turion64, 2.0 GHz, 1.0 GB of RAM)

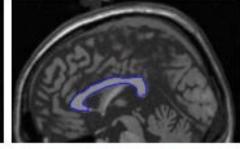
Images dimensions: 217x140 pixels





Overlapped images before the registration

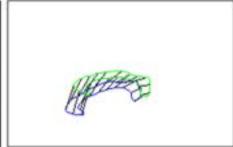
Moving image and contour (MRI)





Overlapped images after the registration

Matching found





Difference between the images after the registration





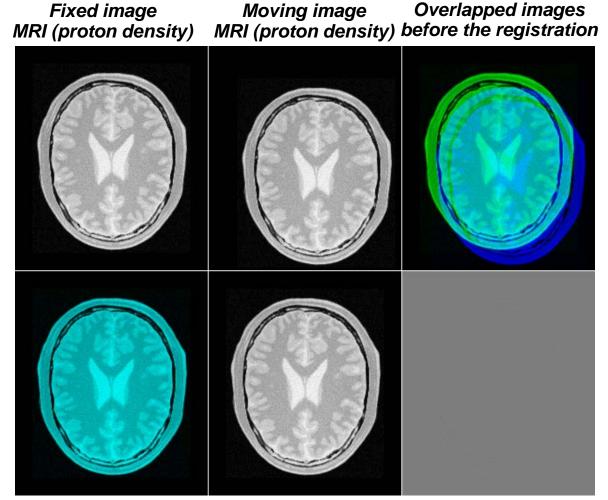
Registration based on Direct Maximization of the CC

Example 2

Registration: 2D, monomodal, intrasubject

Processing time: 2.1 s (AMD Turion64, 2.0 GHz, 1.0 GB of RAM)

Images dimensions: 221x257 pixels



Overlapped images after the registration

Sum of the images Difference of the images after the registration after the registration





Example 3

Registration: 2D, multimodal, intrasubject (without pre-registration)

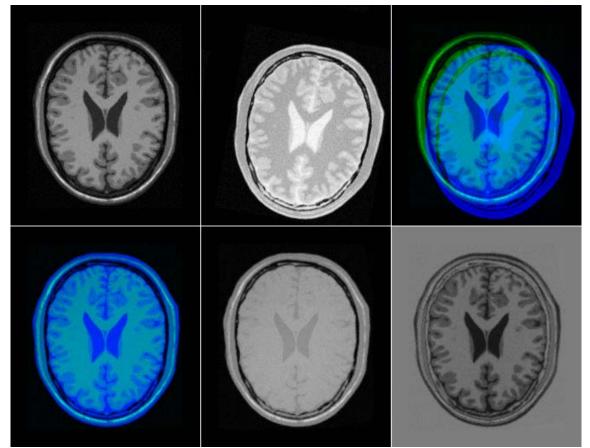
Similarity measure: MI

Processing time: 5.4 s (AMD Turion64, 2.0 GHz, 1.0 GB of RAM)

Images dimensions: 221x257 pixels

Fixed image (MRI - T1)

Moving image Overlapped images (MRI - proton density) before the registration



Overlapped images

Sum of the images Difference of the images after the registration after the registration after the registration





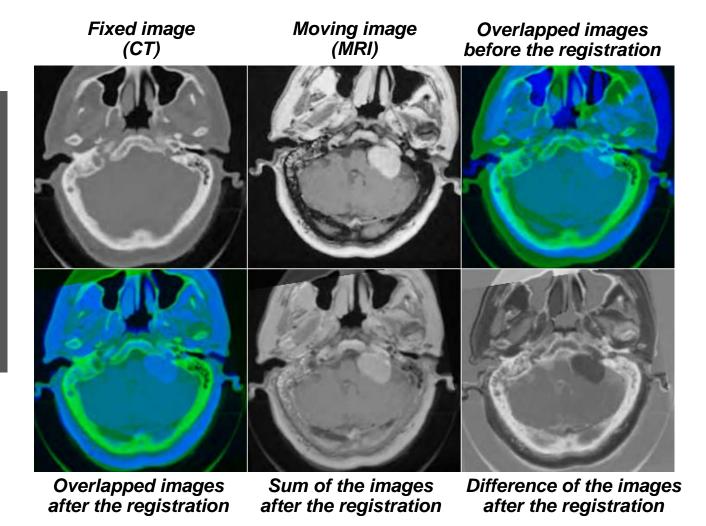
Example 4

Registration: 2D, multimodal, intrasubject (without pre-registration)

