Blood Vessel Segmentation in Angiograms using Fuzzy Inference System and Mathematical Morphology

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***Abstract*— Angiography is a widely used procedure for vessel observation in both clinical routine and medical research. Often for the subsequent analysis of the vasculature it is needed to measure the angiogram area covered by vessels and/or the vessel length. For this purpose we need vessel enhancement and segmentation. In this paper, we evaluate the performance of a fuzzy inference system and morphology filters for blood vessel segmentation in a noise angiograms image.**

Keywords— blood vessel segmentation; Image processing;Fuzzy logic;Mathematical Morphology;Angiography

1.INTRODUCTION

Segmentation of blood vessels is one of the essential medical computing tools for clinical assessment of vascular diseases. It is a process of partitioning an angiogram into non-overlapping vascular and background regions. Based on the partitioning results, surfaces of vasculatures can be extracted, modeled, manipulated, measured and visualized [1]. Edge detection is an essential task in computer vision. It covers a wide range of application, from segmentation to pattern matching. It reduces the complexity of the image allowing more costly algorithms like object recognition [2],[3],object matching [4], object registration [5], or surface reconstruction from stereo images[6],[7] to be used. Their detection is interesting for different goals. They can be used to measure parameters related to blood flow or to locate some patterns in relation to vessels in angiographic images. They can also be used as a first step before registration [5], [8], [9]. Conventionally edge is detected according to some early brought forward algorithms like sobel algorithm, prewitt algorithm and Laplacian of Gaussian operator [10]. But in theory they belong to the high pass filtering, which are not fit for noise medical image edge detection because noise and edge belong to the scope of high frequency. In real world applications, medical images contain object boundaries and object shadows and noise. Therefore, they may be difficult to distinguish the exact edge from noise or trivial geometric features. In this paper, we novel a fuzzy inference system and morphology filters for vessel edge detection or vessel segmentation. Figure1 depicts the applied process.

2. IMAGE PREPROCESSING

During input image preprocessing stage, 4 linear filters were employed, as shown in Figure 1.

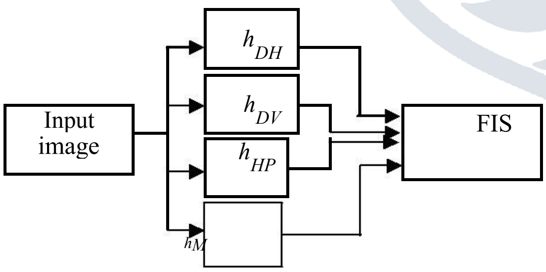

Fig.1. pre-processing system applied Sobel operators used to estimate the first derivative of Input image angiogram in horizontal and vertical directions. h_{HP} and h_M are the kernels of a high-pass and low-pass filters.

Sobel operators h_{DH} and h_{DV} are kernels with 3x3 elements given by [11, pages 123 -129]:

$$h_{DH} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad (1)$$

$$h_{DH}=\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{2}$$

As a high-pass filter, we adopted also a 3x3 kernel, given by:

$$h_{HP}\begin{vmatrix} \frac{-1}{16} & \frac{-1}{8} & \frac{-1}{16} \\ \frac{-1}{8} & \frac{3}{4} & \frac{-1}{8} \\ \frac{-1}{16} & \frac{-1}{8} & \frac{-1}{16} \end{vmatrix} \tag{3}$$

Filter h_M in turn, was chosen in such a way as to guarantee that the gray level in each pixel of the output image is the arithmetic mean of the gray levels in a 5x5 neighborhood of the same pixel in the input image.

Given the kernels associated with each filter, the filtered images may be computed through a bi dimensional convolution operation:

$$DH = h_{DH} * I \tag{4}$$

$$DV=h_{HP} * I \tag{5}$$

$$HP= h_{HP} * I \tag{6}$$

3. FUZZY SETS AND FUZZY MEMBERSHIP FUNCTIONS DEFINITIONS

The system implementation was carried out considering that the input image I and the output image obtained after defuzzification are both 8-bit quantized; this way their gray levels are always between 0 and 255. These values define the working interval of the output variable and the input variable G (the other input variables are not guaranteed to be less than 255). Besides, three fuzzy sets were created to represent each variable's intensities; these sets were associated to the linguistic variable "low", "medium" and "high".

