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Spatial continuity incorporated multi-attribute fuzzy clustering algorithm for blood vessels segmentation

HAO JuTao[1]*, ZHAO JingJing[2] & LI MingLu[3]

[1] *School of Optical-Electrical and Computer Engineering, University of Shanghai for Science and Technology, Shanghai* 200093*, China;*
[2] *Department of Electrical Engineering, Shanghai University of Electric Power, Shanghai* 200090*, China;*
[3] *Department of Computer Science and Engineering, Shanghai Jiaotong University, Shanghai* 200240*, China*

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Abstract A three-dimensional representation of vasculature can be extremely important in image-guided neurosurgery, pre-surgical planning. In this paper, a spatial continuity incorporated multi-attribute fuzzy clustering algorithm (MAFCM_S) is proposed to segment entire blood vessels from TOF MRA images. This clustering method takes both the intensity information and the geometrical information into account, while most of the current clustering methods only deal with the former. In this method, a new dissimilarity measure, which integrates the intensity and the geometry shape dissimilarity, is introduced. Because of the presence of the geometrical information, the new measure is able to differentiate the pixels with similar intensity values within different geometrical shape structures. Experimental results show that the new algorithm can get better segmentation.

Keywords fuzzy c-means clustering, scale space analysis, spatial continuity, blood vessel segmentation, multi-attribute fuzzy clustering

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1 Introduction

Vessel analysis in medical images is important both for diagnostic and intervention planning purposes, especially, a three-dimensional representation of vasculature can be extremely important in image-guided neurosurgery, pre-surgical planning. A common approach is to use a maximum intensity projection (MIP) where three-dimensional (3D) data is projected onto a 2D plane by choosing the maximal intensity value along that projection direction. A major drawback of this method is that background artifacts and other tissues may occlude vascular structures of low contrast and small width. Thus, it is desirable to extract the vasculature tree before it is visualized. A variety of approaches have been proposed for the segmentation of vasculature in MRA datasets [1, 2]. These methods can be classified into four categories: scale space analysis, deformable models, statistical models, and hybrid methods.

In multiscale filtering, each image is convolved with a series of Gaussian filters at different scales. The eigenvalues of the Hessian matrix at each voxel in the image is analyzed to determine where it belongs

*Corresponding author (email: jt_hao@usst.edu.cn)

to blood vessels or a background. The output of this filter is used to define an enhanced set of images in which blood vessels are brightened, while background noise and planar structures such as skin are darkened. Enhanced images are either visualized directly [3], thresholded [4], or segmented using an active contour method [5].

Geodesic active contours were proposed to segment MRA speed image [6]. In [7] flux maximizing geometrical flows were proposed to segmenting elongated structures that appear as bright regions in an intensity image but may have low contrast. The key idea is to incorporate not only the magnitude but also the direction of an appropriate vector field. An implicit deformable model with a soft shape prior was used to segment blood vessels [8].

Statistical models for extraction blood vessel from TOF data were proposed in [9, 10]. Both speed and phase information provided by PCA are fused together to enhance the vessel segmentation [11]. Iso-intensity structural orientation was used in [12] to segment blood vessels, which exploits the coherence in the intensity profile.

Magnetic resonance angiography (MRA) is a noninvasive MRI-based flow imaging technique. Its wide variety of acquisition sequences and techniques, beside its ability to provide detailed images of blood vessels, enabled its use in the diagnosis and surgical planning of the cerebrovascular diseases. There are three techniques commonly used in performing MRA; time-of-flight (TOF) angiography, phase contrast angiography (PCA), and contrast enhanced MRA (CE-MRA). TOF relies on the difference in the amplitude of longitudinal magnetization between flowing and static spins. The TOF technique is not as quantitative but it is widely used clinically because it is fast and provides high contrast images, which is the main motivation behind our work.

There are many factors make blood vessels segmentation to be a challenging task. First, in essence, blood vessels are elongated structures whose widths vary largely from great arteries to blood capillary. Second, the theory of TOF MRA imaging makes the gray-scale range of blood vessels wide. Furthermore, noise and artifacts exert additional difficulties on the segmentation.