Similarity measure: MI

Processing time: 4.6 s (AMD Turion64, 2.0 GHz, 1.0 GB of RAM)

Images dimensions: 246x234 pixels











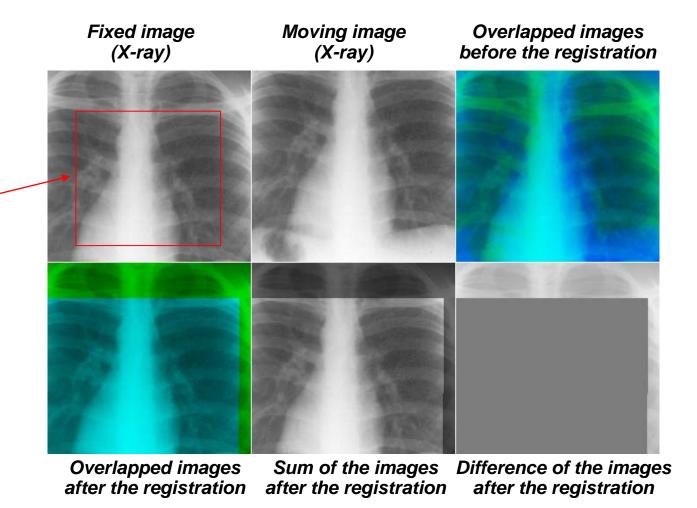
Example 5

Registration: 2D, monomodal, intrasubject (without pre-registration)

Similarity measure: MSE computed only in the ROI defined

Processing time: 1.6 s - AMD Turion64, 2.0 GHz, 1.0 GB of RAM

Images dimensions: 230x216 pixels

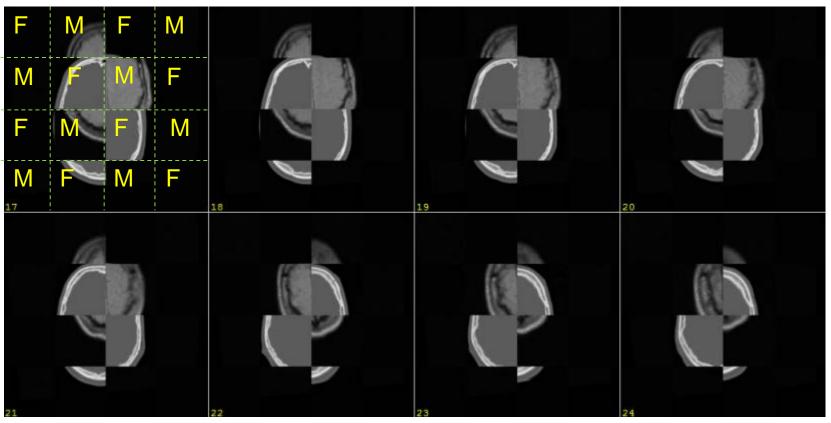






Example 6 – 3D

"Checkerboard" of the images before the registration (CT/MRI-PD, brain)



The "checkerboard" image is built by interchanging square patches of both images and preserving their original spatial position in the fixed (F) and moving (M) images

