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Comparison of Traditional Morphology and Fuzzy Watershed Transformation in Medical Image Segmentation

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Abstract: In this study, an algorithm using traditional morphology for the extraction of blood vessels in cardio angiographic images is compared with that of the fuzzy watershed transformation. Blood vessels usually have poor local contrast and the existing Edge Detection algorithms do not give better results. In traditional morphology, an edge detection operation based on laplacian of Gaussian is performed but in fuzzy morphology, a fuzzy morphological multigradient watershed transformation is carried out to extract the boundary of vessels. In fuzzy watershed transformation, the marker extraction of the gradient image is obtained by a thresholding technique to avoid over segmentation and given as input to the watershed transformation. Finally, a set of alternating filters are used to segment the vessels from the cardiac images in both the methods. Simulation results show that the proposed algorithm using fuzzy watershed transformation produces better segmentation result on the basis of quality and takes less execution time when compared to the algorithm using traditional morphological filters.

Key words: Cardio angiography, blood vessel, edge detection, fuzzy watershed transformation, morphology, segmentation

INTRODUCTION

The coronary angiogram is an important tool used in medical field for the diagnosis of heart problem. In clinical practice, angiographic images of the human cardiovascular system are acquired using a medical procedure called Cardiac catheterization. The angiographic image obtained by cardiac catheterization consists of more noise. Further, the segmentation of vessels from 3D medical images (Worz and Rohr, 2004) is difficult and challenging. The main reasons are: the width of vessels depends on the type of vessel, the width typically varies along the vessel, the images are noisy and the boundary between the vessels and surrounding tissues are locally difficult to recognize and segmentation of linear structures from 3D images is much more difficult. A variety of techniques have been proposed for segmenting the vessels from angiogram. Among them segmentation of vessels using morphology, (Zhang *et al*., 2009) gives better results when compared to the earlier researches done by Sappa (2006) and Chaudhuri *et al*. (1989) on the basis of edge. In the former research (Zana and Klein, 2001), detection of second order zero crossings and the corresponding edge operator called the Laplacian is used for edge detection.

This method leads to some false detection of vessels. In another research (Latha and Senthilkumar, 2012a, b), the use of fuzzy watershed transformation involving simple fuzzy erosion, fuzzy dilation, fuzzy opening and closing operations are used to eliminate the noise in the background.

Watershed segmentation, a very prominent segmentation scheme (Beucher and Meyer, 1993) has many advantages for image segmentation. Moreover, it ensures the closed region boundaries and gives solid results. But it poses the serious over-segmentation problem (Latha and Senthilkumar, 2012a, b). This problem is due to the noise particles which lead to roughness of morphological gradient. The gradient image is threshold to extract the marker. Then, the fuzzy watershed transformation is applied on the gradient image using the marker. This would reduce the over segmentation problem.

In this study, researchers have compared the methods for extraction of blood vessels from cardio angiographic images that works on the marker extractions of the fuzzy multiscale morphological gradient image and traditional morphological filters based on PSNR value and execution time of the algorithm. The behaviour of the

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algorithm is studied on a set of angiographic images of normal patients. Results show that accurate vessel boundaries are detected by fuzzy watershed transformation with the extracted vessel contour as marker for shape and location of vessel when compared to vessels extracted by traditional morphological filters.

MORPHOLOGICAL OPERATORS

Gray morphological operators: Some of the basic definitions of morphological operators are given. More details can be found by Serra (1982). Consider a digital image $F = \{f_{ij}, i = 1, ..., u; j = 1, ..., v\}$ and a structuring element $B = \{b_{mn}, m = -M, ..., M; n = -M, ..., M\}$. Morphological erosion of image by the structuring element B is defined as:

$$\varepsilon(F, B) = \left\{\min (F_{i-m, j-n} - b_{mn}) | m, n = -M, ..., M\right\} \quad (1)$$

Morphological dilation is defined in a similar way for image F by the structuring element B as:

$$\delta(F, B) = \left\{\max (F_{i-m, j-n} - b_{mn}) | m, n = -M, ..., M\right\} \quad (2)$$

