Comparison of Different 3D Edge Detection Methods to Define Landmarks for Point-Based Warping in Autoradiographic Brain Imaging

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Abstract. Warping can be used to reduce interindividual structural variations of 3D image datasets of brains by generating a standard brain and subsequent matching of individual datasets to this reference system. Point-based warping uses structural information (landmarks) to construct the spatial correspondence between the datasets. For this we compare the performance of three landmark detection algorithms. The first two approaches use a threshold-based definition of landmarks, the third spatial derivations of voxels. The warping is based on a distance-weighted method with an exponential weighting function. All methods tested are able to reduce structural variations, best results are obtained by the derivation approach.

1 Introduction

The analysis of image datasets obtained from different animals requires the reduction of interindividual variations. Nonlinear geometric transformations, so called warping [1], can be used to reduce these variations by transforming the individual datasets to a reference system, e.g. a "standard brain". The warping process consists of two main steps: First, the spatial correspondence between the datasets and the reference system has to be determined. Second, using this correspondence information the individual datasets are transformed to the reference system. According to the determination of the spatial correspondence, warping algorithms can be divided in two classes: Intensity-based warping methods maximize local gray value distribution to match the source dataset to the target [2]. Model-based warping approaches use high-level information such as surfaces of anatomical structures [3] or single points [4] on prominent morphological sites. In datasets, which are obtained by functional imaging techniques, the different spatial gray value distribution is of biological or medical interest. Therefore, the spatial gray value distribution cannot be used to construct the spatial correspondence between these datasets. In this study, the datasets were obtained by functional labeling of gerbil brains, so that we investigate model-based warping strategies, i.e. point-based warping. For point-based warping methods at first corresponding points (=landmarks) between all the datasets have to be defined. Setting of a small number of landmarks between 2D images can be done by hand, but definition of a greater number of landmarks between large 3D image datasets by a human expert is highly time-consuming and subjective. Consequently, we developed automatic procedures for landmark definition. Furthermore, we try to adjust already published landmark detection methods to our datasets.

2 Image Preprocessing

Six gerbils (*Meriones unguiculatus*) were acoustically stimulated after injecting the radioactive 2-fluoro-deoxyglucose (2FDG). This method visualizes brain activity by accumulation of the non-metabolisable sugar 2FDG in certain brain areas proportional to their electrical activity. After 45 min exposure time the animals were scarified and the brains were removed. The brains were sectioned and the single slices were exposed on an X-ray film. After exposure, the films were developed and the autoradiographed slices were digitized with a camera (768 * 512 * 49 slices, 256 gray values).

In order to reconstruct the original 3D object, each slice is aligned by means of translating and rotating. We used a fully automatic computational method of principal axes alignment followed by a cross-correlation method. The last step is to align the 3D datasets to each other.

3 Landmark detection

The first 3D landmark detection method uses Monte-Carlo techniques to realize the search of edges within the dataset. Initially a multiscale 3D grid is placed on each dataset to define non-overlapping subvolumes. Next edges are searched with random movements of a single point within each of subvolume. An edge is defined if the search point detects a gray value difference between two neighboring voxel, which exceeds a constant threshold. If an edge is detected, the procedure stops within this subvolume and the position of the search point is stored. This procedure is iterated for all subvolumes and for all grid-scaling levels in all datasets. To get a reliable spatial definition the whole process is repeated 10 times. The final position of each selected point (1 per subvolume) is the average across these repetitions. Only if an edge in a given subvolume is found in all datasets, this individual point is taken as a landmark [5].

In the second approach the searching points move along rays, which have the origins at the centers of gravity of substructures. These origins are defined in one brain for the whole group. To ensure correspondence, the origins have identical locations in all datasets and the angles between the rays are similar in all datasets. The points move along the rays and stop if an edge is found. As in the first approach, an edge is defined as a gray value transition, which is greater than a given threshold. If on the corresponding ray of all datasets an edge is found the position of the searching point for each dataset defines the landmark.