In this paper, a spatial continuity incorporated multi-attribute fuzzy clustering algorithm (MAFCM_S) is proposed to segment entire blood vessels from TOF MRA images. This clustering method takes both the intensity information and the geometrical information into account while most of the current clustering methods only deal with the former. In this method, a new dissimilarity measure, which integrates the intensity and the geometry shape dissimilarity, is introduced. Because of the presence of the geometrical information, the new measure is able to differentiate the pixels with similar intensity values within different geometrical shape structures. Experimental results show that the new algorithm can get better segmentation results.

2 Geometrical attribute of blood vessels

2.1 Features of time of flight MRA images

The speed image of TOF MRA provides information of the patients' blood flow. The intensity values in the image are proportional to the flow velocity. Because of the blood viscosity, frictional force slows down the blood flow near the vascular wall. As such, the intensity profile is nonuniform within the vascular structures. As shown in Figure 1, the intensity value is relatively low at the boundary of vessels in the angiogram, while the intensity value is high near the center of the vessels. The intensity inhomogeneity is a challenge if the vascular segmentation is to be robust. Analyzing TOF MRA images structure of the grey value distribution within a local neighborhood of a pixel plays an important role. One possible approach to local structure analysis is the local orientation. This property which is also main motivation behind our work has been applied in image segmentation [4, 7] and enhancement [3].

Based on the theory of MRA imaging and cylinder-like geometrical shape of blood vessels, several multi-scale approaches to modeling tubular in intensity images have been proposed. In this paper, Frangi's multiscale vessel enhancement filter will be exploited to extract geometrical attribute from original intensity image.

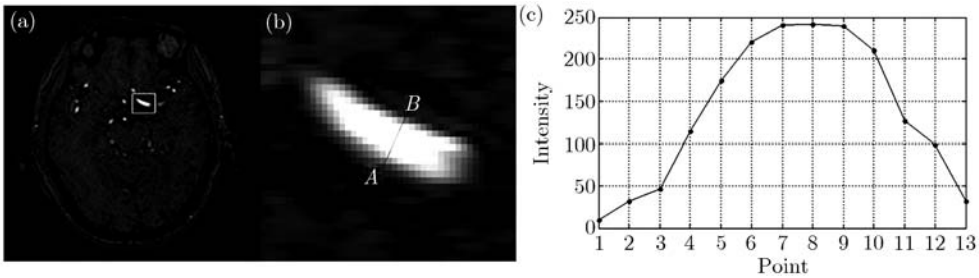

Figure 1 (a) TOF MRA image; (b) close-up of the square region in (a); (c) intensity profile of line AB in (b).

2.2 Geometrical shape feature based enhancement

Several multi-scale approaches to modeling tubular structures in intensity images have been based on properties of the Eigen values λ_1, λ_2, λ_3 of the Hessian matrix H. We choose to focus here on Frangi's vesselness measure because it incorporates information from all three eigenvalues [3]. With the eigenvalues sorted such that $|\lambda_1| \leqslant |\lambda_2| \leqslant |\lambda_3|$, three quantities are defined to differentiate blood vessels from other structures:

$$R_A = \frac{|\lambda_2|}{|\lambda_3|}, \tag{1}$$

$$R_B = \frac{|\lambda_1|}{\sqrt[2]{|\lambda_2 \lambda_3|}}, \tag{2}$$

$$S = \sqrt[2]{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}, \tag{3}$$

where R_A is essential for distinguishing between plate-like and line-like structures, R_B differentiates sheet-like objects from other structures. S is used to ensure that random noise effects are suppressed from the response.

The vesselness measure is then defined by

$$V(\lambda) = \begin{cases} 0, & \lambda_2 < 0 \text{ or } \lambda_3 < 0, \\ \left\{ \left(1 - \exp\left(-\frac{R_A^2}{2\alpha^2}\right)\right) \exp\left(-\frac{R_B^2}{2\beta^2}\right) \left(1 - \exp\left(-\frac{S^2}{2c_2}\right)\right) \right\}, & \text{else}, \end{cases} \tag{4}$$

where α, β and c are thresholds which control the sensitivity of the line filter to the measures R_A, R_B and S. The idea behind this expression is to map the features R_A, R_B and S into probability-like estimates of vesselness according to different criteria. The different criteria are combined using their product to ensure that the response of the filter is maximal only if all three criteria are fulfilled. In all the results presented in this work α and β were fixed to 0.5. The value of the threshold c depends on the grey-scale range of the image and half the value of the maximum Hessian norm has proven to work in most cases.

