Study on Detection of Vascular Inner Wall with IVUS Image

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Abstract. Images obtained by Intravascular ultrasound (IVUS) technology play a key role in detecting the lining of blood vessels. However, IVUS images are not clear enough usually, it is difficult to detect the inner wall of the blood vessels. It further affects the diagnosis results. In view of this situation, we first applies the pseudo-color enhancement algorithm to enhance the image; Second, the images were dichotomized by Support Vector Classification (SVC), and the images were divided into internal and external parts; then Hough gradient transform based on Canny operator is applied to detect the inner wall of blood vessels. The proposed method was applied to detect 100 frames of IVUS images and compared with the actual judgment results of doctors. The detection results showed that the detection results of blood vessel lining in 97 frames were consistent with the doctors' judgment results, and the detection accuracy could reach 97%. Experimental results show that the method can effectively highlight the characteristics of the inner wall of blood vessels and detect the inner wall of blood vessels. It can greatly improve the diagnostic accuracy in the actual medical process.

Keywords: IVUS · SVC · False color enhancement · Detection of blood vessel lining

1 Literature Review

Due to its convenience, noninvasive and flexible features, IVUS technology has been playing a high role in vascular diagnosis in recent years. However, because the recognition result image of this technology is visually presented as gray image, it is not clear enough, difficult to identify and other characteristics, which has played a great obstacle to doctors' medical diagnosis [1–7].

Current studies on the detection of vascular inner wall with IVUS images can be seen as follows: In 2012, aiming at the detection problem of IVUS images, Li Yilin et al. from Beijing University of Technology proposed to use grayscale co-occurrence matrix and grayscale gradient co-occurrence matrix to extract image eigenvalues, and then designed Support Vector Machine (SVM) classifier to train and classify the extracted eigenvalues. Cross Validation method (CV) was used to evaluate the results, which was

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characterized by excessive computation and complicated processing [8]. In 2018, Yuan Shaofeng et al. from Southern University of Science and Technology used the deep full convolutional network (DFCN) model to process the original IVUS image, and then used the shape information of the inner wall of the blood vessel to reduce the influence of the wrong pixels, and finally carried out the image segmentation operation. The calculation process of the model is complicated and difficult to achieve in the actual medical diagnosis process [9]. In 2018, Wu Yupeng et al. from South China University of Technology proposed to use three network models based on U-Net, Dense-U-Net and Res-U-Net to segment the studied area in the intima of blood vessels, and then establish deep learning models for lipid, fiber and calcified plaques respectively. This model needs to be further strengthened in three aspects: sample data adoption, model optimization and clinical application [10]. In 2021, Zhang Wenzhen et al. from Shandong University took U-net as the network framework and used active contour model, edge operator and K-means clustering algorithm to build a segmentation model for IVUS image. This model can simplify doctors' diagnosis and treatment process and provide data support. However, the scale of its data set is small and the model generalization ability is weak [11]. In 2021, Li Kai et al. from Zhejiang University of Science and Technology constructed an automatic detection model of vascular intima boundary in IVUS images. This model combined artificial features and higher-order semantic features, screened out the most featured data subset through improved cuckoo search, and input it into the dictionary for the classification and boundary detection of vascular inner wall. The self-comparison experiment proved that the recognition accuracy and effectiveness of the model were significantly improved, but the method was too complicated [12]. In 2018, Huang Zhijie et al. from Southern Medical University firstly adopted filtering binary processing for the original IVUS image. After more image texture features are obtained, the IVUS images are classified by linear classifier, random forest and other classification methods. Experimental results show that the recognition accuracy is greatly improved, but the processing process is complicated [13]. In 2011, Sun Zheng et al. from North China Electric Power University proposed a 3D parallel segmentation algorithm based on snake model. The algorithm firstly weakens the noise of the original image, so as to obtain the four longitudinal views of the IVUS image sequence. After extracting the divided boundaries, the boundary curve is mapped to obtain the initial contour in the view. Finally, the initial contour is used as the initial shape of the snake model. The boundary features of each frame IVUS image are obtained. The segmentation results of this method are not high in accuracy [14]. In 2016, Wang Ling et al. from Tianjin University obtained the local optimal solution of IVUS image segmentation by using dynamic programming algorithm, time-domain noise reduction preprocessing and active contour model. This method has good repeatability, high accuracy and stability, but the processing process is complex [15].

