Automated Segmentation of Carotid Artery Vessel Wall in MRI

Bo Wang[1](✉), Gang Sha[2], Pengju Yin[3,4], and Xia Liu[1]

[1] School of Automation, Harbin University of Science and Technology, Harbin 150080, China
{hust_wb, liuxia}@hrbust.edu.cn
[2] School of Computer Science, Northwestern Polytechnical University, Xi'an 710068, China
shagang@mail.nwpu.edu.cn
[3] School of Life Science and Technology, XiDian University, Xi'an 710126, China
pengju.yin@outlook.com
[4] Xi'an Realme 3D Co. Ltd., Xi'an 710075, Shannxi, China

Abstract. Automatic or semi-automatic segmentation of carotid artery wall in MRI is an important means of early detection of atherosclerosis. In this paper, a new algorithm is proposed for the automated segmentation of the lumen, outer boundary and plaque contours in carotid MR images. It uses the ellipse fitting to detect the outer wall boundaries. By using the outer wall boundaries as the constraint condition, the lumen is detected using an improved fuzzy C-Means (FCM). The plaque is located by obtaining the area changing of lumen. The experimental results show that our method achieves 95.7% of region overlaps when compared to the gold standard results. This new automated method can enhance reproducibility of the quantification of vessel wall dimensions in clinical studies.

Keywords: Medical image segmentation · Carotid artery MRI
Ellipse fitting · Fuzzy C-Means

1 Introduction

Atherosclerosis is a progressive disease which, at an early stage, is characterized by vessel wall thickening causing outward remodeling, then narrowing of the lumen, and at a later stage by the formation of plaque lesions inside the vessel wall [1]. Medical image segmentation is an important means of early detection of atherosclerosis, through the MR image to detect carotid artery atherosclerotic lesions, the urgent need for an automatic or semi-automatic carotid artery segmentation method to help doctors on the diagnosis of atherosclerosis or treatment. However, MR images are susceptible to factors such as speckle noise, artifacts, and weak boundaries, which result in segmentation failure. Therefore, the design of the highly robust MR carotid artery wall segmentation method is still a challenging problem in the field of medical image processing.

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Currently, quantitative assessment of the vessel wall dimensions is based on manual tracing of the lumen and outer wall boundaries, which is time-consuming and subject to inter- and intra-observer variation. Consequently, computerized segmentation techniques have been developed to overcome these limitations [2–9]. Petroudi *et al.* [10] put forward the active contour and level set method segmentation vascular access IMC (intima-media complex). The continuous curve is obtained by active contour method to represent the carotid artery boundary, then the energy functional method based on level set boundaries to get blood vessels. But other organizational structures of the blood vessel image often overlaps with carotid artery blood vessels or deformation fuzzy boundaries. This is expected to result in the decline in the method segmentation accuracy greatly. Yang *et al.* [11] put forward by using Hoff round model transformation and dynamic programming method to determine the boundary of the carotid artery, the shape and size of the area to get blood vessels by judging center, but this method is to obtain the outer wall of the carotid artery, not the specific segmentation internal cavity. Menchón-Lara and Sancho-Gómez [12] propose the method based on an artificial neural network of the blood vessels image segmentation, and then machine learning and statistical pattern recognition is used to measure the thickness of the carotid artery middle IMT (Intima Media Thickness). Despite the lining thickness of the carotid artery is measured to identify the location of the plaques, but on the judgement of the size and shape of the plaques have certain limitations.

Accordingly, the purpose of this study was to develop a highly automated image segmentation technique for the detection of the lumen and outer wall boundaries, as well as the contours of the plaques in MR vessel wall images of the carotid artery. The basis of this method is ellipse fitting-based segmentation combined with fuzzy C-Means. The accuracy and reproducibility of this method in measuring the contours and total wall area were implemented using *in vivo* MR images of carotid arteries.

2 Methods

The mainly target of this method is to detect the lumen, outer boundary and plaque contours of carotid artery vessel wall in MR images. The structure of this method is illustrated Fig. 1.