3 Multi-attribute based fuzzy clustering algorithm

The fuzzy C-means algorithm (FCM) has been utilized in a wide variety of image processing application such as medical imaging [13, 14]. Its advantages include a straightforward implementation, fairly robust behavior, applicability to multichannel data, and the ability to model uncertainty within the data.

Mathematically, FCM is derived to minimize the following objective function with respect to the membership functions μ_{ij} and centroids ν_{ij}

$$J_{\mathrm{FCM}} = \sum_{j \in \Omega} \sum_{i=1}^{C} (\mu_{ij}^m \parallel y_j - \nu_i \parallel^2), \tag{5}$$

where y_j is the observation at pixel j, C is the number of clusters or classes, and Ω is the image domain. The parameter $m(m > 1)$ is a weighting exponent on each fuzzy membership and determines the amount of "fuzziness" of the resulting classification. The membership functions are constrained to be positive and to satisfy

$$\sum_{i=1}^{C} \mu_{ij} = 1. \tag{6}$$

It is apparent from eq. (6) that the FCM objective function does not take into consideration any spatial dependence between observations. Thus, the computed membership functions can exhibit sensitivity to noise in the observed image. Spatially constrained fuzzy clustering algorithms were proposed in [15, 16]. The objective function of the spatial constraints FCM (FCM_S) was defined as follows:

$$J_{\mathrm{FCM\_S}} = \sum_{j=1}^{N} \sum_{i=1}^{C} (\mu_{ij}^{m} \parallel y_j - \nu_i \parallel^2) + \frac{\alpha}{N_R} \sum_{j=1}^{N} \sum_{i=1}^{C} \mu_{ij}^{m} \sum_{r \in N_j} \parallel y_j - \nu_i \parallel^2, \tag{7}$$

where N_j stands for the set of neighbors falling into a window around j and N_R is its cardinality. The parameter α controls the effect of the penalty.

Though FCM_S is more robust in dealing with noise than traditional FCM, it only utilizes the intensity information of the original images and the dissimilarity measure is a function of the distance between the feature vectors and the centroids without the knowledge of the geometrical shape of the blood vessels. Generally, fuzzy c-means cannot give satisfactory segmentation for MRA images because the dissimilarity measure solely using the intensity information may lose many thin blood vessels due to low contrast with background.

In order to obtain a more exact classification, a multi-attribute based fuzzy clustering algorithm will be adopted in which geometrical attribute of blood vessels has incorporated. Firstly, we use a multiscale vessel filter to enhance the original images. In the enhanced images, the blood vessels are brightened, while background noise and planar structures are darkened. Thus, the contrast between blood capillary and background is enlarged which is helpful for segmenting tiny branch. Secondly, the intensity attribute in original images and geometrical shape information of blood vessels in enhanced images are incorporated in to a fuzzy clustering algorithm. Observing Frangi's enhancement filter we can find that the output of the filter has no direct relation with the real intensity of original image but only to capture the geometrical information of the blood vessels in the image. The newly proposed algorithm can deal with the problems of traditional FCM algorithm. On the one hand, due to the use of geometrical information, the proposed MAFCM_S can prevent the misclassification of blood capillary and background, meanwhile, high intensity noise and great arteries. On the other hand, the use of intensity attribute of blood vessels can greatly improve the capability in classifying blood vessels and other tubular structures.