2 Introduction

In this paper, based on MATLAB and python language, aiming at the problem of low resolution of IVUS image, a new method for processing IVUS image is proposed. In this process, pseudo-color transformation is applied to enhance the original image of

IVUS. Then the appropriate kernel function is used to classify the image by support vector machine. Further, Hough gradient transform based on Canny operator was used to extract the range of the inner wall of the blood vessel to realize the detection process. The method was used to detect 100 frames of images, and compared with the actual judgment results of doctors. The results showed that 97 frames of images were consistent with the judgment results of doctors, and the recognition accuracy could reach 97%. It can be proved that the above method can improve the accuracy of diagnosis in the actual process of diagnosis and treatment.

3 Methods

In this paper, the original IVUS image processing, the first use of false color enhancement algorithm in MATLAB, the original IVUS image false color enhancement. By using python language, the key pixel points of the enhanced image were selected, and the support vector machine classification model was trained using the key pixel points, and the original image was segmented using the obtained model. The range of the inner wall of the blood vessel was obtained by gray scale transformation, median filtering, Canny operator edge detection and Hough gradient transformation for the segmented image, so as to realize the detection of the inner wall of the blood vessel. The specific scheme is shown in Fig. 1.

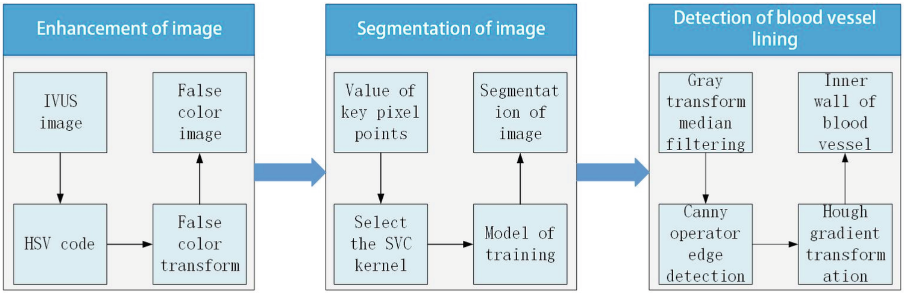

Fig. 1. Schematic diagram of the method

3.1 Enhancement of Image

Intravascular ultrasound (IVUS) is a kind of tomography technology. The obtained image is a gray image in human eye recognition, which has the characteristics of small brightness difference of pixels and is not easy to recognize. Therefore, this paper uses the pseudo-color enhancement algorithm to process the image, increase the computer's identification of the image, and improve the processing efficiency of the subsequent algorithm on the IVUS image.

Firstly, the mapping relationship between the three basic RGB colors and gray scale function $g(x, y)$ is established by constructing three color transfer functions $R(x, y)$,

$G(x, y)$ and $B(x, y)$. Then, the constructed color functions $R(x, y)$, $G(x, y)$ and $B(x, y)$ are linearly accumulated to achieve the purpose of image enhancement.

The relation between pixel value C of the pseudo-color image and the original IVUS image is shown in Formula (1):

$$C = R(x, y) + G(x, y) + B(x, y) \tag{1}$$

In the formula, $R(x, y)$, $G(x, y)$ and $B(x, y)$ are the three color transfer functions constructed respectively, and the formulas are (2), (3) and (4) as follows:

$$R(x, y) = \begin{cases} 0, & 0 \le f(x, y) < 64; \\ 255(f(x, y) - 64)/64, & 64 \le f(x, y) < 128; \\ 255, & 128 \le f(x, y) < 256; \end{cases} \tag{2}$$

$$G(x, y) = \begin{cases} 0, & 0 \le f(x, y) < 128; \\ 255(f(x, y) - 128)/96, & 128 \le f(x, y) < 224; \\ 255, & 224 \le f(x, y) < 256; \end{cases} \tag{3}$$

$$B(x, y) = \begin{cases} 255, & 0 \le f(x, y) < 64; \\ 255(128 - f(x, y))/64 & 64 \le f(x, y) < 128; \\ 0, & 128 \le f(x, y) < 256; \end{cases} \tag{4}$$

The above process converts the original IVUS image into RGB false color image, which enhances the color difference of the shaded part and improves the accuracy of subsequent segmentation and recognition.

3.2 Segmentation of Image

Image segmentation is to divide the image into non-intersecting and meaningful subregions, the essence is to classify the pixel value of the image. This process can improve the accuracy of the subsequent detection of the blood vessel lining.