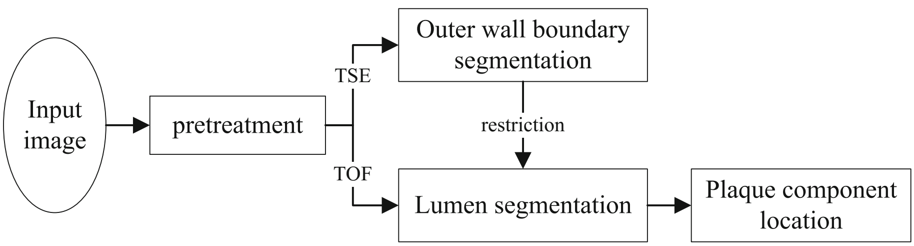


Fig. 1. Overall structure of the method.

2.1 Pretreatment of Carotid Artery Vessel Wall in MRI

Pretreatment is an important part of the process of image segmentation. The input image is distinct from the image acquisition environment. Such as the illumination level and the performance of the device, the image noise, contrast the defect of low doped and so on. In addition, the distance, focal length and other factors lead to vascular uncertainty in the size and position of the image in the middle. In order to ensure the consistency of the vessel size, location and the quality of the carotid artery vessels, the image must be pre-processed.

This algorithm first introduced into the algorithm of pre-processing line gray level stretches, and the gray scale of the original image is converted to [0, 255], the linear stretches is defined as follows:

$$h(x,y) = \frac{255}{(B-A)}(f(x,y) - A). \tag{1}$$

where A, B is the original image gray scale minimum and maximum, $h(x, y)$ and $f(x, y)$ are the images after and before stretching, respectively.

After the linear stretching of the image from the existence from isolated mutations of the noise point, so the algorithm uses the two-dimensional zero mean discrete Gauss smoothing, which is defined as follows:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}. \tag{2}$$

Blood vessel location is to obtain the blood vessel position and provide the basis of the following blood vessel segmentation. Image enhancement is to improve the quality of the image, not only to make the image more clearly, and make the image more conducive to computer processing and recognition. The goal of the normalized work is to obtain the same normalized blood vessel images of the same size as the gray scale.

2.2 Outer Wall Boundaries Segmentation

In this paper, the outer wall of the blood vessel is segmented by using ellipse fitting. Firstly, the least squares method is used to find the parameter set.

$$Ax^2 + Bxy + Cy^2 + Dx + Ey + F = 0. \tag{3}$$

In order to avoid zero solution, the parameters are restricted to A + C = 1. Obviously, the direct application Eq. (3) of the edge detection of the discrete points for the least squares, objective function $f(A, B, C, D, E, F)$, when the objective function values, minimum satisfies:

$$f(A,B,C,D,E,F) = \sum_{i=1}^{x} \left(Ax_i^2 + Bx_iy_i + Cy_i^2 + Dx_i + Ey_i + F\right)^2. \tag{4}$$

$$\frac{\partial f}{\partial A}=\frac{\partial f}{\partial B}=\frac{\partial f}{\partial C}=\frac{\partial f}{\partial D}=\frac{\partial f}{\partial E}=\frac{\partial f}{\partial F}=0. \tag{5}$$

When there is an impurity in the sample point, result in considerable error of ellipse fitting, cannot meet the accuracy requirements of medical diagnosis. In order to obtain the accurate edge of the vessel boundary, the major a axis, the short b axis and the center point (x, y) of the ellipse is obtained by the ellipse fitting. By changing the setting of a, b and the ellipse angle, many different ellipse can be obtained. Calculate the average gray value of all points on the ellipse, to find the best ellipse as the outer wall boundary of the blood vessels through the gray level of the adjacent ellipse between the Laplace operators.

$$\vec{P}_i=\frac{\sum_{i=1}^{n}h(x_i,y_i)}{n} \tag{6}$$

$$dp_i=p_i-p_{i-1}. \tag{7}$$

$$ddp_i=dp_i-dp_{i-1}. \tag{8}$$

Although the algorithm uses elliptical model to obtain the outer wall boundary, but there is still a big error in the actual vessel boundary, the images of the external wall of the carotid artery were converted to polar coordinate system, and the x axis in polar coordinates was expressed as the angle of the image in cartesian space(the connection between the points and the origin of the image, and the angle formed by the x axis), angle range of [−π, π], the y axis represents the radius (image under the cartesian coordinate space in point-to-point distance), the radius of [0, R]. The dynamic programming method is to do the best path from the first column to the last column in the polar coordinates.