The adopted membership functions for the fuzzy sets associated to the input G and to the output were Triangular functions with means 0, 127.5 and 255, as shown in Fig.2(a). For the sets associated to the other input images, Triangular functions were also adopted for the linguistic variables "low" and "medium", but for the variable "high" a sigmoid function was chosen (Fig.2(b)), since in this case we can not guarantee that the input values will be restricted to the interval [0,255].

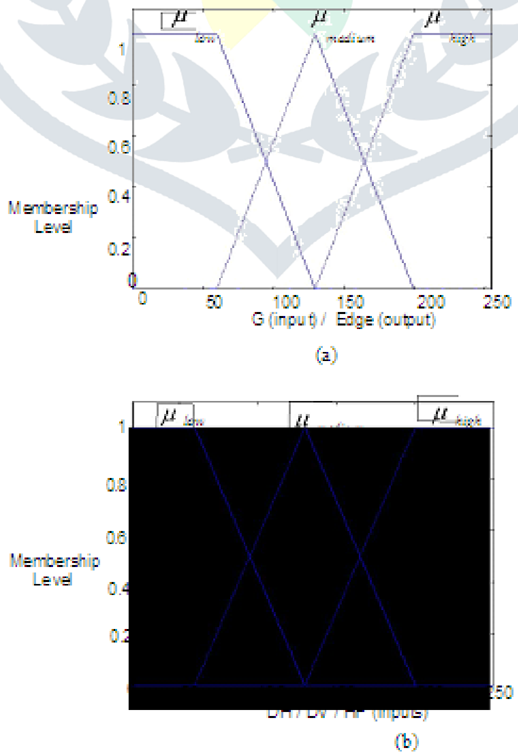

Fig.2. Membership functions of the fuzzy sets

3.1 FUZZY LOGICAL OPERATIONS AND DEFUZZIFICATION METHOD DEFINITIONS

The functions adopted to implement the "and" (norm-T) and "or" (norm-S) operations were the minimum and maximum functions, respectively. The Mamdani method was chosen as the defuzzification procedure, which means that the fuzzy sets obtained by applying each inference rule to the input data were joined through the add function; the output of the system was then computed as the centroid of the resulting membership function [12, pages 148-161].

3.2 INFERENCE RULES DEFINITIONS

The fuzzy inference rules were defined in such a way that the FIS system output ("Edges") is high only for those pixels belonging to edges in the input image. A robustness to contrast and lighting variations were also in mind when these rules were established.

The first 3 rules were defined to represent the general notion that in pixels belonging to an edge there is a high variation of gray level in the vertical or horizontal directions:

1. (DH low) and (DV low) $\rightarrow$ ("Edge low")
2. (DH medium) and (DV medium) $\rightarrow$ ("Edges" high).
3. (DH high) or (DV high) $\rightarrow$ ("Edges" high).

To guarantee that edges in regions of relatively low contrast can be detected, the two following rules were established to favor medium variations of the gray level in a specific direction in regions of low frequency of the input image (HP "low"):

4. (DH medium) and (HP low) $\rightarrow$ ("Edges" high).

5.(DV medium) and (HP low) $\rightarrow$ ("Edges" high).

Rules 6 and 7 were chosen in such a way as to avoid including in the output image pixels belonging to regions of the input were the mean gray level is lower. These regions are proportionally more affected by noise, supposed it is uniformly distributed over the whole image. The goal here is to design a system which makes it easier to include edges in low contrast regions, but which does not favor false edges by effect of noise.

6. (DV medium) and (G low) $\rightarrow$ ("Edges" low).
7. (DH medium) and (G low) $\rightarrow$ ("Edges" low).