Given a dataset $\Gamma = \{y_1, y_2, \ldots, y_N\} \in \mathbb{R}^L$ the task of clustering means partitioning Γ into C clusters. Suppose each datum y_j=$\{y_{j1}$,$y_{j2}, \ldots, y_{jL}\}$. The proposed multi-attribute based fuzzy clustering algorithm (MAFCM_S) is to minimize the following objective function:

$$J_{\mathrm{MAFCM\_S}} = \sum_{j=1}^{N} \sum_{i=1}^{C} \sum_{k=1}^{L} (\mu_{ij}^{m}) \Bigg(\parallel y_{jk} - \nu_{ik} \parallel^2 + \frac{\alpha}{N_R} \sum_{r \in N_j} \parallel y_{rk} - \nu_{ik} \parallel^2 \Bigg). \tag{8}$$

An iterative algorithm for minimizing (8) can be derived by evaluating the centroids and membership function that satisfy a zero gradient condition. Taking the partial derivative of (8) with respective to and setting this partial derivative to zero yields

$$\mu_{ij} = \frac{(\sum_{k=1}^{L} (\parallel y_{jk} - \nu_{ik} \parallel^2 + \sum_{r \in N_j} \parallel y_{rk} - \nu_{ik} \parallel^2))^{-\frac{1}{m-1}}}{\sum_{\omega=1}^{C} (\sum_{k=1}^{L} (\parallel y_{jk} - \nu_{\omega k} \parallel^2 + \frac{\alpha}{N_R} \sum_{r \in N_j} \parallel y_{rk} - \nu_{\omega k} \parallel^2))^{-\frac{1}{m-1}}}. \tag{9}$$

Minimizing (8) with respect to ν_{ij}, we obtain the iterative function

$$\nu_{ik} = \frac{\sum_{j=1}^{N} \mu_{ij}^{m} (y_{jk} + \frac{\alpha}{N_R} \sum_{r \in N_j} y_{rk})}{(1+\alpha)\mu_{ij}^{m}}. \tag{10}$$

The spatial continuity incorporated multi-attribute fuzzy clustering algorithm (MAFCM_S) can be summarized briefly as follows:

1. Let $t = 1$, initialize $v_i^{(t-1)} = (v_{i1}, v_{i2}, \ldots, v_{iL}), 1 \leqslant i \leqslant C$;
   Set $J_{\text{MAFCM\_S}}^{(t-1)} = \xi$, where ξ is a small constant.
2. Compute $\mu_{ij}^{(t)}$ according to (9);
3. Calculate v_{ik}^{t} based on (10);
4. Obtain $J_{\text{MAFCM\_S}}^{(t-1)}$ with (8);
5. If $|J_{\text{MAFCM\_S}}^{(t)} - J_{\text{MAFCM\_S}}^{(t-1)}| < \xi$, stop.
   Else $t \leftarrow t + 1$, go to step 2;
   End if.

4 Experimental results

In this section, our MAFCM_S algorithm has been tested on 2D MIP image and 3D images. In the experiments, the parameters are set as follows: $C = 3; m = 2, \alpha = 0.2, N_R = 4$ (for 2D images) or N_R=6 (for 3D image). A notation MAFCM is introduced here which refers to the multi-attribute based fuzzy clustering algorithm without spatial continuity constraints.

4.1 Experiment on 2D images

We conducted FCM, and our proposed MAFCM_S on 2D images. In order to illustrate the performance of MAFCM_S intuitively, we exert our algorithm on the MIP images. An original MIP image is shown in Figure 2(a), from which we can see that intensity range of blood vessels is very large. Enhanced image with a scale σ =0.8 is shown in Figure 2(b). Figure 2(c) and (d) show the binary segmentation results of FCM and MAFCM_S respectively, from which we can see that MAFCM_S has great capabilities in detecting tiny branches than only intensity information used FCM algorithm.

4.2 Experiments on 3D images

In this section, our proposed algorithm has been tested on several 3D TOF MRA datasets obtained from Tongji Hospital. These datasets shown here are acquired on a 1.5T MRI scanner with different voxel sizes and image sizes. Vessel surfaces are rendered in 3D using the visualization toolkit (VTK).

To evaluate the performance of our algorithm, comparisons are done not only with the maximum intensity projection (MIP) images but also segmentation results obtained by Hassouna's approach [9].