Based on the combination of these operators, opening and closing are defined as opening:

$$\gamma(F, B) = \delta(\varepsilon(F, B), B) \quad (3)$$

Closing:

$$\Phi(F, B) = \varepsilon(\delta(F, B), B) \quad (4)$$

Top-Hat transformation is a technique used to extract brilliant or dark objects from a gray level image and is defined as Top-Hat:

$$TH(F, B) = F - \gamma(F, B) \quad (5)$$

Fuzzy morphological operators: A gray level image I is a subset of $\Re^3$ whose graph is given by the set:

$$G(I) = \left\{(x, f(x)) | x \in Z^2: f(x) \in \{0, 1, 2, ..., 255\}\right\} \quad (6)$$

where, $f: G \subset Z^2 \rightarrow [N_{min}, N_{max}]$ is a function denoting gray intensities in each pixel, being $[N_{min}, N_{max}]$ the natural interval in which the minor and major levels of gray are represented by its ends (Gonzalez and Woods, 1992). Every level of gray is associated with a value between zero and one as shown in Table 1. To this end, a continuous and strictly decreasing function

Table 1: Levels of gray value

Categories	Truth value
Absolutely black	0.0
Almost black	0.1
Quite black	0.2
Somewhat black	0.3
More black than white	0.4
As white as black	0.5
More white than black	0.6
Somewhat white	0.7
Quite white	0.8
Almost white	0.9
Absolutely white	1.0

$u: \{0, 1, 2, ..., 255\} \rightarrow [0, 1]$ called fuzzy function is defined which when composed with the image function results in a fuzzification of the image, i.e., $u \circ f: Z^2 \rightarrow [0, 1]$. In view of the fact that traditional morphology depends on set theory, fuzzy morphological operators can be defined by means of fuzzy logic (Maccarone, 1996). The fuzzy morphological erosion of an image f by a structuring element B is defined as:

$$\varepsilon^F(f, B) = E(f, B) \quad (7)$$

The fuzzy morphological dilation of an image f by a structuring element B is defined as:

$$\delta^F(f, B) = 1 - E(1-f, B) \quad (8)$$

Based on the combination of these operators, fuzzy opening and fuzzy closing are defined as:

$$\gamma^F(f, B) = 1 - E(1 - E(f, B), B) \quad (9)$$

$$\Phi^F(f, B) = E(1 - E(f, B), B) \quad (10)$$

Fuzzy Top-Hat transformation is defined as:

$$TH^F(f, B) = f - \gamma^F(f, B) \quad (11)$$

MORPHOLOGICAL FILTER FOR GEOMETRIC FEATURE EXTRACTION

Structuring element: The main difference between Traditional Mathematical Morphology (TMM) and Fuzzy Morphological filter (FMM) lies in which the Structuring Element (SE) is considered. Traditional morphology considers it as an image, i.e., the structuring element is a $B: DomB \subseteq Z^2 \rightarrow \{0, 1, 2, ..., 255\}$ function. Whereas fuzzy morphology considers it as a fuzzy set. A simple way to obtain fuzzy structuring elements is to compose function B with the fuzzy function u. Thus, building fuzzy structuring elements becomes an easy task. In both TMM and FMM, disk shape structuring element with diameter of 20 pixels which is slightly bigger than the maximum vessel width is used in top-hat transformation. The SE is designed bigger than the dimension of vessel in order to get the information of background of vessel. For the background estimated, the vascular tree could be enhanced by Top-Hat operator.

Linear opening by reconstruction: With traditional morphological filters, geodesic reconstruction of the opened images into the original image f is used to recover some of the capillaries in the original image:

$$Sup_{op} = \gamma^{rec}(MAX_{i=1,2,\ldots,12}(\gamma\{f, B^i\})) \tag{12}$$

The length of the linear shape structuring element is chosen as 15 pixels as it is the diameter of the biggest vessels for 512×512×8 cardio angiographic images. In the filtered image Sup_{op}, every isolated round and bright zone whose diameter is <15 pixels has been removed.

In fuzzy mathematical morphology, linear intensity normalization is used to stretch the intensity scope to interval [0, 1]. Then, the image can be treated as a fuzzy set with intensity of each pixel representing the grade of membership belonging to vascular tree or not. In this case also twelve linear structuring elements (every 15° between zero and 180°) with 15 pixels length is chosen to fuzzy open the normalized image, respectively. The pixel-wise maximum of the twelve fuzzy openings is the result of supremum of fuzzy opening filter. Then, reconstruction of the fuzzy opened images into the original image f is used to recover some of the small vessels in the original image:

$$Sup_{op}^{F} = \gamma^{recF}(MAX_{i=1,2,\ldots,12}(\gamma^{F}\{f, B^i\})) \tag{13}$$

In the filtered image Sup_{op}^{F}, vessels with diameter <15 pixels has been removed with better quality and enhancement.

