Fuzzy Clustering Driven Anisotropic Diffusion: Enhancement and Segmentation of Cardiac MR Images

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Summary

Image processing techniques are greatly devoted to locate boundaries of objects in addition to clear images from noise. Methods like anisotropic diffusion that work on a scale-space achieve good general results encouraging intra- rather than inter-region diffusion by using differential information of the data. Perona and Malik [1] have proposed a space-variant blurring which leads to the anisotropic diffusion equation

$$\frac{\partial I(x,y)}{\partial \tau} = \nabla \cdot (c(x,y) \nabla I(x,y)), \quad (1)$$

where c is the monotonically decreasing function of the magnitude of the gradient of the intensity:

$$c = g(\|\nabla I\|) = \frac{1}{1 + (\frac{\|\nabla I\|}{k})^2}. \quad (2)$$

A conductance function defined in this manner weakens the diffusion process for values of the gradient of the intensity larger than a parameter k. As a consequence the conductance function allows diffusion at edges with low gradient values (which are presumed to be spurious edges) and prevents diffusion at edges with high gradient values (which are presumed to be significant edges).

However, we notice that this and other geometry-driven approaches rely only on the local differential structure of the data while ignoring the global characteristics of the system [2]. As a consequence results are still poor in regions of the images with low contrast and low signal-to-noise ratio, where the differential characteristics of data do not provide the required information. Moreover, most works oversimplify the conductance function of the diffusion process and ignore important features of the system such as non-homogeneous data sampling [3, 4].

In previous articles [5, 6] we proposed a second rank tensor conductance function with an explicit dependence on the space coordinates and the data function. This scheme gives the equations an intrinsic anisotropic character not present in previous approaches, and allows the use of *a priori* knowledge of the system in multi-feature and multi-dimensional images.

In this article we extend that scheme by introducing a fuzzy clustering algorithm that, using information about the intensity distribution, divides the image domain into regions and assigns every pixel in the image a degree of membership to the clusters, *i.e.* a probability of belonging to each of the regions. For this purpose we employ a fuzzy c-means algorithm [7] in which we introduce *a priori* knowledge about the system by using a planispheric coordinate system that exploits the approximate elliptic-paraboloidal shape and symmetry of the left ventricle.

The fuzzy classification of the image domain provides a measure of the probability that neighbouring pixels belong to the same tissue type, and is therefore incorporated into the diffusion process by means of the conductance function. The clustering is updated at regular intervals during the diffusion process, and the initially coarse segmentation of the image is gradually improved until it converges to a meaningful segmentation of the image regions as the smoothing action of the diffusion process clears the image from noise.

The combined diffusion-clustering algorithm penalizes inter-cluster diffusion and encourages intra-cluster diffusion, resulting in homogeneous intensity clusters with high contrast between them. The two driving mechanisms of the diffusion process are on the one hand, the gradient based function governed by the differential structure of the image, and on the other hand, the intensity and spatial based clustering through which knowledge has been introduced about the shape of the relevant structures in the image. Since the clustering scheme uses non-local information in order to perform the classification, the diffusion process is enriched with information about the global characteristics of the image.

We have applied this method to cine volumetric (4D) cardiac images. In figure 1 we show edge detection results of standard anisotropic diffusion and those of the proposed scheme on a 2D MR image. The first row shows, from left to right, the original image, the image processed with standard anisotropic diffusion, with cluster-driven anisotropic diffusion, and on the extreme right, the segmentation results of the clustering scheme. The second row shows the magnitude of the gradient of the corresponding images above, except for the last column where the colour palette for images on the third row is shown.

In the third row we use the graphic device GER-RGB (graphic edge representation from red, green and blue) [6] that facilitates the comparison of the edges' positions and sharpness between two or three different images. The gradient images of the second row were thresholded using Canny's noise estimator [8] and the resulting binary images have been coloured and laid over the original MR image (blue for the original image, red for the standard diffusion and green for cluster-driven diffusion).