The definition of the cost function $k(i, j)$ for the final determination of the ellipse to get the most close to the boundary of the vessel wall, which is defined as follows [13]:

$$k(i,j)=w_s s(i,j)+w_g g(i,j)+w_d d(i,j). \tag{9}$$

where (i, j) are the coordinates of a point in polar coordinates. w_s, w_g and w_d are the weight of the corresponding components of the cost function, respectively. s, g and d are the edge strength, the size of the blood vessels, and expectations deviation of gray, respectively.

$$s(i,j)=\frac{\max(y')-y'(i,j)}{\max(y')}. \tag{10}$$

$$g(i,j)=\frac{g_{\max}-g(i,j)}{g_{\max}-g_{\min}}. \tag{11}$$

where $\max(y')$ is the maximum gradient value, $y'(i, j)$ is the vertical direction gradient value of each point.

In the polar coordinate image, the value component assigns the same value to the pixel at the same radius length at different angles, unless the swollen shape is an absolute circle, otherwise it cannot appear at the same radius length at different angles. The pixels have the same edge information. It is judged that it belongs to a certain region by obtaining information on the difference in the luminance value between the pixel point and the neighboring point. The new definition of the cost component is $r(i, j)$ instead of $d(i, j)$, which is defined as follows:

$$r(i,j) = \sqrt{G(i,j)^2 + G(i,j-1)^2 - 2G(i,j)G(i,j-1)}. \tag{12}$$

After the end of the optimal path is determined, then the reverse sequence is used to find the pixels of each column in this path.

2.3 Lumen Segmentation and Plaque Location

In this paper, the classical FCM algorithm is improved to extract the blood vessel cavity, the segmentation of the cavity is mainly in the outer wall of the wall based on the extraction of the inner wall and plaque positioning.

Fuzzy *C* means clustering method is a method of avoiding the problem of setting a threshold, and it can solve the segmentation problem of multiple branches which are difficult to solve. *FCM* is suitable for the characteristics of the uncertainty and ambiguity of the image. Specific definitions are as follows: FCM divides the data set into C fuzzy group $\boldsymbol{X} = \{x_1, x_2, \ldots, x_n\}$, and seek the clustering center of each group, the value function of non-similarity index reaches the minimum. *FCM* makes a given data point in (0, 1) between the membership to determine the degree of belonging to each group. However, in accordance with the provisions of the normalization, the membership of a data set and the total is equivalent to 1:

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1, \ldots, n. \tag{13}$$

Then, the value function (or objective function) of FCM is illustrated as follows:

$$J(U, c_1, \ldots, c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j}^{n} u_{ij}^m d_{ij}^2. \tag{14}$$

where the u_{ij} value range of the objective function is [0, 1], c_i clustering center for fuzzy group $\boldsymbol{X}$. $d_{ij} = \|c_i - x_j\|$ is expressed as the i cluster center and the j data point between the Euclidean distance. m is a weighted index, range in $[1, \infty)$, construct a new objective function, which is described as follows:

$$
\begin{aligned}
J(U, c_1, \ldots, c_c, \lambda_1, \ldots, \lambda_n) &= J(U, c_1, \ldots, c_c) + \sum_{j=1}^{n} \lambda_i (\sum_{i=1}^{c} u_{ij} - 1) \\
&= \sum_{i=1}^{c} \sum_{j}^{n} u_{ij}^m d_{ij}^2 + \sum_{j=1}^{n} \lambda_i (\sum_{i=1}^{c} u_{ij} - 1)
\end{aligned} \tag{15}
$$

where λ_i is the Lagrange factor. The first order derivative of all input parameter, the necessary conditions for making the Eq. (14) to the minimum:

$$
c_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m}. \tag{16}
$$

$$
u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}}. \tag{17}
$$

FCM algorithm is a simple iterative procedure. When the processing mode is running, FCM uses the following steps to determine the clustering center and the membership matrix:

(1) In the (0, 1) interval, the random initial membership matrix U, which satisfies the constraint conditions in the Eq. (13);
(2) Calculate C clustering center by the Eq. (16);
(3) The value function is calculated according to Eq. (14). If it is less than a certain threshold, or is relative to the last value function by altering the amount is less than a threshold, then the algorithm stops.
(4) Using the Eq. (17) to calculate the new U matrix, the return step 2.

In the process of the segmentation of the carotid artery and the location of the plaque, the range of the outer wall of the vessel region restricted to the inner wall partition. By using the improved fuzzy C mean algorithm, the segmentation of the luminal and the patch of MR blood vessel images is carried out, through the same dynamic programming the inner wall contour and patch refinement. Through the analysis of the size of the patch area and the proportion of the internal cavity, the degree of damage of the carotid artery was judged.

3 Experimental and Results Analysis

3.1 Experimental Setup

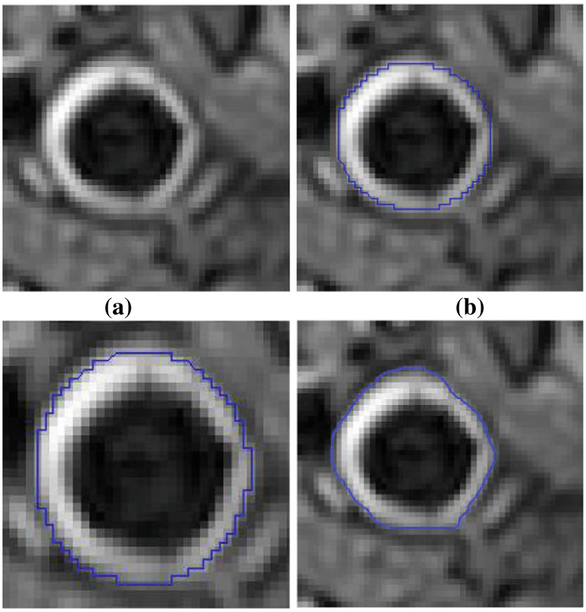
All of the dataset used in our experiments was from hospital that included 40 MR images containing carotid artery luminal and 70 images of external wall of the carotid artery. Slice spacing is 1 cm. Pixel size is 512 × 512. The experiments were implemented in the CPU of Intel Core I5 4200M that internal memory is 8 GB. The type of

GPU is NVIDIA GeForce GT 755M, and its memory is 2 GB. Software environment: the operating system is Windows 8.1, MATLAB 2013a.

The same set of data is carried on the gold standard, the common ellipse fitting blood vessel segmentation and the improved ellipse fitting algorithm, compared with the results of the segmentation of blood vessel wall and the segmentation of the inner chamber of the vessel.

3.2 Results and Analysis

Figure 2 shows the result of segmentation the outer wall of the blood vessel of the various algorithms.



(a) (b) (c) (d)

Fig. 2. The result of segmentation the outer wall of the blood vessel of the various algorithms. (a) the original image, (b) the general ellipse fitting result, (c) the improved ellipse fitting result, (d) the gold standard image.

In this paper, an improved analytical method based on the receiver operating characteristic curve is made to analyze the experimental data. *TP* is really positive, *FP* is false positive, *TN* is really negative, *FN* is a false negative. Analysis of the data of the image region overlaps the ratio of the gold standard image and the improved ellipse fitting. *AO* is defined as follows:

$$AO = \frac{TP}{TP + FN + FP} * 100\% \tag{18}$$

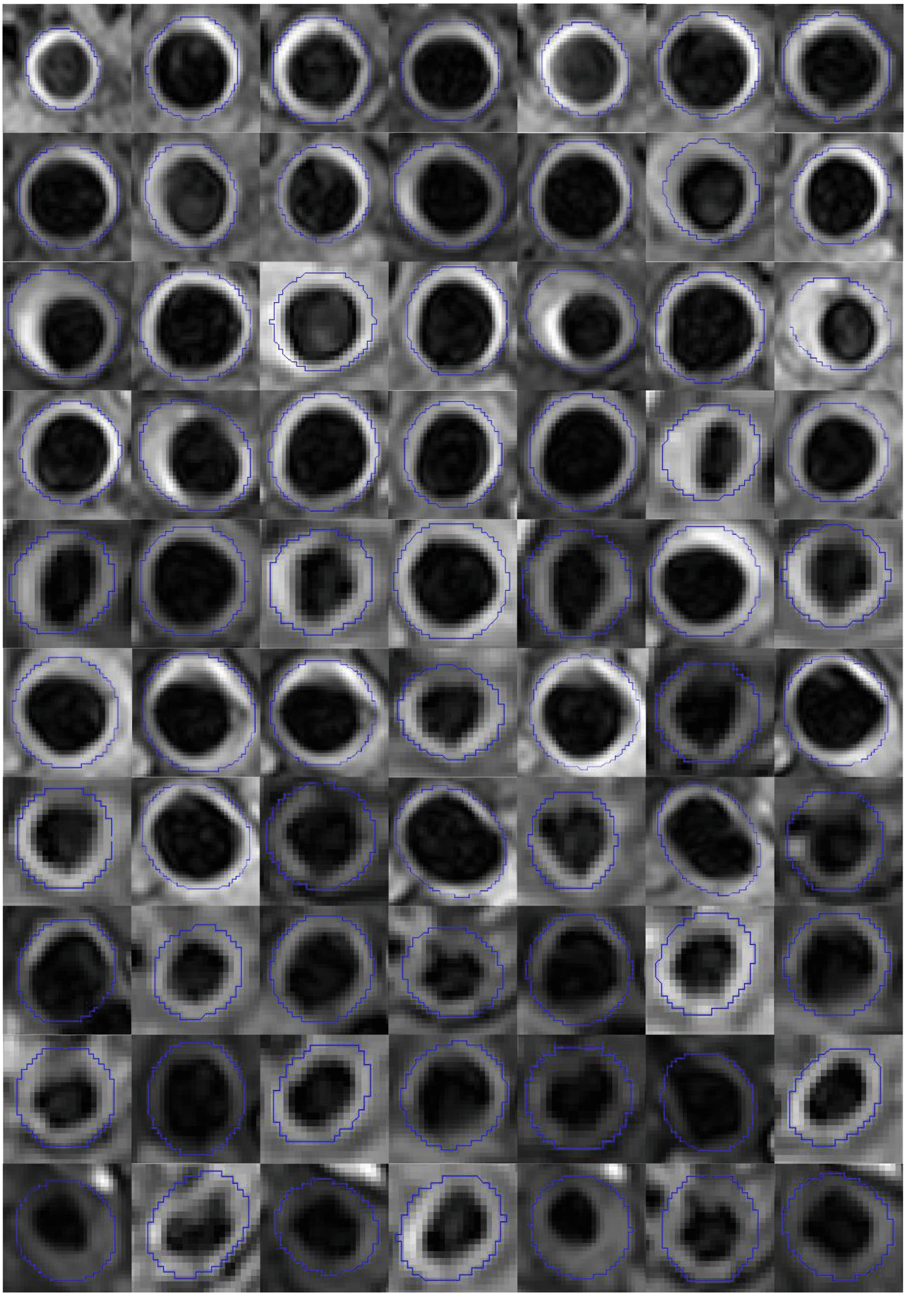


Fig. 3. The results of the modified ellipse fitting algorithm for the segmentation of blood vessel wall.

Figure 2(a) contains the outer boundary of the vessel, the blood vessel boundary was clear and obvious after pretreatment. Figure 2(b) contains the effect of the image of the vessel wall on the segmentation of the common ellipse fitting algorithm. Figure 2 (c) is the result of the improved ellipse fitting algorithm; the effect of the external boundary of the blood vessels obtained by manual segmentation of the gold standard in Fig. 2(d). The *AO* value of the overlap region is 95.7%. The *AO* value of the ordinary ellipse fitting algorithm is 94.6%. We selected 70 sections of the carotid artery blood vessels to segmentation the results as illustrated in Fig. 3.