The third approach uses 3D differential operators e.g. the quotient of the determinant and the trace of a matrix of first partial derivatives of image values around a given position [6]. The 3D reference points are defined by searching for local maxima of operator values, which are greater than a preset threshold value. To ensure correct correspondence of the reference points again a 3D grid approach is used, as in the case of the Monte-Carlo method. Only if a sub-volume contains a reference point in all datasets, these reference points are determined as landmarks [7].

The correct correspondence of the found landmarks has not been verified, since our approach was to compare the different landmark generators regarding the quality of the subsequent warping. Anatomical verifications of the found landmarks were not taken into account.

4 Warping

The standard brain, i.e. the reference template for warping, is generated by averaging the positions of the corresponding individual landmarks across the datasets. The warping method used here is based on a distance-weighted method [8]. The displacement is determined by the weighted sum of all displacement vectors. The exponential weighting function consists of a global weighting factor and the distance of a given voxel to a certain landmark.

5 Results

The Monte-Carlo method found 360 landmarks in approx. 39,000 s (SGI Origin 200). The ray-based method found 1,285 landmarks in 120 s and the 3D-operator approach found 180 landmarks in approx. 10,800 s. Fig. 1 illustrates as an example a surface view of a manually segmented gerbil brain dataset together with the landmarks found with each method. The left figure shows the landmarks, which are determined by the Monte-Carlo method, in the middle the landmarks obtained by the ray method and the right figure the landmarks obtained by the 3D operator method.

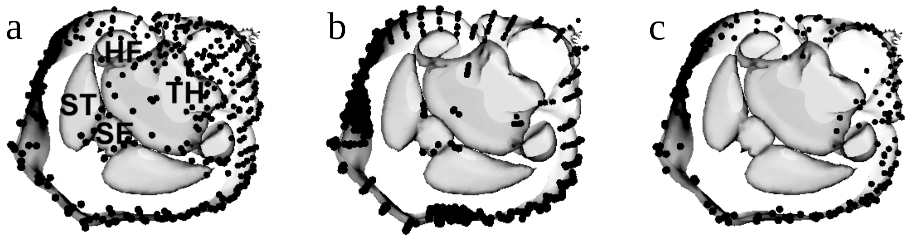

Fig.1 Surface views of a 3D brain dataset together with the generated landmarks. The outer surface of the brain and four structures were segmented manually and then surface rendered by the visualization software Amira (Indeed GmbH). a) Landmarks after application of Monte-Carlo method, b) after application of the ray method and c) after application of the 3D operator approach. SE septum, ST striatum, TH thalamus, HF hippocampal formation.

The quality of warping is quantified by applying 2 similarity functions before and after warping (linear cross-correlation coefficient, *cc*; volume overlap index, *oi*). Following average values were obtained (increase after warping): Monte-Carlo method: *cc*: +1.29 %, *oi*: +1.67 %; ray-based method: *cc*: +1.79 %, *oi*: +3.00 %; and 3D operator approach: *cc*: +2.25 %, *oi*: +2.27 %.

6 Discussion

In this study, we investigated 3 different, fully automatic procedures to detect landmarks for distance-weighted warping. The landmarks are successfully used for generating a reference template and the similarity of the individual datasets increases after warping in all cases tested. The quality of warping, as indicated by the similarity functions used, varies between the different landmark generators. The best cross-correlation coefficient is achieved by the 3D operator approach, whereas application of the ray-based method results in the best volume overlap index. The reason for this is that the ray-based method generates relatively more landmarks at the outer brain contour as compared to the other methods. Consequently, the outer edges are registered with a higher precision. For biological questions demanding quantitative evaluation of gray values, the cross-correlation coefficient gives more information about the quality of the warping procedure than pure geometric overlap indices. Therefore, the 3D operator method proved to be the most suitable tool in this study to make complex biological structures inter-individually better comparable and therefore facilitate a quantitative group comparison in functional autoradiographic brain imaging studies.

7 References

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