In this paper, the support vector machine classification algorithm is used to segment the image in python. The kernel function takes a cubic polynomial. This algorithm converts low-dimensional data into high-dimensional data, and seeks an optimal hyperplane that can separate the two types of key data in the high-dimensional space, so as to achieve the purpose of data set classification and segmentation. The processing process is shown in Fig. 2.

Before the segmentation operation, the segmentation samples to be processed are selected in advance. According to the doctor's guidance, 10 image key points and 10 segmentation target key points were artificially selected on the image after the pseudo-color enhancement processing in the previous step, and their RGB values were extracted. As shown in Fig. 3 and Fig. 4.

The extracted two sets of key points are converted into x vector and y vector respectively.

The cubic polynomial kernel function selected by the SVC model is shown in formula (5):

$$K(x, y) = [(x, y) + 1]^3 \tag{5}$$

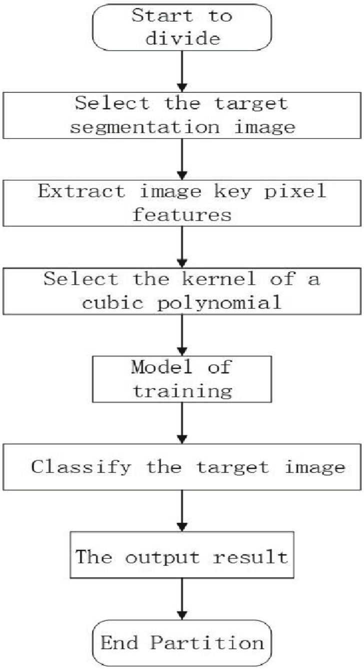

Fig. 2. SVM-based segmentation process

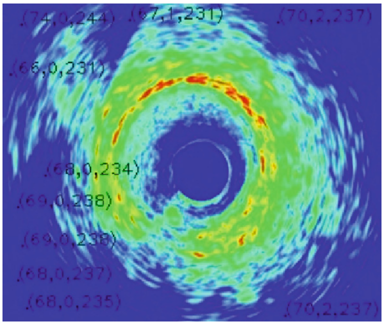

Fig. 3. Image key point value

The discriminant function of support vector machine construction is shown in Formula (6):

$$h(t) = sign\left\{ \sum\nolimits_{i=1}^{s} \alpha_i y_i [(x, y) + 1]^3 - b \right\} \tag{6}$$

In the formula, s is the number of support vector machines; x and y are image key point vectors and segmentation target key point vectors respectively; i and b are constants.

After x vector and y vector are trained in the constructed SVC model, the model is used to predict and segment the whole original image, so as to get the segmtioned image.

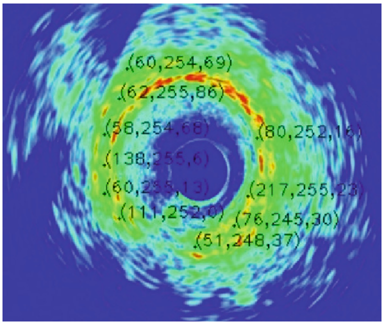

Fig. 4. The value of the target key point of image segmentation

3.3 Detection of Vascular Inner Wall Based on Hofer Transform

In order to simplify the operation, the inner wall of the actual blood vessel was approximately treated as a ring. After the segmentation of the enhanced IVUS image, the obtained image is processed by gray scale transformation and median filtering, and then the ring boundary is extracted by Hough gradient transformation based on Canny operator to detect the inner wall of the blood vessel. In this process, Hoff gradient transform can improve the efficiency of computer recognition, and it is simple and effective.

Grayscale Transformation and Median Filtering. Since image noise has a great impact on the edge detection process, before using Hough transform detection technology, in order to reduce the impact of noise, the gray scale transformation of the segmented image is firstly carried out. In addition, due to the complex imaging of the vascular image itself, the quality of the photo is poor, so the image should be processed by the median filtering, in order to perform the Hough transform more effectively.

The grayscale transformation formula is shown in Formula (7):

$$g(x,y) = \begin{cases} \frac{c}{a} f(x,y) & 0 \le f(x,y) < a; \\ \frac{d-c}{b-c}[f(x,y) - a] + c & a \le f(x,y) < b; \\ \frac{M_g - d}{M_f - b}[f(x,y) - b] + d & b \le f(x,y) < M_f; \end{cases} \tag{7}$$

In the formula, $f(x,y)$ is the segmented image; a and b are the piecewise values of input image pixel brightness; c, d is the piecewise value of the output image pixel brightness; M_f and M_g are the maximum brightness values of input image and output image pixels respectively.