The fourth and fifth columns show respectively the red-green and red-green-blue superpositions of the colour thresholds described above. It is clear that the proposed diffusion scheme preserves some regions of the boundary of the myocardium that are eroded by standard anisotropic diffusion and also that it enhances edges obscured by noise in

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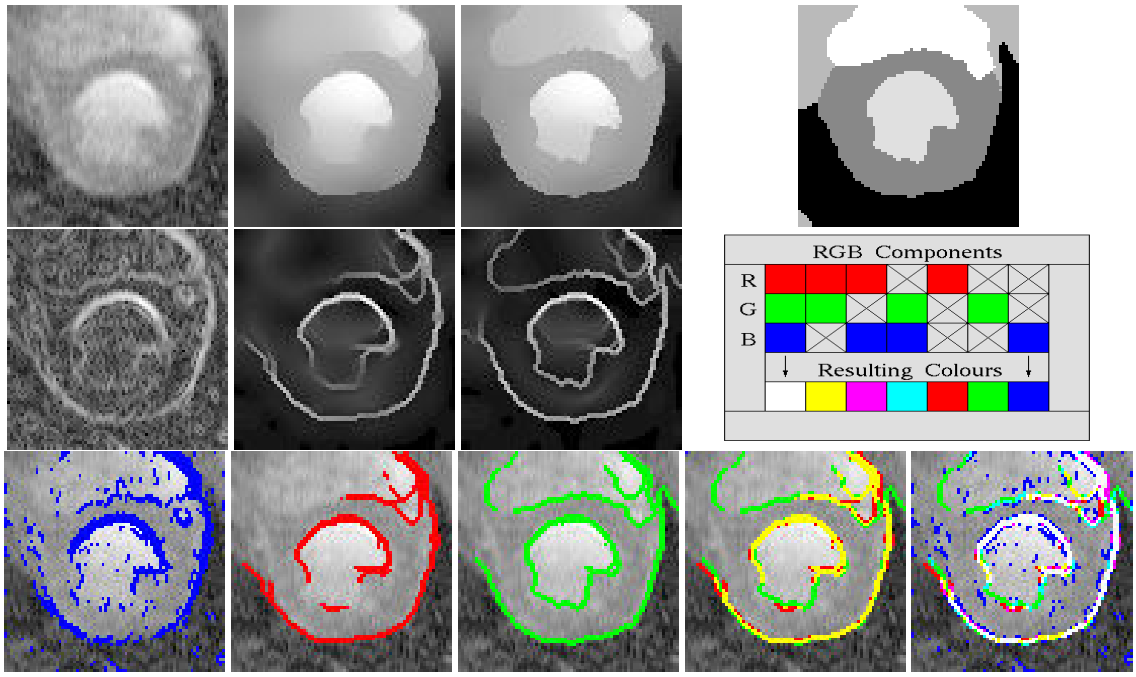

Figure 1: Comparison, using the GER-RGB device, between the results of a 2D MR image diffused with standard anisotropic diffusion and with cluster-driven anisotropic diffusion.

the original image.

Figure 2 shows the isosurface volume rendering of the left ventricular endocardium produced from 3D MR data after 5 (top) and 50 (bottom) iterations of the proposed diffusion process. The segmentation results exclude the papillary muscle from the LV chamber.

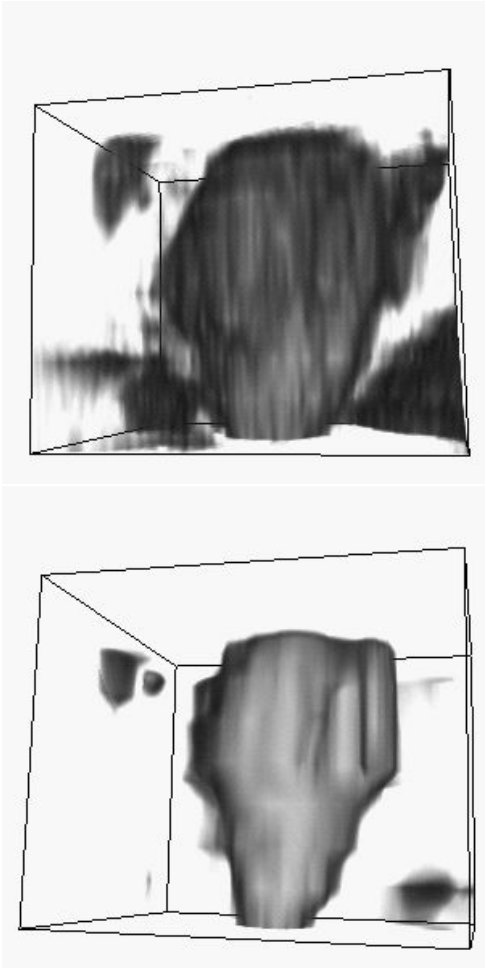

Figure 2: Volume rendering of the left ventricular endocardium produced from MR data after 5 (top) and 50 (bottom) iterations of the proposed diffusion process.

I. References

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