We exert our algorithm on the first dataset with voxel size of 0.859 mm×0.859 mm×1.0 mm and image size of 256×256×123 voxels. Figure 3(a) shows the maximum-intensity projection of the dataset. Segmentation results using FCM and MAFCM_S are shown in Figure 3(b) and (c) respectively. Segmentation by Hassouna's approach is illustrated in Figure 3(d). In this experiment, our goal is to obtain thin vessels as much as possible. Therefore, the scale is defined as a constant and fixed to σ=0.8. Comparing Figure 3(b), (c) and (d), we can find that due to both intensity and geometrical information have been incorporated into traditional FCM framework, the newly proposed MAFCM_S algorithm is able to capture more thin vessels than other method in which sole intensity information is used.

Furthermore, our method has been applied to another dataset which has the image sizes 256×256×115 with spatial resolution 0.859×0.859×1.017. The segmentation results are shown in Figure 4. In this figure, (a) shows the MIP image. Segmentation results using FCM and FCM_S are shown in Figure 4(b) and (c) respectively. The segmentation results using both intensity and geometrical information are presented in Figure 4(d) and (e), and the difference between them is in (e) spatial constraint has been considered. Segmentation results of our approach and Hassouna's are presented in (e) and (f), respectively.

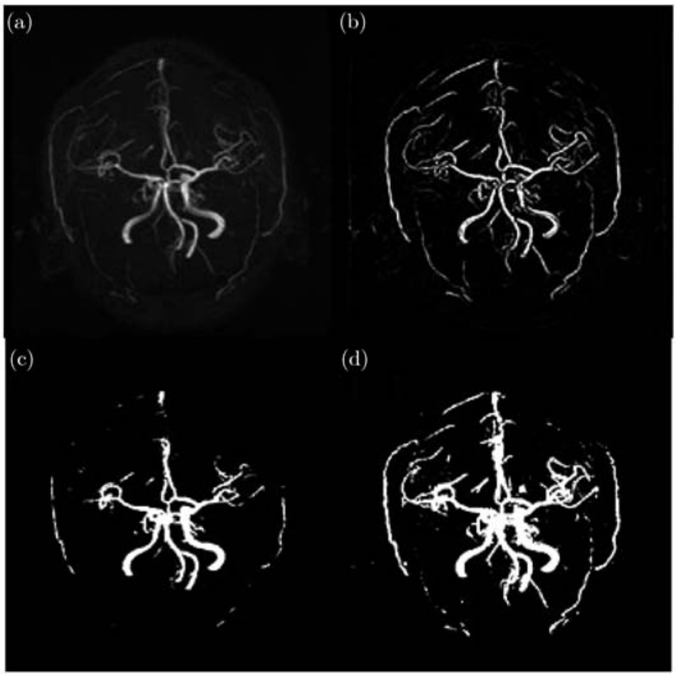

Figure 2 Comparison segmentation results of FCM and MAFCM_S on MIP image. (a) Original MIP image; (b) enhanced image with a scale σ=0.8; (c) and (d) binary segmentation results of FCM and MAFCM_S respectively.