Rules 8 to 11 were established to avoid forming double edges in the output image (they tend to appear due to shadows in the natural images). Considering that high variations in gray level in horizontal direction correspond to vertical edges, we conclude that high values of $DH\ (i, j)$ and $DH\ (i, j \pm 1)$ do not imply edges pixels in (i, j) and $(i, j \pm 1)$, simultaneously.

Analogously, high values of $DV\ (i, j)$ and $DV\ (i \pm 1, j)$ do not correspond to edge pixels in (i, j) and $(i \pm 1, j)$.

8. (DV high) and (DV $(i +1, j)$ high) $\rightarrow$ ("Edges" medium).
9. (DH high) and (DH $(i, j +1)$ high) $\rightarrow$ ("Edges" medium).
10. (DV medium) and (DV $(i +1, j)$ high) $\rightarrow$ (" Edges" low).
11. (DH medium) and (DH $(i, j +1)$ high) $\rightarrow$ ("Edges" low).

Finally, rule 12 was defined to avoid including isolated pixels in the output image, favoring only continuous lines. It also avoids including points by effect of noise, since this tends to generate isolated pixels in the image which represents the input's edges.

12. (DV $(i, j +1)$ low) and (DH $(i +1, j)$ low) and (DV(i, j 1) low) and ($DH\ (i$ 1, $j)$ low) $\rightarrow$ ("Edge" low).

The threshold value to be applied may be estimated given the root mean square value (RMS) associated to the input image [11, page 77-51].

The outputs of fuzzy interference system generally determined the edge of vessels. On account of existing of noise in that outputs we in following use mathematical morphology system for better noise cancelling and edge detection.

4. MORPHOLOGY FILTERS

Mathematical morphology is a new mathematical theory which can be used to process and analyze the images [13-14]. It provides an alternative approach to image processing based on shape concept stemmed from set theory [15], not on traditional mathematical modeling and analysis. In the mathematical morphology theory, images are treated as sets, and morphology transformations which derived from Minkowski addition and subtraction are defined to extract features in images. As the performance of classic edge detectors degrades with noise, morphology edge detector has been studied [16].

The basic mathematical morphology operators are dilation and erosion and the other morphology operators are the synthesization of the two basic operations. In the following, we introduce some basic mathematical morphological operators of grey-scale images.

Let $F(x, y)$ denote a grey-scale two dimensional image, B denote structuring element. Dilation of a gray-scale image $F(x, y)$ by a grey-scale structuring element $B(s,t)$ is denoted by

$(F \oplus B)(x, y) = \max\{F(x - s, y - t) + B(s,t)\}$. (7)

Erosion of a grey-scale image $F(x, y)$ by a grey-scale structuring element $B(s,t)$ is denoted by

$$(F \ominus B)(x, y) = \min\{F(x + s, y + t) - B(s,t)\}. \qquad (8)$$

Opening and closing of grey-scale image $F(x, y)$ by grey-scale structuring element $B(s,t)$ are denoted respectively by

$$F \circ B = (F \ominus B) \oplus B,$$

$$F \bullet B = (F \oplus B) \ominus B.$$

Erosion is a transformation of shrinking, which decreases the grey-scale value of the image, while dilation is a transformation of expanding, which increases the grey-scale value of the image. But both of them are sensitive to the image edge whose grey-scale value changes obviously. Erosion filters the inner image while dilation filters the outer image. Opening is erosion followed by dilation and closing is dilation followed by erosion. Opening generally smoothes the contour of an image, breaks narrow gaps. As opposed to opening, closing tends to fuse narrow breaks, eliminates small holes, and fills gaps in the contours. Therefore, morphological operation is used to detect image edge, and at same time, denoise the image.

In medical image edge detection, we must select appropriate structuring element by texture features of the image, and the size, shape and direction of structuring element must been considered roundly. Usually, except for special demand, we select structuring element by 3x3 square that in this paper applied:

$$B = \begin{vmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{vmatrix} \qquad (9)$$

In this paper, a novel mathematical morphology edge detection algorithm is proposed. Opening-closing operation is firstly used as preprocessing to filter noise. Then smooth the image by first closing and then dilation. The perfect image edge will be got by performing the difference between the processed image by above process and the image before dilation.