Morphological enhancement: In traditional mathematical morphology, the image enhanced by sum of Top-Hat transformation has clear tree shape blood vessels than before. However, there is still much noise within vessel and background. This causes discontinuity of intensity along vascular tree direction and non uniformity in the background.

In case of fuzzy mathematical morphology, the morphological opening operation is performed with fuzzy structuring element. The sum of Top-Hat transformation is obtained by subtracting the fuzzy opened image $\gamma^{F}\{f, B^i\}$ from fuzzy filtered image Sup_{op}^{F}. All cardiac blood vessels will be brightened whatever may be their direction including tiny or twisted vessels even in images with low signal to noise ratio. The large homogeneous pathological areas will be set to zero, since they are unchanged by linear morphological opening, however the Sup_{op}^{F} image contains a lot of details corresponding to background linear features that can be confused with vessels in some parts that do not meet all the requirements of the shape and size of blood vessels. Such vessels are also enhanced by the sum of Top-Hat transformation.

Detection of vessel boundary: In traditional morphology, edge detection is obtained using laplacian of Gaussian. Laplacian images are highlighted around zero. In fuzzy morphology, the gradient image, G(f) is morphologically obtained by subtracting the fuzzy eroded image from its dilated version. A multiscale gradient, MG(f) is the average of morphological gradients taken for different scales of the structuring element, Bi (Urbach and Wilkinson, 2008). Where Bi is a SE of size:

$$(2i+1)\times(2i+1) \tag{14}$$

The watershed transformation (Levner and Zhang, 2007) applied directly to the gradient image can cause over segmentation due to serious noise patches or other image irregularities. Here, the multiscale gradient image is threshold to extract the markers. The marker image M(f) is a binary image such that a pixel is a marker (to be black) if it belongs to a homogeneous region, a pixel will be white if it does not belongs to homogeneous region. Thus, the marker image contains a set of black pixels and a set of white pixels which remain unassigned to any region. The improper selection of threshold value will lead to over segmentation or under segmentation. Then, the fuzzy watershed transformation is applied on the multiscale gradient image using marker image as a marker. The Fuzzy algorithm was designed to segment the main vessels and remove all possible false detection under various kinds of noise.

Then, finally linear alternating filters are used to remove vessels that are not linear (large bright or dark areas, bright or dark thin irregular zones, small bright or dark areas) and also segment vessels from angiographic images of low signal to noise ratio concerning the intensity of vessels.

SEGMENTATION RESULTS

The proposed algorithm using traditional morphological filters and fuzzy watershed transformation is implemented on the original image of Fig. 1 and the results are shown in Fig. 2 and 3.

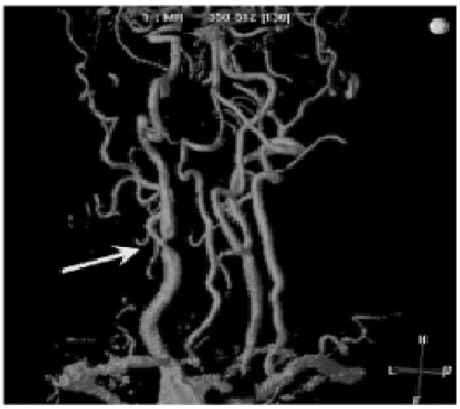

Fig. 1: Original angiogram

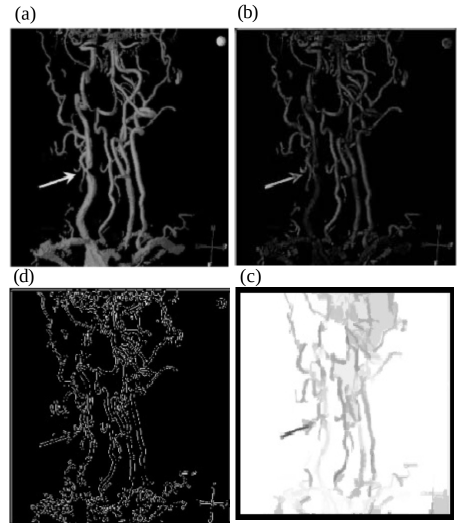

Fig. 2: Traditional morphological filter. a) Reconstructed image of Fig. 1; b) Sum of Top-Hat of ‘a’; c) Edge detection by Log and d) Final segmented image using traditional alternating filter