The median filtering processing formula is shown in Formula (8):

$$p(x,y) = Med_{(s,t)\in\varpi_{xy}} g(s,t) \tag{8}$$

In the formula, $p(x,y)$ is the image after median filtering; ϖ_{xy} is a square adjacent domain centered on points x and y; $g(s,t)$ is the input image.

Canny Edge Detection. Canny edge detection before Hough transformation can improve the accuracy of the value of the inner wall of the blood vessel. The essence of this algorithm is to find the pixels with the largest gradient amplitude change in the image and save the statistics. Canny edge detection steps are as follows:

The Image Pixel Value is Smoothed by Gaussian Filter to Eliminate Noise. The filter definition is shown in Formula (9):

$$T(x, y) = f(x, y) * H(x, y) \tag{9}$$

$$H(x, y) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\delta^2}} \tag{10}$$

where, $f(x, y)$ is the original image; $T(x, y)$ is the output image; $H(x, y)$ is the Gaussian filter.

Calculate the Gradient and Direction of Amplitude. Let T_x and T_y be the row and column filters after smooth processing, and the expression is (11), (12) as shown below:

$$T_x = [f(x+1, y) - f(x, y) + f(x+1, y+1) - f(x, y+1)]/2 \tag{11}$$

$$T_y = [f(x, y+1) - f(x, y) + f(x+1, y+1) - f(x+1, y)]/2 \tag{12}$$

The amplitude $M(x, y)$ and azimuth $\theta(x, y)$ of the corresponding gradient can be calculated using the coordinate transformation relation. It is defined as formula (13), as shown in Formula (14):

$$M(x, y) = \sqrt{T_x(x, y)^2 + T_y(x, y)^2} \tag{13}$$

$$\theta(x, y) = \arctan(\frac{T_x(x, y)}{T_y(x, y)}) \tag{14}$$

Suppression of Non-maximum and Double Threshold Detection. The suppressed maximum value means that the maximum value of pixel gradient in each column of the image is reserved, while the other pixel gradient values are set to zero. This method can determine whether the current pixel is the maximum point of the surrounding pixel gradient, eliminate the adverse effects of edge detection, and find the local maximum position of the pixel through the direction. Double threshold detection is to first compare two fixed values with gradient values, then eliminate the pixels whose gradient value is less than the low threshold, and unify the pixels whose gradient value is greater than the high threshold into the high threshold, so as to determine the boundary range of the inner wall of the blood vessel.

Hough Gradient Transform Detection. After the Canny operator was used to detect the boundary of the bleeding tube wall in the previous step, Hough gradient transform was further used to confirm the geometric center and effective range of the vessel wall, and circled in the original image.

Introduction to Hough Gradient Transformation. Hough gradient transform is a circle detection method based on Hough circle transform. Based on the gradient direction of each edge point calculated by Canny edge detection algorithm in the previous step, the pixel points contained in each gradient direction line are voted, and the pixel points with the most voting times are defined as the geometric center of the image. Then, the number of distance occurrences from the center of the circle to the edge was summed up, and the distance with the largest number of occurrences was defined as the radius, and the range of the inner wall of the blood vessel was determined according to the obtained center and radius.

Hough Gradient Transformation Calculation Process. Since the inner wall of the blood vessel is approximated as a ring, its definition is shown in Formula (15):

$$(x-a)^2 + (y-b)^2 = r^2 \tag{15}$$

In the formula, a and b are the center of the circle in Cartesian coordinates; r is the radius of the circle.

By using Hough gradient method and using Sobel operator on the boundary of pipe wall detected by Canny algorithm, the gradient value can be obtained by calculating the first derivative of the direction for the determined non-zero point.

Sobel operator is defined as (16):

$$\nabla f(x, y) = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \frac{\partial f}{\partial y} \end{bmatrix}^T \tag{16}$$

In the formula, $\nabla f(x, y)$ represents the modulus of the gradient; $f(x, y)$ represents the function image to be processed.