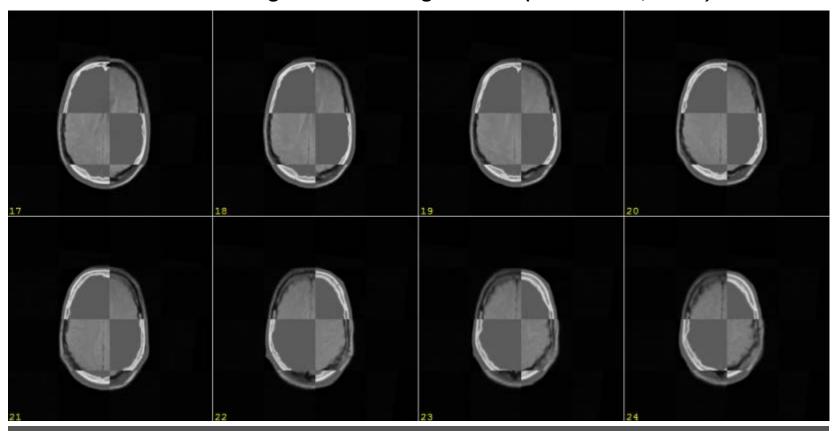




Registration based on Iterative Optimization

Example 6 – 3D

Checkerboard of the images after the registration (CT/MRI-PD, brain)



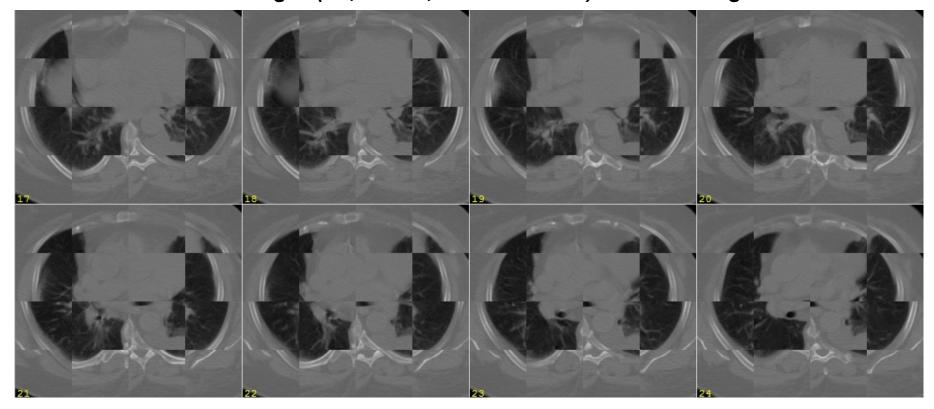
Registration: 3D, multimodal, intrasubject; Similarity measure: MI





Example 7 – 3D

Checkerboard of the images (CT, thorax, \Delta t: 8.5 months) before the registration

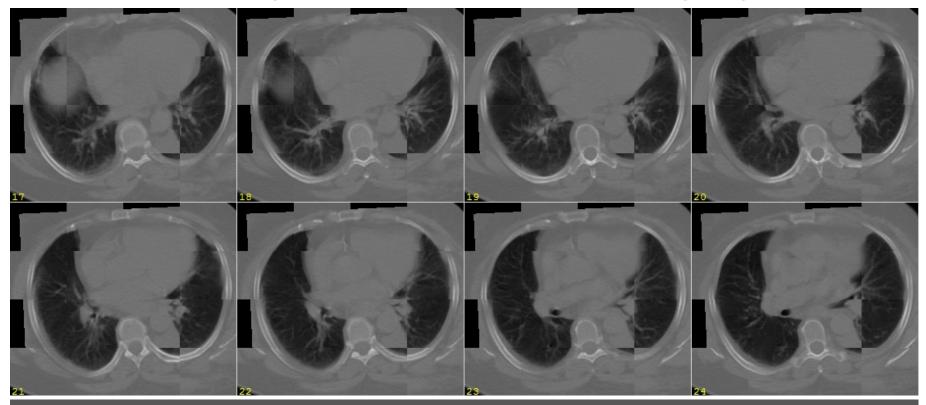






Example 7 – 3D

Checkerboard of the images (CT, thorax, \Delta t: 8.5 months) after a rigid registration



