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A Framework for Shape Matching in Deformable Image Registration

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Abstract. Many existing image registration methods have difficulties in accurately describing significant rotation and bending of entities (e.g. organs) between two datasets. A common problem in this case is to ensure that the resulting registration is physically plausible, i.e. that the registration describes the actual bending/rotation occurring rather than just introducing expansion in some areas and shrinkage in others. In this work we developed a general framework for deformable image registration of two 3D datasets that alleviates this problem. To ensure that only physically feasible and plausible solutions to the registration problem are found, a soft tissue deformable model is used to constrain the search space for the desired correspondence map while minimizing a similarity metric between the source and reference datasets. Results from a deformable phantom experiment were used to verify and evaluate the framework.

Keywords. Image registration, Distance fields, Soft tissue models

Introduction

A group of algorithms for registration of CT/MR images are based on minimization of a similarity measure. This measure is used to derive expressions for forces driving the registration through iterative image deformation. A physically motivated motion model is typically used to regularize the resulting transformation. The demons [1] and viscous fluid [2] registration methods are two examples of such methods that have been favoured for registration problems involving large global deformations combined with complex local deformation. Some limitations in accurately describing significant rotation and bending of organs between datasets have been reported however. Rather than resulting in physically plausible deformations only, these models can introduce incorrect organ expansion in some areas and shrinkage in others. An example of this can be found in e.g. [2]. In this work we regularize the evolution of the registration process to alleviate this problem.

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1. Method

We propose a framework that combines physical motion models in selected regions of interest (ROIs) with intensity based image registration. The framework is based on the following ideas:

1. Using an elastic soft tissue model for maintaining a physically plausible morphology for organs. In areas of the 3D datasets where no information is available about the tissue type an intensity based method (e.g. [1] or [2]) is used instead. All organ shapes and intensities are registered simultaneously.
2. Making use of as much prior information as possible. When registering images in which organs have already been segmented we wish to take advantage of this information to regularize the registration. This includes using auto-segmentation whenever possible (of e.g. bone structures in CT images). Also, we utilize physical properties of our segmented volumes - e.g. that bones are rigid and that the bladder typically undergo changes in volume.
3. Supporting structural dependencies between shapes - e.g. that vertebra in the neck are connected by discs.

We use a particle based representation of the available source ROIs. Each of these are represented as a set of N nodes (or particles) which are either isotropically distributed in a regular grid interior to the ROI or located on the ROI's surface. The purpose of the surface particles is to limit the amount of internal particles in the ROI while still retaining the shape.

For driving the registration of shapes we suggest a metric based on Euclidian distance fields: For each ROI we generate the distance field ϕ (on a discrete grid). This scalar field denotes the signed distance to the ROI's surface for any given spatial position with negative distances inside the ROI. The resolution of each particle system is independent of the resolution of the corresponding distance field representation. Let the distance fields ϕ_S and ϕ_R refer to the original configuration of source and reference ROIs respectively. As a measure of similarity we then propose the following expression:

$$\mathcal{D}[\phi_R, \phi_S; p^d] = \sum_{i=1}^{N} \left(\phi_S(p_i^o) - \phi_R(p_i^d)\right)^2 + \sum_{i=1}^{N} \left(\nabla^2\phi_S(p_i^o) - \nabla^2\phi_R(p_i^d)\right)^2$$

Finding the direction that locally minimises the Gateaux derivative of this yields:

$$\vec{F}(p^d) = \left(\phi_S(p_i^o) - \phi_R(p_i^d)\right) \nabla\phi_R|_{p_i^d} + \left(\nabla^2\phi_S(p_i^o) - \nabla^2\phi_R(p_i^d)\right) \nabla(\nabla^2\phi_R)|_{p_i^d}$$

where $|_{p_i^d}$ means evaluation at p_i^d. These forces are used to accelerate the particles in the source ROI representation towards their desired position in the reference ROI. Verlet integration is used for evolving the source ROI movement from source to reference shape. Many soft tissue deformations models been proposed previously, most prominently the spring-mass model and finite element models. The framework is flexible to allow any desired model to be integrated in the solver. At present we have obtained good results using a soft tissue model in which the position of each particle is described relatively to a set of particle triplets [3].

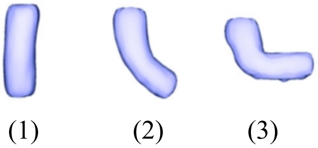

Figure 1. Rendering of the three configurations of our modelling clay phantom.

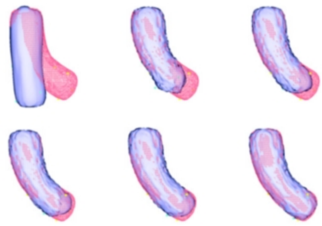

Figure 2. Registration of a modelling wax phantom. The red triangular mesh depicts the surface of the reference shape, the blue surface represents the deformed source ROI corresponding to six selected iteration steps.

Shape ID		**Before registration**		**After registration**	
Src.	Ref.	Mean	std. dev.	Mean	std. dev.
(1)	(2)	12.9	11.9	2.48	0.744
(2)	(1)	12.9	11.9	2.80	0.850
(1)	(3)	24.3	23.1	3.99	1.30
(3)	(1)	24.3	23.1	3.82	1.51
(2)	(3)	13.5	13.1	2.40	0.824
(3)	(2)	13.5	13.1	2.89	0.821

Table 1. Euclidian distances between marker positions before and after registration (mean value over 8 positions). Shape IDs refer to fig. 1. Measures are in millimetres.

2. Results

To evaluate our method we acquired three CT scans of a modelling wax phantom (one reference scan and two source scans) with lead markers attached (fig 2). The markers were not used in the registration process but for evaluation purposes only. Registration result statistics can be seen in table 1. A significant reduction in marker displacement is achieved indicating that the transformation is physically plausible. The evolution of the source ROI when registering shape (1) to shape (2) can be seen in fig. 2. Each registration takes 1-2 minutes on a standard CPU.

3. Conclusion / discussion

We have outlined a framework that guarantees a physically plausible registration of 3D shapes given no other information than a binary mask representation of a source and reference ROI in the data. A phantom registration experiment verified that the resulting transformation was physically plausible. The framework is flexible and configurable with respect to both the choice of the similarity measure driving the registration, and to the soft tissue deformable model constraining the evolution of the registration process. Different organs can be registered using different similarity measures and constraint models by allowing e.g. a combination of deformable organ movement and rigid movement of bones.

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