5. RESULTS

In this section, the proposed fuzzy inference system and morphological operators for blood vessel segmentation is compared with a canny method for edge detection.

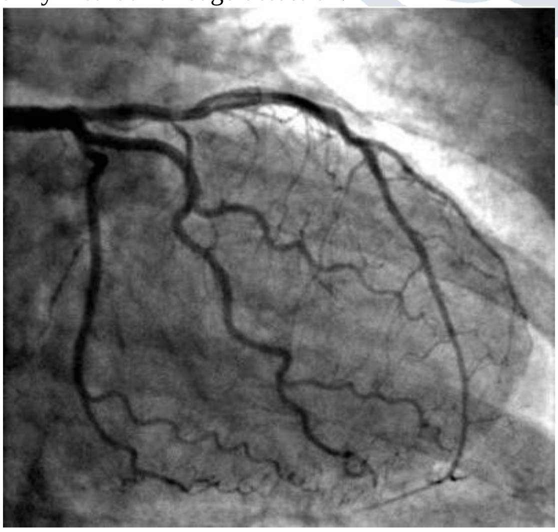

Fig.3. Original Angiogram Image

Fig.3 is the original angiogram image, Fig.4 is the results of processed angiogram image after applying canny edge detector, Fig.5 is the results of processed angiogram image by fuzzy inference system and Fig.6 is the results of processed angiogram image by fuzzy inference system and morphology operators. According to the results shown in Fig.4 and Fig.5 canny edge detector and fuzzy interference system are not successful and both of them can not filter the noise. By Fig.6

the fuzzy inference system and morphologic operators are succeed in segmentation of blood vessels.

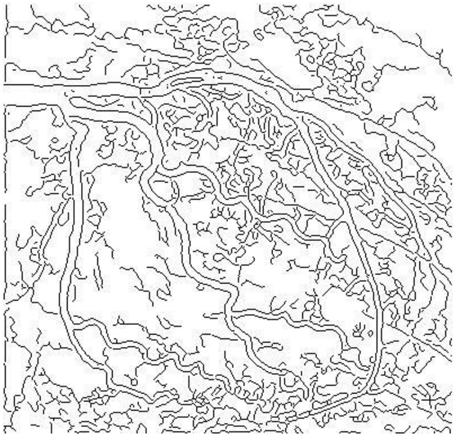

Fig.4. Angiogram Image Processed by Canny method.

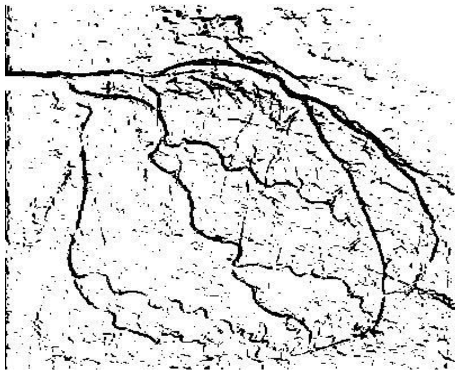

Fig.5. Angiogram Image Processed by FIS

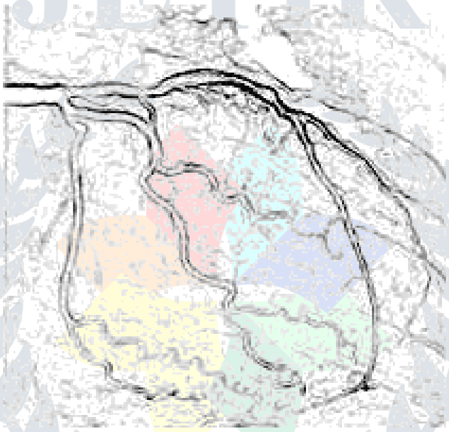

Fig.6. Angiogram Image Processed by FIS and Morphological operators

6. CONCLUSION

In this paper, a novel fuzzy inference system and mathematical morphologic algorithms is proposed to segmentation of blood vessels. The results show that the algorithm is more efficient for segmentation of angiogram images and noise cancelling than other methods such as canny method.

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