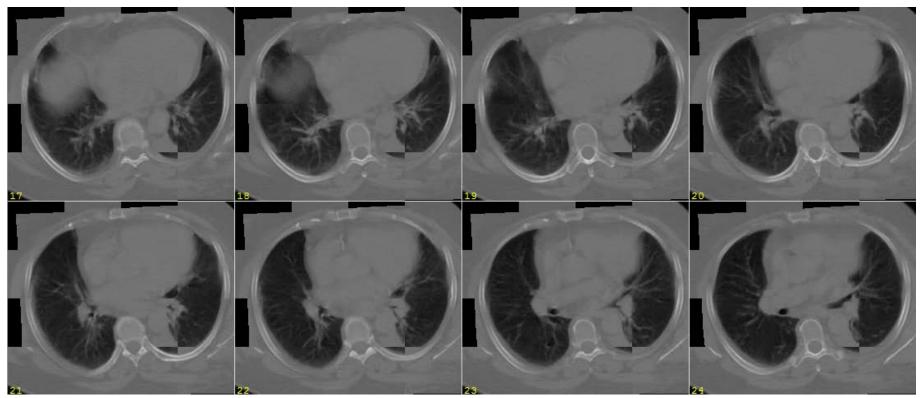
Registration: 3D, monomodal, intrasubject; Similatity measure: MI





Example 7 – 3D

Checkerboard of the images (CT, thorax, \Delta t: 8.5 months) after a cubic B-spline registration



Registration: 3D, monomodal, intrasubject; Similatity measure: MI

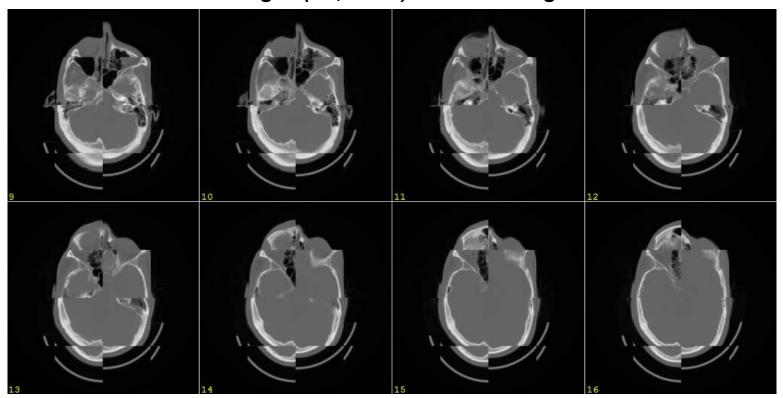






Example 8 – 3D

Checkerboard of the images (CT, brain) before the registration

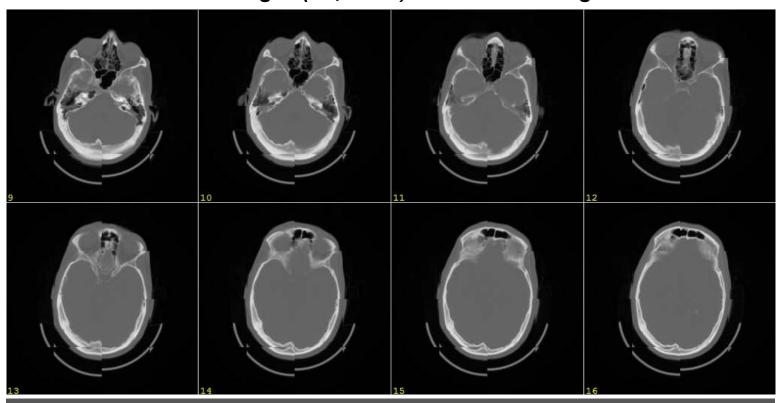






Example 8 – 3D

Checkerboard of the images (CT, brain) after an affine registration



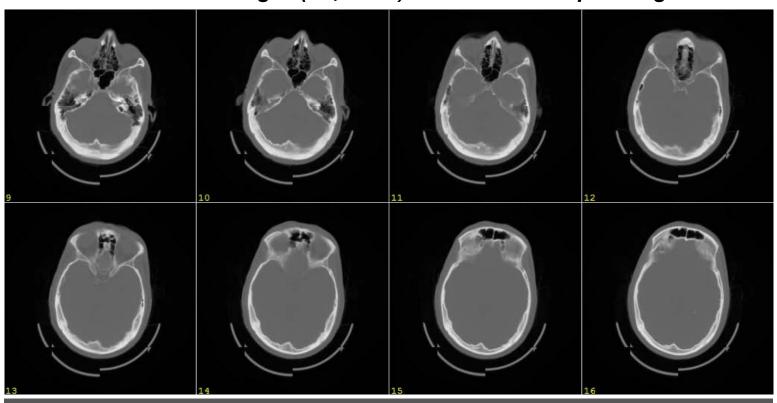
Registration: 3D, monomodal, intersubject; Similarity measure: MI