Figure 4 shows the AO value trend of improved ellipse fitting and ordinary ellipse fitting algorithm.

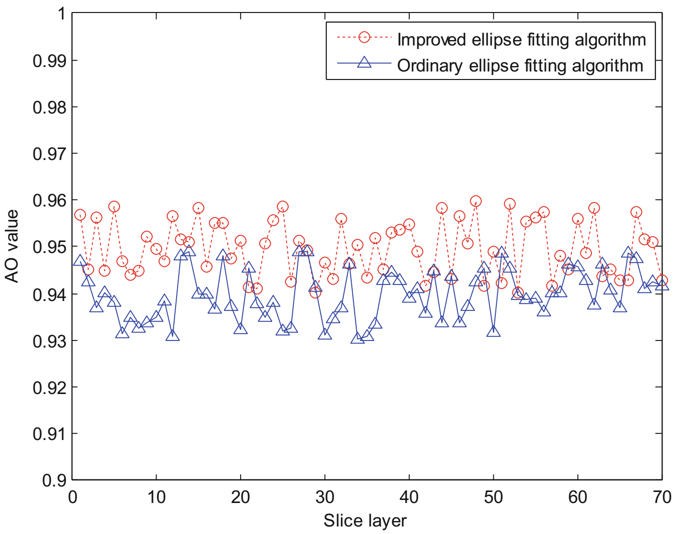


Fig. 4. The AO value trend of improved ellipse fitting and ordinary ellipse fitting algorithm.

From Fig. 4, we can see that the AO value of the modified ellipse fitting algorithm is significantly higher than that of the classical ellipse fitting segmentation algorithm. The contour of the segmentation of the external wall of the carotid artery is limited by the segmentation of the inner chamber. Through the improved FCM algorithm, a series of successive segmentation of the inner segment of the carotid artery is segmented, and Fig. 5 shows the segmentation results.

The location and size of the vascular luminal can be obtained by comparing the segmentation results of continuous carotid artery. In this paper, the cavity ratio q is used for data analysis, which defined as follows:

$$q = \frac{n}{n + b}. \tag{19}$$

where n is the luminal area, b is the plaque area.

