# Analysis of 3D Deformation Fields for Appearance-Based Segmentation

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Segmentation methods for brain MR images typically employ manual and/or automatic knowledge-based models specific to the structure of interest (SOI). The technique presented here overcomes some of the limitations of current methods. It requires no manual intervention, is fast, fully 3D, and generic yet constrained by some form of prior structure information. The novelty of this work resides in its *a priori* Principal Components Analysis (PCA) of non-linear registration data of a volume of interest (VOI), represented by dense 3D deformation fields from ANIMAL [1]. The results are used in an Appearance Model, inspired by Cootes [2], able to segment any SOIs contained within the VOI, in the atlas-independent framework described by Collins [1]. This article presents the theoretical basis for and initial work towards hippocampus segmentation on subject images from the MNI International Consortium for Brain Mapping (ICBM) database.

*Methods:* In the appearance-based matching proposed by Cootes, a model of the grey-level variations is combined with an Active Shape model. For the former, PCA is used to reduce the dimensionality of the grey-level data and generate a linear grey variation model [2]:

$$\mathbf{g} = \bar{\mathbf{g}} + \mathbf{P_g B_g} \tag{1}$$

where $\bar{\mathbf{g}}$ is the mean normalised grey-level vector, $\mathbf{P_g}$ is a set of orthogonal modes of variation and $\mathbf{B_g}$ is a set of grey-level parameters. In place of the 2D ASM we propose to use a 3D Warp Model, generated by statistical analysis of a large number of example deformation fields. To simplify computations, the 3D deformation vector fields are decomposed into volumes of orthogonal deformation components $x, y, z$. With PCA the linear warp variation model is expressed as:

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{P_x B_x};\ \mathbf{y} = \bar{\mathbf{y}} + \mathbf{P_y B_y};\ \mathbf{z} = \bar{\mathbf{z}} + \mathbf{P_z B_z} \tag{2}$$

Using the same notation as [2], this linear model allows any new warp instance $\mathbf{w(x, y, z)}$ to be approximated by $\bar{\mathbf{w}}$, the mean warp, $\mathbf{P_w}$, the set of orthogonal modes of warp variations, and $\mathbf{B_w}$, the set of warp parameters. The space of all possible elements expressed by eq. 2 is called the Allowable Warp Domain. Since there may be correlations between the grey-level and warp variations, grey-level and warp parameters are concatenated as follows

$$\mathbf{B} = [\mathbf{W'_g B'_g}\ \mathbf{B'_x}\ \mathbf{B'_y}\ \mathbf{B'_z}] \tag{3}$$

W. Niessen and M. Viergever (Eds.): MICCAI 2001, LNCS 2208, pp. 1189–1190, 2001.

where $\mathbf{W_g}$ is a diagonal matrix of weights accounting for differences in dimensions between grey-level (intensity) and warp variations (distances). PCA of eq. 3 yields a super-set of parameters describing the complete appearance model

$$\mathbf{B} = \mathbf{QC} \tag{4}$$

where $\mathbf{Q}$ are appearance eigenvectors and $\mathbf{C}$ is a vector of parameters controlling both the warp and the grey-levels of the model. The core of the segmentation method consists then in matching a new grey-level image to one synthesized by the model using the appearance parameters. The iterative method described in [2] is used. After convergence, the solution explicitly contains warp variation parameters, which can be expressed back into $x, y, z$ components of the warp field and concatenated into ANIMAL vector format. Segmentation of the VOI is then possible using any structure model defined on the ANIMAL reference volume. It is achieved by applying the inverse of the deformation field to structures defined in the standard volume and then mapping those onto the subject.

*Results:* The SOI for initial testing was the left hippocampus. Normal subjects ($n = 40$) were selected for the training set from the ICBM database. VOIs of $55 \times 79 \times 68$ voxels were defined on T1-weighted MR images, with isotropic resolution ($1mm^3$). This volume captured the hippocampus irrespective of normal inter- and intra-individual variability. VOIs were linearly registered into stereotaxic space to reduce positional variations which would propagate as unwanted noise in the morphometric PCA modelling. Segmentation of an additional 10 subjects from the same database was performed using ANIMAL [1] and the Appearance-based (AB) method. Overlap statistics between manual segmentation and ANIMAL ($\kappa = 0.69, \sigma_\kappa = 0.03$), and manual vs AB ($\kappa = 0.65, \sigma_\kappa = 0.05$) indicate that the two methods have similar accuracy. A 12-to-1 decrease in segmentation processing time (ANIMAL: 2 hr/side/subject; AB model: <10 min/side/subject) was observed.

*Discussion and Conclusions:* The principle and applicability of an Active Appearance model based on the analysis of 3D deformation fields for segmentation has been demonstrated. Accuracy and robustness remain to be thoroughly assessed but early results suggest that the AB method is as accurate as ANIMAL, while being significantly faster. Promising features of this novel approach include (1) its speed compared to locally available segmentation methods; (2) reliance on all grey-level voxels and deformation vectors as "landmarks" and hence maximum use of information; (3) fully 3D and automated; and (4) flexibility in the choice of SOI/VOI. The major constraint is the restriction to the domain of structure neighborhoods whose non-linear registration is achievable using ANIMAL for the training of the 3D Warp Model.

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[1] D. L. Collins, *Human Brain Mapping*, vol. 3, pp. 190–208, 1995.
[2] T. F. Cootes, in *ECCV* (Springer), pp. 484-498, 1998.