Automated segmentation of liver metastases in diffusion-weighted echoplanar images using region growing and snakes based on fuzzy sobel edge detector

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Introduction. Diffusion MRI is gaining importance as a non-invasive and early biomarker for response to anti-cancer chemotherapies [1]. This is most relevant in metastatic diseases, which are often treated with experimental therapies with attendant morbidities [2]. Accurate diffusion MR imaging requires co-registration of multiple images obtained at different b-values. In visceral organs, motion between image data sets precludes direct registration, and current state-of-the-art involves manual circumscription of ROIs, which is time-consuming. Accurate automated segmentation of lesions would greatly facilitate these analyses and could potentially allow pixel-by-pixel, instead of ROI, determination of diffusion coefficients, ADC. However, such images present a difficult segmentation problem due to the presence of speckle, motion artifacts, low SNR and fuzzy boundaries (fig. 1). Snakes are a good choice for detecting lesion boundaries automatically, and models such as the Kass snake [3] and Gradient Vector Flow (GVF) snake [4] have been introduced. These can suffer from initialization problems and non-convergence in the presence of noise. Earlier efforts to solve the problem of initialization do not work well with these data sets [5, 6]. Introduction of additional forces can improve convergence yet requires considerably more computation time. We have solved these problems by integrating edge and region information to provide the initialization for the snake close to the lesion boundary. Fuzzy edge information is then used to guide the Kass snake to the lesion boundary.

Methods The study consisted of diffusion weighted echo-planar images liver (128x128 matrix, 6mm slice thickness) acquired on a 1.5T GE Signa scanner from patients undergoing treatment for metastatic breast cancer. The block diagram for the proposed segmentation approach is shown in fig. 2. At the outset, the images are median filtered to eliminate noise. The user initiates the next step by providing two seed points, one inside the lesion and one outside. A set of pixel values around the seed points is averaged to define characteristic intensities of the lesion (μ_{lesion}) and surrounding tissue (μ_{liver}). These μ_{lesion} and μ_{liver} are then used to automatically calculate upper (T_U) and lower (T_L) hysteresis thresholds for thresholding the gradient map obtained using a Sobel edge detector. The resulting edge map is post-processed using edge linking and isolated edge pixel cleaning. In the third step, region growing begins from the seed point inside the lesion and progresses in four directions. Average intensity and moments in an eight-connected neighborhood around each “pixel under test” (PUT) is compared with that of the growing region. The PUT is merged into the region based on gray level and moment similarities. The process terminates when the growing criterion fails or the PUT is an edge pixel or the distance from the region centroid exceeds a pre-determined size. The list of candidate boundary pixels is updated. Once all the pixels in the region are tested, Euclidean distance from each of the candidate boundary pixels to the region centroid is determined. Outliers are eliminated from the list using the average Euclidean distance statistic. A closed contour is formed using the remaining points. Due to Fuzzy boundaries, probably arising from partial volume effects, this contour is not an accurate representation of the lesion boundary. To obtain accurate segmentation results, this contour is used as the initialization for the snake. The energy function of a snake in its discrete form is written as, $E_{snake} = \alpha*E_{cont} + \beta*E_{curv} + \gamma*E_{image}$, where E_{cont} represents the energy due to discontinuities points, E_{curv} represents the curvature energy of the contour due to bending and E_{image} is the image force which is the gradient magnitude of the image calculated using a modified Fuzzy Sobel operator [7]. Fuzzy sets are constructed without the use of a difference histogram, making the procedure computationally faster than the modified Fuzzy Sobel operator. The contour that minimizes this energy function is determined using a greedy algorithm [8] within a few iterations due to the proximity of the initial contour.

Results

Figure 1A: Image slice

Figure 1B: Points selected automatically

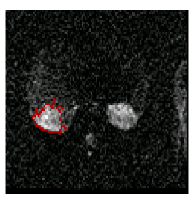

Figure 1C: Boundary detected

Image Number	1	2	3	4	5	6	7	8
MANUAL SEGMENTATION	207	239	248	152	207	227	202	183
AUTOMATIC SEGMENTATION	203	231	243	155	203	222	205	180

Table 1: Number of pixels with automated and manual segmentation

Image Number	FNR	FPR
1	0.023	0.015
2	0.019	0.033
3	0.030	0.008
4	0.022	0.015
5	0.038	0.029

Table 2: FPR and FNR in segmenting lesions

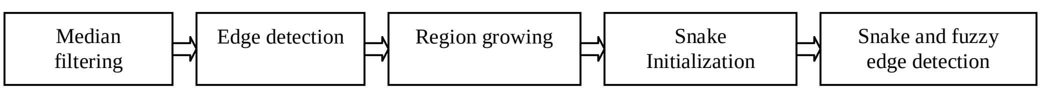

Figure 2: Block diagram

Figure 1A shows a diffusion-weighted image of the liver. The set of points selected on the lesion boundary automatically at the end of step 3 is shown in fig. 1B. The snake applied to the initial contour formed using these points, converges to the lesion boundary as shown in fig. 1C. Automatically segmented data sets were quantitatively compared to data obtained by manual ROI circumscription by an experienced radiologist. Table 1 shows the number of pixels identified in 8 lesions, showing that number of pixels were almost identical between computer-aided and manually circumscribed methods. Table 2 compares the data on a pixel-by-pixel basis. The false negative ratio (FNR) is the percent of lesion pixels in the hand-segmented data that were labeled as non-lesion pixels by the automated scheme. The false positive ratio (FPR) is the percent of lesion pixels in the automated assignment that were labeled as non-lesion pixels by the radiologist. As shown, the maximum error observed by this analysis was 3.8%. We did not observe any systematic relationship between the magnitude of these errors and lesion size or signal intensity.

Conclusion A method for combining edge detection and region growing with the snake model is presented. The edge and region information provides the snake model with shape and size information of the lesion by means of an initial contour. The thresholds for edge detection are calculated automatically. The user interaction is limited to providing two seed points to the algorithm. The snake, guided by fuzzy edge information deforms from the initial contour thus formed, providing accurate representation of the lesion boundary. Results obtained from this algorithm are comparable to those obtained from manual segmentation by an experienced radiologist.

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