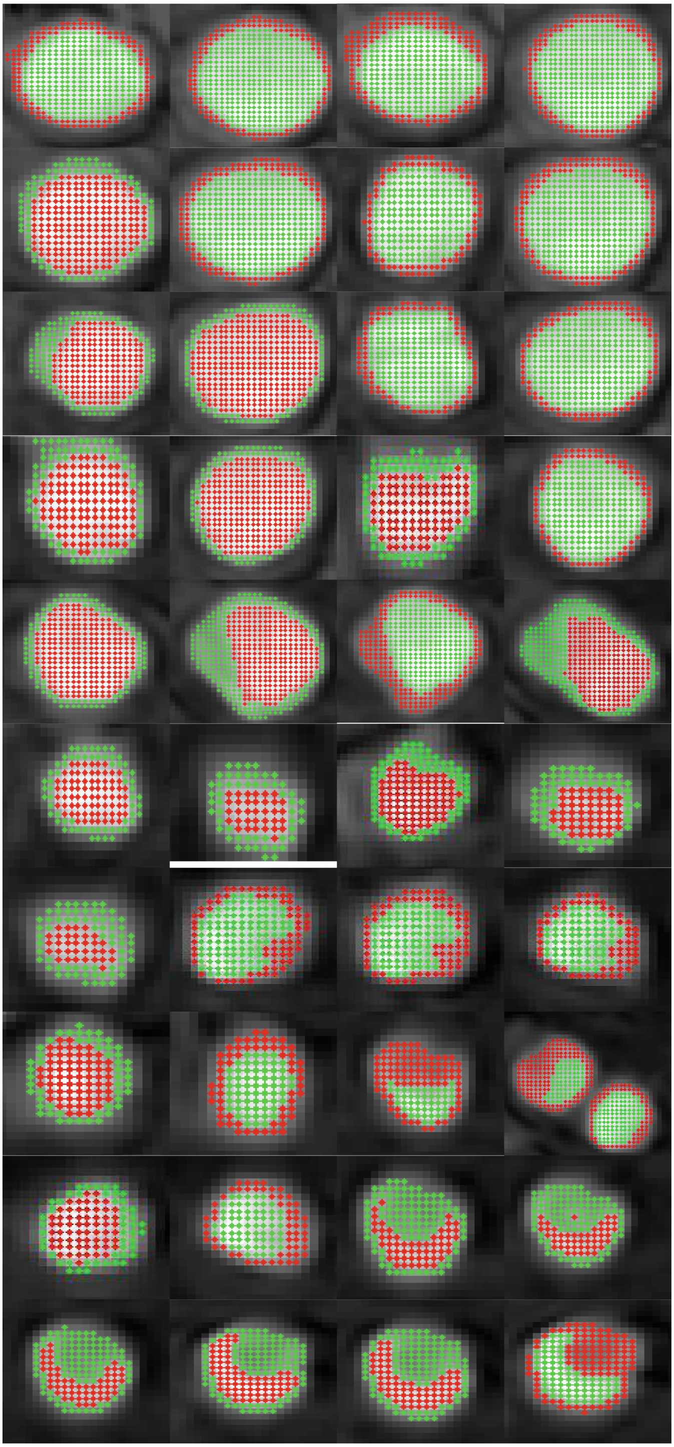


Fig. 5. Improved FCM algorithm for segmentation of the luminal and plaque size.

Figure 6 shows the q ratio of the improved and the ordinary FCM algorithm.

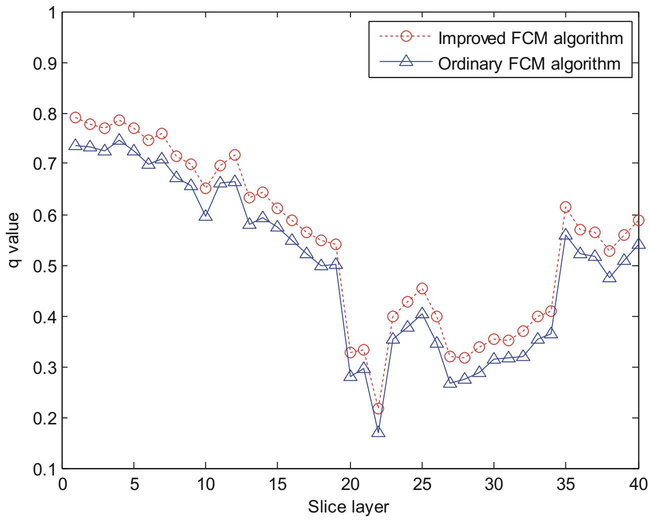


Fig. 6. The q ratio of the improved and the ordinary FCM algorithm.

From Fig. 6, we can see that the percentage of the initial carotid artery plaque area ratio was lower. At this point, the q value is about 0.75. However, with the change of the slice position, the plaque area is gradually increasing, the ratio of the area occupied by the 10^{th} slices was decreased, and the ratio of the inner cavity of the 12^{th} slices was the lowest. At this point, the q value is 0.2189. The proportion of plaque at this time was the largest. Through the upper and lower two curves, we found that the improved FCM algorithm was significantly larger than the ordinary FCM algorithm, which can achieve higher accuracy of plaque location results.

4 Conclusions

In this paper, we propose a method of automatic segmentation and plaque localization of carotid artery based on multi-modal MR images. This method achieved the automatic segmentation of the lumen and outer wall boundaries, as well as the precise position of plaque. Experiments show that this method can ensure the accuracy of vascular segmentation and plaque positioning is relatively close, while shortening the time of segmentation, to achieve the reproducibility. Although this method accurately divides the boundary between blood vessels and plaques, there are still a lot of problems to be solved for plaque component analysis. The next step is to study the specific constituent structure of the segmented patches.

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