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Segmentation of ROIs/VOIs from small animal images for functional analysis

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Abstract

Segmentation of anatomical structures and tumors is an important prerequisite for the interpretation and further quantitative analysis of tomographic images. A method for segmenting regions-of-interest or volumes-of-interest (ROIs or VOIs) from small animal MRI images for functional analysis of co-registered PET images was developed. The method consists of automatic image enhancement, semi-automatic segmentation and a coded contour-based interface to region-based functional analysis software. Two semi-automatic segmentation approaches, a dynamic programming-based and an active contour-based approach, were compared regarding user interaction and segmentation consistency. The results obtained from six MRI data sets of different resolution and image quality show that both semi-automatic approaches are a good choice to deal with different kind of images, image quality and regions.

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Keywords: Anisotropic diffusion; Semi-automatic segmentation; Dynamic programming; Active contours; Contour coding

1. Introduction

Segmentation of anatomical structures and tumors can support co-registration of multi-modal or multi-spectral images and is an important prerequisite for the interpretation and further quantitative analysis of these images [1]. Which structures are to be examined depends on the particular research being done; e.g., differentiation of brain from non-brain structures for improving co-registration and assisting functional brain analysis, or segmentation of tumors for measuring growth and metabolism.

Furthermore, the image quality can vary greatly depending on the imaging modality, the acquisition system and the measurement sequence.

In order to deal with this kind of image variability, semi-automatic segmentation methods which are as automatic as possible without losing flexibility seem to be the right choice since user interaction makes them more adaptive than purely automatic methods.

2. Methods

2.1. Pre-processing

In order to deal with different images and image quality, an automatic data-driven noise reduction method was developed based on egde-preserving anisotropic filters [2]. These *filters* were integrated into a closed-loop system (Fig. 1a) to automatically determine the two-filter parameters—diffusion factor k and number of iterations *it*—based on an *evaluation* of the difference image during the filtering process. Evaluation values Mp on the function ridge in Fig. 1b are considered near optimum, and the optimum is *adjusted* with an iterative approximation scheme.

Small animal images of Section 3 were enhanced with the biased version of the Weickert filter [3,4]. Fig. 2 shows a Wt1rsl slice. In order to show the de-noising more clearly,

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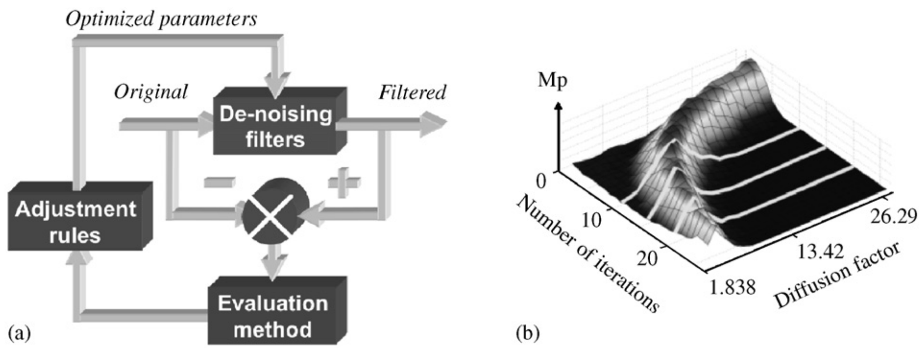

Fig. 1. (a) Diagram of the automatic paramterization method, (b) evaluation values $Mp(k,it)$ [2].

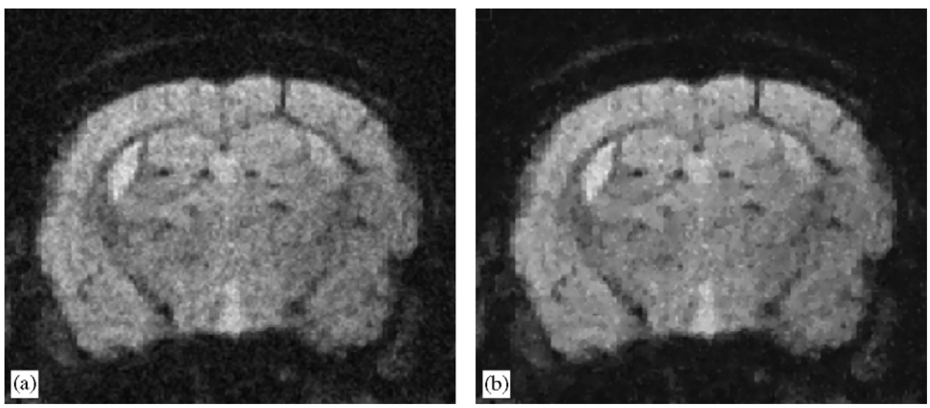

Fig. 2. (a) Wt1rsl with additional Rician noise, (b) filtering result.

additional Rician noise was applied (Fig. 2a). The filter parameters were found to be $k = 1012$ and $it = 16$. Fig. 2b shows the result.

2.2. Semi-automatic segmentation approaches

2.2.1. Sequential method

A live wire-based approach [5] was developed. Treating images as cost-weighted graphs, dynamic programming [6] is used to find the optimal path between a user-defined start and end point. This path represents the segmented contour piece.

In order to extract the whole contour of a single region, setting the end point of the next contour piece and finding the next optimal path alternates until the contour is closed (sequential method). If the segmented contour piece is insufficient, the user can try again by choosing another end point. The longer the automatically extracted paths are, the less user interaction is needed.

2.2.1.1. Cost function. Assuming the pixels of an image as nodes and the link between neighboring pixels as edges of a cost-weighted graph (Fig. 3), the optimal path between two nodes is the one with the minimum cumulative cost calculated as a sum of local costs along this path.

The live wire approach is based on image features describing the region borders. The most important are gradient-based features describing the image edges with continuous or binary values. In order to reach a certain flexibility in applying this method to different kinds of images, four edge filters were implemented.

The feature *gradient magnitude* G can be obtained with an optimized Sobel filter or a filter based on the first derivation of the Gaussian function. The second filter allows steering the image smoothness.

Binary features B are useful to snap the path to the edge independent from its gradient strength and can be obtained with an optimized Laplacian filter or a Canny edge filter. In the first case, the zero-crossings of the resultant image are used, and a threshold to reduce uncertain zero-crossings. In the second case, non-maxima-suppression and hysteresis thresholding were implemented to binarize the results.

The gradient features will be linearly or non-linearly transformed (Fig. 4c) since high gradient magnitudes should correlate with low costs and vice versa. The gradient-based cost C_G (Fig. 4a) and the binary cost C_B (Fig. 4b) are combined in the static local cost C_{local} (Eq. (1)) (Fig. 4d). The cost function can be adjusted by weights, with $w_B = 1 - w_G$:

$$C_{\mathrm{local}} = w_G C_G + w_B C_B = w_G f(G) + w_B f(B) \quad (1)$$

A ‘‘training on the fly’’ can be switched on to allow adaptive calculation of dynamic local costs depending on the previously segmented contour.