The gradient modulus can be expressed by formula (17):

$$|\nabla f(x, y)| = \left[\left(\frac{\partial f}{\partial x} \right)^2 + \left(\frac{\partial f}{\partial y} \right)^2 \right]^{\frac{1}{2}} \tag{17}$$

The definition of gradient direction is shown in Eq. (18):

$$\alpha(x, y) = \arctan\left[\frac{G_y}{G_x} \right] \tag{18}$$

The corresponding line segment can be determined and its pixels saved by combining the gradient direction $\alpha(x, y)$ and the distance from the non-zero of the boundary. When more pixels are accumulated, that is, more line segments intersect the pixel, the point can be determined as the geometric center of the blood vessel wall, and the range of the blood vessel wall can be determined by combining with the ring boundary detected by the Canny operator.

4 Experiment and Results

In this paper, repeated experiments were carried out according to the above method, and a number of detection results were obtained. In order to verify the feasibility of this method, the statistical results were compared with the actual judgment results of doctors.

The results show that 97 frames can accurately identify the inner wall of blood vessels among the 100 frames processed by this algorithm, and the recognition accuracy can reach 97%. It is proved that the method in this paper can effectively identify the vascular wall, and the operation method is simple and easy. Part of the experimental results are shown in the figure below (Figs. 5, 6, 7 and 8):

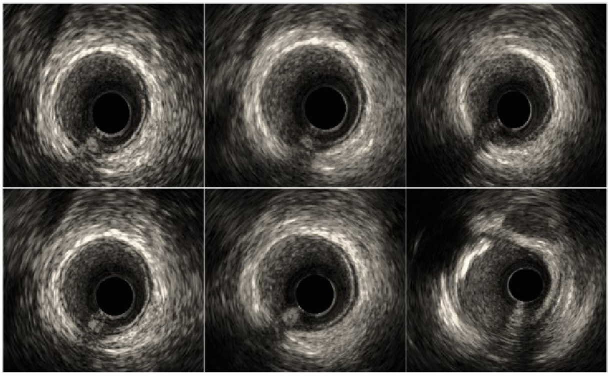

Fig. 5. Original image of IVUS

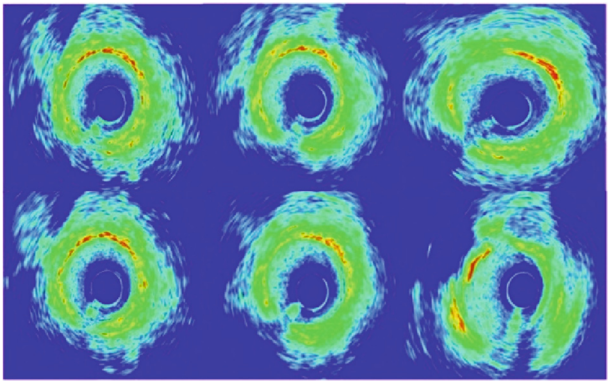

Fig. 6. IVUS enhanced image

The specific operation method for the accuracy verification of the model is as follows: Firstly, RGB values of 10 image key points and 10 segmentation target key points are selected respectively from 100 images after enhanced processing under the guidance of doctors, and they are taken as x vector and the y vector. Then, x vector and y vector are taken as parameters and put into the set SVC model for training, and the model after training is obtained. Then the trained model is used to predict and segment the original image, so as to get the segmented image. Then Hough gradient transformation was performed on the segmentation image to obtain the range of the inner wall of the blood vessel. The test results obtained by the method in this paper are compared with the actual judgment results of doctors to determine the validity of the model.

