Non-rigid Image Registration Using a Statistical Spline Deformation Model

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Abstract. We propose a statistical spline deformation model (SSDM) as a method to solve non-rigid image registration. Within this model, the deformation is expressed using a statistically trained B-spline deformation mesh. The model is trained by principal component analysis of a training set. This approach allows to reduce the number of degrees of freedom needed for non-rigid registration by only retaining the most significant modes of variation observed in the training set.
User-defined transformation components, like affine modes, are merged with the principal components into a unified framework. Optimization proceeds along the transformation components rather then along the individual spline coefficients.
The concept of SSDM's is applied to the temporal registration of thorax CR-images using pattern intensity as the registration measure. Our results show that, using 30 training pairs, a reduction of 33% is possible in the number of degrees of freedom without deterioration of the result. The same accuracy as without SSDM's is still achieved after a reduction up to 66% of the degrees of freedom.

1 Introduction

Image registration involves finding a coordinate transformation that maps each point in one image onto its geometrically corresponding point in the other, such that information contained in each image about a particular object of interest can be compared or combined into a single representation. Retrospective registration aims at computing such a transformation from the image content itself by optimization of an appropriate similarity measure that evaluates the alignment of corresponding image features, typically landmark points, object surfaces or individual voxels. While rigid body or affine registration only compensates for overall differences in pose or size between corresponding objects in the images to be registered by global translation, rotation, scaling and skew, defined by a small number of registration parameters, non-rigid registration allows to recover local deformations between both images, involving a much larger number of degrees of

* Frederik Maes is Postdoctoral Fellow of the Fund for Scientific Research - Flanders (FWO-Vlaanderen, Belgium).

C.J. Taylor and J.A. Noble (Eds.): IPMI 2003, LNCS 2732, pp. 463–474, 2003.

freedom. In its most general form, non-rigid image registration models the registration transformation between both images as a vector field of displacement vectors from each voxel in the first image onto the corresponding location in the other. However, because not all deformations are physically feasible or realistic and because the image intensity information may be insufficient to unambiguously define the deformation field in each voxel (in homogeneous image regions or along object boundaries for instance), regularization of the deformation field is needed to impose local consistency or smoothness on the deformation and to propagate the registration result from areas with salient registration evidence into areas where registration features are largely absent. Such regularization approaches include: parametrization of the deformation field as a weighted sum of smooth basis functions with either local (e.g. B-spline [1]) or global (e.g. thin plate spline [2]) support; modelling of the image to be deformed as a physical medium with appropriate material properties (typically elastic [3] or viscous fluid [4]) whose deformation is governed by its equation of motion (typically elasticity or Navier-Stokes equations); or the use of a biomechanical model that allows to include tissue-specific deformation properties [5].

In this paper, we propose a statistical deformation model that constrains the parameters of a spline-based deformation field based on their likelihood as derived from a training set of similar non-rigid registration cases. Each pair of images in the training set is registered first without constraining the spline parameters. Correlation between the various degrees of freedom is subsequently exposed by principal component analysis (PCA) of the spline parameters and the major modes of deformation, explaining most of the deformation variability in the training set, are extracted and used to re-parameterize the deformation field as a linear combination thereof. This modelling approach is largely similar to that presented previously by Rueckert [6]. Yet new to our approach is to optimize in the re-parameterized field. This makes it possible to reduce the number of registration parameters while maintaining sufficient local variability (if it is assumed that the training set is sufficiently representative) by including the most relevant deformation modes only. It is also expected to increase robustness and to reduce computation time of registration of new similar cases not included in the training set.

We have implemented and validated this approach for 2-D non-rigid matching of digital radiographs of the thorax of the same subject acquired at different time points. We evaluate the impact of the statistical model on the robustness of a spline-based deformation field whose parameters are optimized using pattern intensity as similarity measure [7] and investigate the influence of the number of deformation modes that is included in the model on registration quality. Our results show that, using 30 training pairs, a reduction of 33% is possible in the number of degrees of freedom without deterioration of the registration accuracy. The same accuracy as without SSDM's is still achieved after a reduction up to 66% of the degrees of freedom.