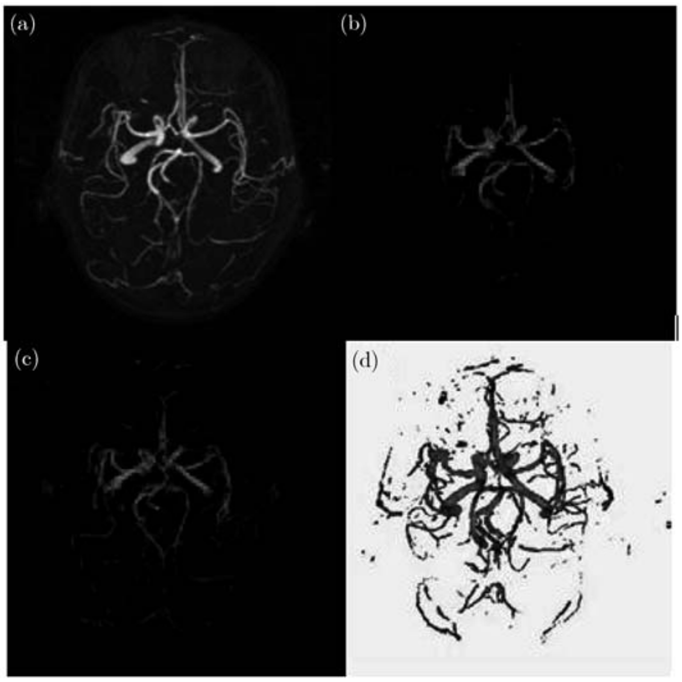

Figure 3 An illustration of segmentation results on 123×256×256 3D MRA image. (a) MIP images; (b) segmentation results using FCM; (c) segmentation results using MAFCM_S; (d) segmentation by Hassouna's approach.

5 Conclusions

In this paper, a spatial continuity incorporated multi-attribute fuzzy clustering algorithm (MAFCM_S) is proposed to segment entire blood vessels from TOF MRA images. This clustering method takes both

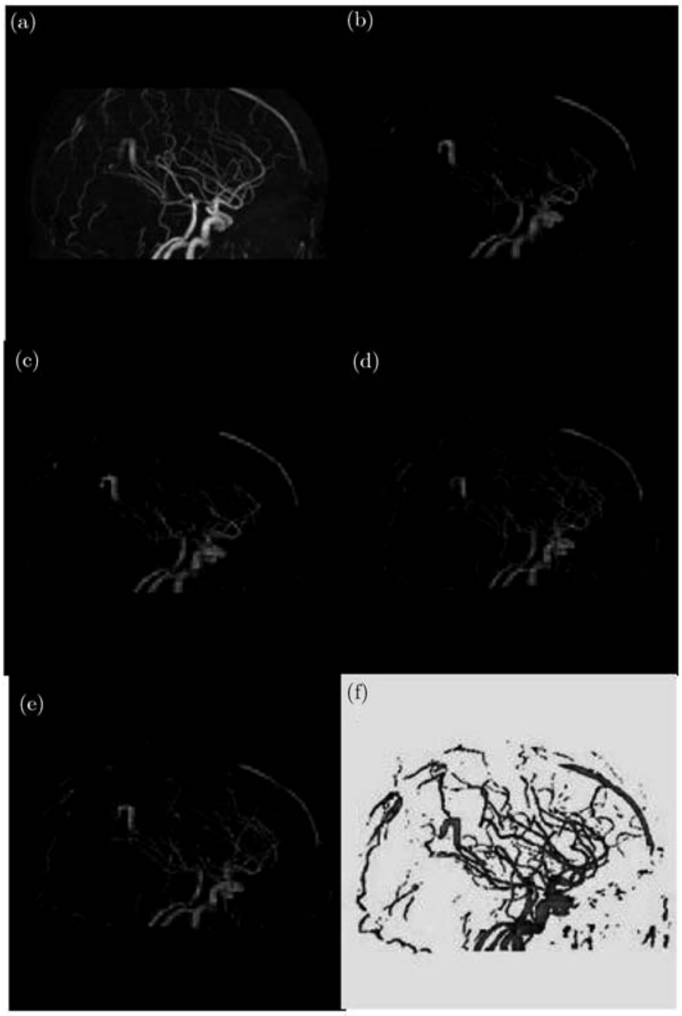

Figure 4 An illustration of segmentation results on 115×256×256 3D MRA image. (a) MIP images; (b) segmentation results using FCM; (c) using FCM_S; (d) using MAFCM; (e) using MAFCM_S; (f) segmentation by Hassouna's approach.

the intensity information and the geometrical information into account while most of the current clustering methods only deal with the former. The segmentation results have won the approval of the experts in Tongji Hospital. The results illustrate that the proposed method can provide a better quality segmentation than sole intensity information used method.

Although more accurate segmentation can be obtained by the proposed method, two problems still remain and need to be further resolved. Firstly, additional computation time shall be taken for the shape feature extraction, and secondly, it involves further research on how to evaluating the performance quantitatively. The proposed algorithm is designed to cope with the large TOF data volume with wide intensity range of blood vessels. However, such situation is very difficult to be simulated. How to accelerate the segmentation process and evaluate the performance quantitatively will be the emphases of our further work.

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