Example 8 – 3D

Checkerboard of the images (CT, brain) after a cubic B-spline registration



Registration: 3D, monomodal, intersubject; Similarity measure: MI

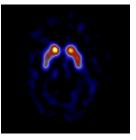




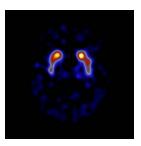
Applications in DaTSCAN SPECT image studies

DaTSCAN SPECT images are used to assist the diagnosis of the Parkinson's disease and to distinguish it from other degenerative diseases. The solution developed is able to:

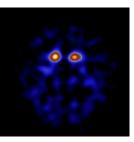
- Segment the relevant areas and perform dimensional analysis
- Quantify the binding potential of the basal ganglia
- Automatic computation of statistical data regarding a reference population
- Provide statistical analysis and comparisons relatively to the reference values of a population



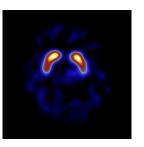
Normal



Alzheimer



Idiopathic Parkinsonism



Essential tremor

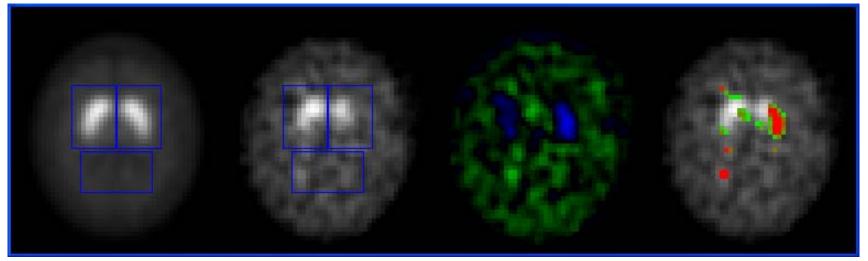




Applications in DaTSCAN SPECT image studies

Example

The 3D volume images are automatically registered



Mean slice from the population used as reference

Corresponding slice of a patient

Difference of intensities

Z-scores mapping over the slice

(The blue rectangles represent the 3D ROIs used to compute the binding potentials, which are based on the counts inside the ROIs. On the z-score mapping image, the red color means high z-score values)

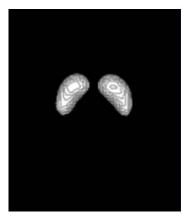




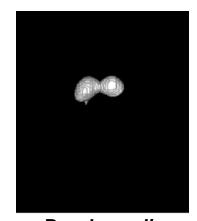
Applications in DaTSCAN SPECT image studies

Example

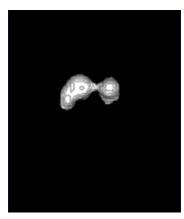
3D basal ganglia shape reconstruction and quantification



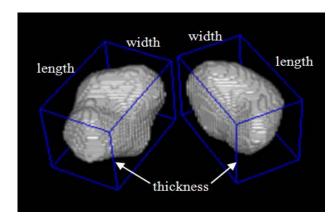
Basal ganglia from a mean image of a normal population

