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Multi-atlas based segmentation using probabilistic label fusion with adaptive weighting of image similarity measures

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ABSTRACT

Label fusion multi-atlas approaches for image segmentation can give better segmentation results than single atlas methods. We present a multi-atlas label fusion strategy based on probabilistic weighting of distance maps. Relationships between image similarities and segmentation similarities are estimated in a learning phase and used to derive fusion weights that are proportional to the probability for each atlas to improve the segmentation result. The method was tested using a leave-one-out strategy on a database of 21 pre-segmented prostate patients for different image registrations combined with different image similarity scorings. The probabilistic weighting yields results that are equal or better compared to both fusion with equal weights and results using the STAPLE algorithm. Results from the experiments demonstrate that label fusion by weighted distance maps is feasible, and that probabilistic weighted fusion improves segmentation quality more the stronger the individual atlas segmentation quality depends on the corresponding registered image similarity. The regions used for evaluation of the image similarity measures were found to be more important than the choice of similarity measure.

1. Introduction and background

Image segmentation is the process of locating object boundaries and to label these for various purposes. In planning of radiotherapy the segmentation process for outlining targets and risk organs is a tedious and costly process with a high degree of inter- and intra-user variability [1] motivating research for automation of the process. The increasing availability of 4D-imaging and imaging at the treatment machine for dose tracking and adaptive radiotherapy further stresses the need for tools to support the image segmentation process.

Atlas-based segmentation use deformable registration to first warp pre-segmented images of one or several carefully contoured atlas patient(s) to images of the current patient, and then transfer the segmentations using the same warping as for the images. This approach has in several publications been demonstrated to increase both efficiency and reproducibility compared to manual segmentation [2–4]. The specific approaches vary and several deformable registration algorithms have been proposed, see e.g. [5–8].

The design of atlas data has attracted considerable attention. The simplest approach is to use a single atlas image, which has the advantage that only one manually delineated

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set of contours needs to be provided. However, because individual patients' anatomy varies, and image registration algorithms are not perfect, the likelihood of succeeding is larger the more similar the atlas image is to the patient image. Hence, with several atlases available, the choice of atlas can significantly influence and improve the registration results. With a set of atlases available, the atlas image to apply can be selected by user preference, by image similarity measures, or even randomly [9]. However, choosing the single atlas image that will yield the best segmentation result is a difficult problem. One possibility is to combine images into an average atlas image [10]. This yields images with low noise levels but also with less specific information. Another strategy is to register several atlases individually, and then combine their segmentations, a strategy known as label fusion. Studies have indicated that fusing segmentations from several registrations can give results significantly better than using a single registration [9,11,12]. Examples of label fusion schemes are label voting [13], STAPLE using expectation maximization with binary volumes [14], shape based averaging [15], voting with globally or locally weighted votes [11,16] and a fusion approach using expectation maximization including an image similarity prior [17]. To reduce computation time and improve segmentation result, careful selection of fewer atlases by similarity to the patient image and fusing their results has also been investigated [18–20].

In this paper we present a multi-atlas label fusion method based on probabilistic averaging of the labelled objects' distance maps, which also enables calculation of the local uncertainty of the resulting segmentation [21]. The fusion method consists of a learning phase, where parameters used for calculating the probabilistic weights are estimated using an atlas database, and an application phase where segmentations are fused using the parameters from the learning phase to calculate fusion weights for the individual atlas proposals based on image similarities of the registered atlas images. The method is applicable with any image registration algorithm, and is tested on a leave-one-out basis with two different non-rigid registration methods; free form deformations modelled by B-splines and Thirion's demons using images for 21 prostate patients subject to radiotherapy with rectal rod positioning [22]. We test several methods for scoring the similarity of the registered images, evaluated over different regions to evaluate combinations of algorithms to realize the strategy. The results are compared to results achieved by direct averaging of the distance maps using equal weights for all proposals, the STAPLE algorithm, and to the selection of the single segmentation with the best corresponding image similarity measure.

2. Methods

In multi-atlas segmentation, a set of atlas images are first registered to a new patient image and the corresponding segmentations are then transformed and fused to yield a final segmentation proposal. Our label fusion method is independent of the image registration method used, but for completeness we start with a description in Section 2.1 of the image registration methods used in the experimental part of this work. The utilized methods for segmentations representations are described in Section 2.2, and the used image similarity measures are summarized in Sections 2.3 and 2.4. The probabilistic weighting method is described in Section 2.5, and the parameter derivation for its learning phase given in Section 2.6. The leave-one-out framework used for evaluation of the final segmentation proposals for the fusion methods in this work is described in Section 2.7

2.1. *Image registration*

An image registration defines a geometrical transformation $\mathbf{T}(\mathbf{x}) : \mathbb{R}^3 \rightarrow \mathbb{R}^3$, which applied to a moving image (atlas) $M(\mathbf{x})$ results in an image as similar as possible to the reference (current patient) image, also called the fixed image $F(\mathbf{x})$. The similarity can be quantified by a similarity measure *SIM* allowing the registration problem to be formulated as an optimization problem, i.e. $\max_{\mathbf{T}(\mathbf{x})} SIM(F(\mathbf{x}), M(\mathbf{T}(\mathbf{x})))$.

In this work we used two different deformable image registration methods, free form deformations modelled by B-splines [8], and Thirion's demons registration [6], both preceded by an affine transform to improve the starting conditions for the deformable registration. All registrations were performed in a multi-resolution fashion, where local optima of the similarity measure were avoided by first registering the images at a coarser resolution, and then using the result as an initial transformation for the next level of iterations at a higher resolution.

In the B-spline method the displacement vectors are calculated by a linear combination of B-spline basis functions which have compact support distributed over a regular grid with spacing larger than the image voxel spacing. The weights for the linear combination are optimized with regard to an image similarity measure [8].

The Thirion's demons method [6] models a force based on optical flow, which assumes conservation of intensities, yielding an iterative scheme for updating of the deformation field according to

$$\mathbf{T}^{i+1}(\mathbf{x}) = \mathbf{T}^{i}(\mathbf{x}) + \frac{(F(\mathbf{x}) - \mathbf{T}(M(\mathbf{x})))\nabla F(\mathbf{x})}{(F(\mathbf{x}) - \mathbf{T}(M(\mathbf{x})))^2 + \frac{1}{K}\left\|\nabla F(\mathbf{x})\right\|^2} \quad (1)$$

where i denotes the iteration order, and K is set to the mean square value of the voxel spacing. The deformation field is regularized by convolving the accumulated field with a Gaussian at each iteration.

2.2. *Segmentation representations*

The prostate segmentations in the database were made by a radiation oncologist using a commercial radiotherapy treatment planning system resulting in a set of polygons which were exported for the involved transversal slices. A binary mask representing the segmentations was created by considering voxels with centres inside the polygons to belong to the mask. The binary mask was transformed using nearest neighbour interpolation to construct the deformed mask on a regular grid. As the deformation not necessarily preserves the topology, there is a possibility that the deformed mask no