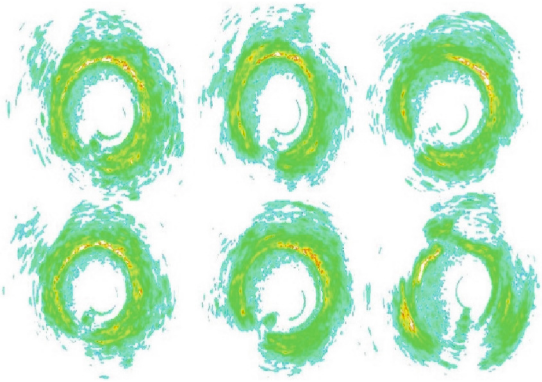

Fig. 7. IVUS segmentation image

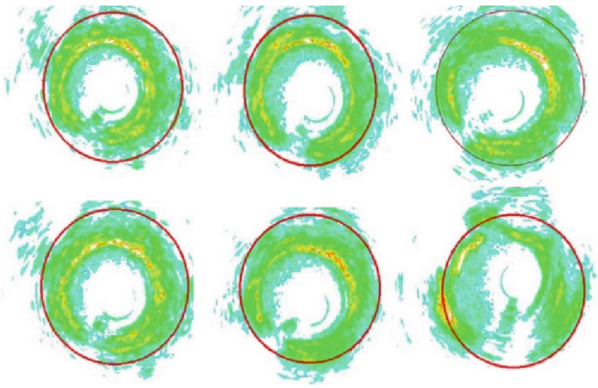

Fig. 8. IVUS Hough transform image

By comparing the experimental results, it can be seen that 97 frames of the 100 frames of IVUS images processed by the detection process in this paper are consistent with the detection results of doctors, and the detection accuracy of the model vascular inner wall can reach 97%.It can be proved that the detection process proposed in this paper can effectively identify the inner wall of blood vessels, effectively simplify the detection process in the actual medical process, and improve the detection accuracy of the inner wall of blood vessels.

To verify the stability of the detection algorithm in this paper. By changing the parameter configuration of Hough gradient transform function, the range of vascular inner wall in IVUS image was redetected. The minimum parameter of the circle radius of the detection function is increased by 10 each time from 1, and the maximum parameter of the circle radius is increased by 1000 each time to achieve this purpose. The running result is shown in Fig. 9.

As can be seen from Fig. 9, by changing the parameters of Hough gradient transformation function, there is no significant difference in the detected blood vessel inner wall. It can be proved that the detection algorithm has stability in the detection process.

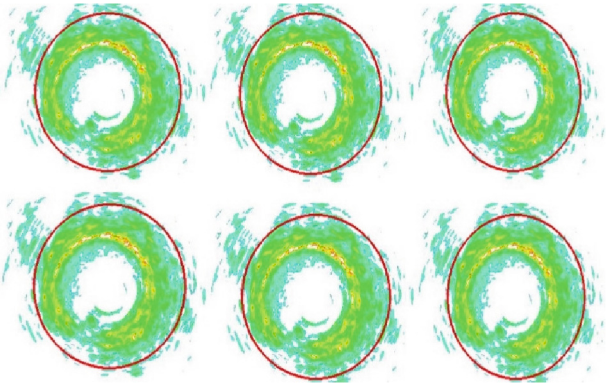

Fig. 9. Redetected IVUS images after adjusting detection function parameters

To verify the effectiveness of SVC segmentation algorithm proposed in this paper. The threshold segmentation method, region segmentation method and K-means segmentation method were successively applied to the IVUS image after pseudo-color transformation. By comparing different segmentation algorithms to generate different segmentation results, the validity of the segmentation algorithm in this paper is verified. The comparison of operation results of different segmentation algorithms is shown in Fig. 10.

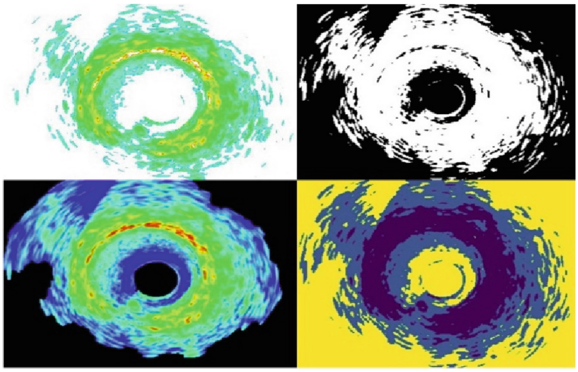

Fig.10. IVUS images segmented under different segmentation algorithms

It can be seen from Fig. 10 that the SVC segmentation algorithm proposed in this paper is relatively effective in predictive segmentation of images from the segmentation results obtained by using different segmentation algorithms.

5 Conclusion

This paper presents an IVUS image detection method based on MATLAB and python. In this method, the original IVUS image was transformed into a false-color image which was easier to be recognized by computer through false-color enhancement. Then, the Support Vector Classification (SVC) was used for image segmentation to make the contour of the blood vessel wall clearly visible. Finally, Hough gradient change based on Canny operator was used to detect the vascular wall image of IVUS image to achieve effective recognition. The above method was applied to detect 100 frames of IVUS original images, and compared with the actual judgment results of doctors. The experimental results show that this method can effectively highlight the characteristics of the inner wall of blood vessels and accurately detect the inner wall of blood vessels, which can improve the diagnostic accuracy in the actual medical process.

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