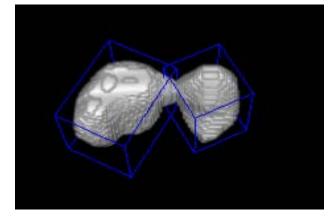


Basal ganglia from a patient with idiopathic Parkinson's disease



Basal ganglia from a patient with vascular Parkinson's disease



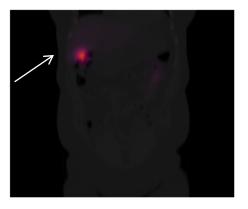


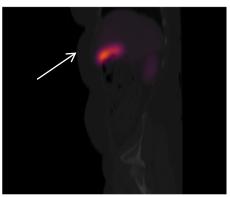


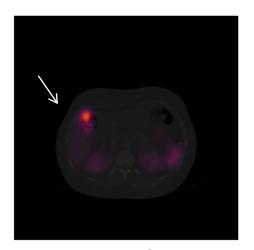


Applications in SPECT/CT registration and fusion

Example

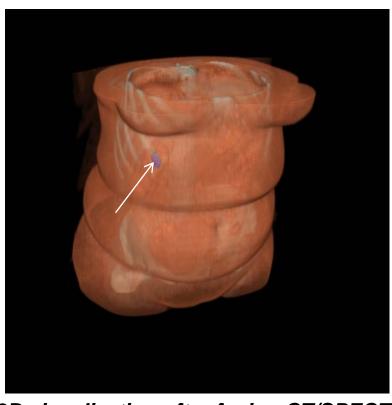








Three slices (coronal, sagittal and axial) after registration and identification of the lesion



3D visualization after fusion CT/SPECT (the lesion identified in the SPECT images is indicated)







Conclusions





Conclusions

- Hard efforts have been done by the Computational Vision community to develop methods more robust and efficient to register image data
- The Biomedical area has been one of the major promoters for such efforts; particularly, due to the requirements in terms of low computational times, robustness and of complexity of the structures involved
- We have been developing several methods that have been applied successfully
- However, several difficulties still to be overcome and better addressed; such as, severe non-rigidity, complex spatio & temporal behaviors, high differences between the data to be registered (e.g. from very dissimilar image sources), etc.





Acknowledgments

- The work presented has been done with the support of Fundação para a Ciência e a Tecnologia (FCT), in Portugal, mainly trough the funding of the research projects:
 - PTDC/SAU-BEB/102547/2008
 - PTDC/SAU-BEB/104992/2008
 - PTDC/EEA-CRO/103320/2008
 - UTAustin/CA/0047/2008
 - UTAustin/MAT/0009/2008
 - PDTC/EME-PME/81229/2006
 - PDTC/SAU-BEB/71459/2006
 - POSC/EEA-SRI/55386/2004

FCT Fundação para a Ciência e a Tecnologia

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Taylor & Francis journal "Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization"

Computer Methods in Biomechanics and Biomedical Engineering:

Imaging & Visualization

Editor-in-Chief: Prof. João Manuel R. S. Tavares

> Universidade do Porto, Portugal tavares@fe.up.pt





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Print ISSN: 2168-1163 Online ISSN: 2168-1171







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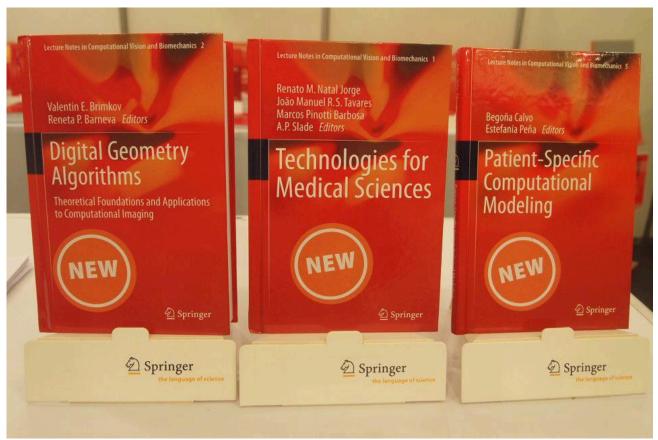




Lecture Notes in Computational Vision and Biomechanics (LNCV&B) Series Editors: João Manuel R. S. Tavares, Renato Natal Jorge

ISSN: 2212-9391

Publisher: SPRINGER



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VipIMAGE2013 - IV ECCOMAS Thematic Conference on Computational Vision and Medical Image Processing Madeira Island, Portugal, October 2013









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Thank you!

Computational Registration of Biomedical Data towards More Effective Image Analysis

João Manuel R. S. Tavares

tavares@fe.up.pt, www.fe.up.pt/~tavares