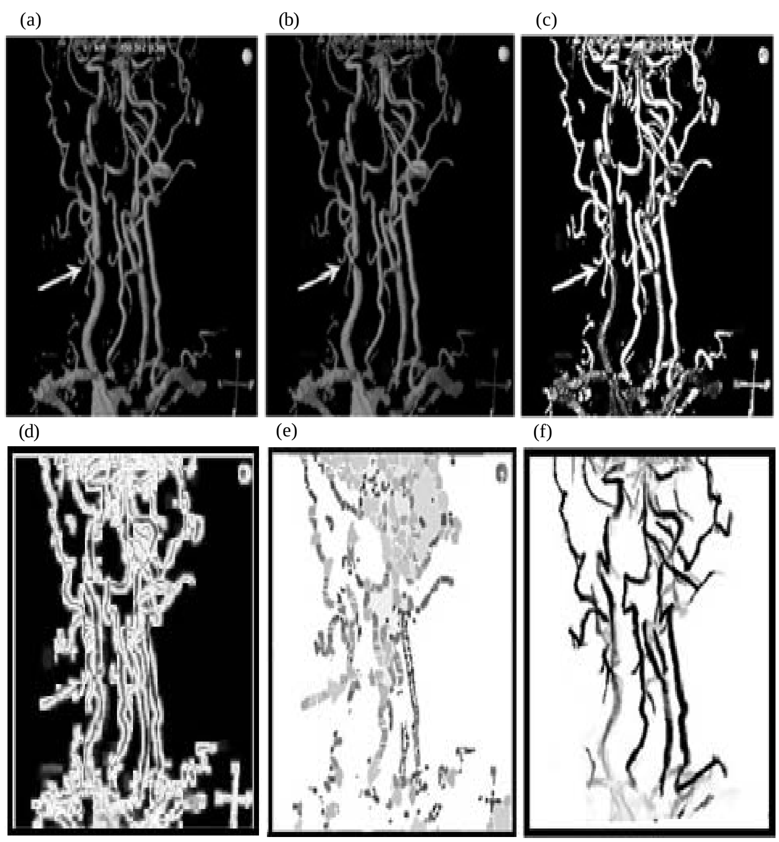

Fig. 3: Fuzzy morphology filter; a) Normalized image of Fig. 1; b) Reconstructed image of ‘a’; c) Sum of fuzzy Top-Hat on ‘b’; d) Multiscale fuzzy gradient image; e) Fuzzy watershed transformation and f) Segmented image using fuzzy alternating filter

COMPARISON OF TRADITIONAL AND FUZZY MORPHOLOGICAL FILTER

The algorithm using traditional morphological filters (Latha *et al*., 2010) has been tested on a set of angiographic images and it works well in most of the cases. However, the algorithm leads to some false detection in the following cases:

- Some features that looks linear
- Bright linear structures with round shape can be mistaken for vessels and they may appear as white isolated circles

Then, the quality of the result with regard to the ability to use this Segmentation algorithm is discussed. For this purpose, four criteria were defined:

- Detection of biggest vessels with good resolution
- Less proportion of false detection of vessels
- Bifurcation points can be identified in the linear structures
- Segmented vessels have good connectivity

The conventional morphological filter produces a binary image that is more selective. Therefore (criterion 1) is not fully satisfied if some small vessels are included. However, this filter gives some false detection of vessels. (criterion 2). The criteria 3 and 4 are satisfied with the same quality as with the LOG Edge Detector algorithm. However, the Fuzzy Morphological Segmentation algorithm leads to less bifurcation points and less false detection. Concerning (criterion 4), this fuzzy filter creates connected linear structures and thus detection of bifurcation points is easy.

Peak Signal to Noise Ratio (PSNR) results in a single value that measures the quality of a segmented image compared with the original image. Segmented images with higher metrics are judged better. The actual metric that is computed here is the Peak Signal to segmented image measure (PSNR). Assume a source image f (i, j) is given that contains m by n pixels and a segmented image is F (i, j) where F is segmented by using the above two different techniques. First the Mean Absolute Error (MAE) of the segmented image is computed as follows:

$$\text{MAE} = 1/mn \sum\sum |f(i, j)-F(i, j)| \tag{15}$$

The summation is overall pixels. PSNR in decibels (db) is computed by using:

Table 2: Comparison of PSNR value

Proposed method	MAE	PSNR value (db)	Execution time (sec)
Traditional Morphological Filters	8686.36	34.0324	0.335
Fuzzy Watershed Transformation	3316.04	43.6621	0.151

$$\text{PSNR} = 10\log_{10}(511^2/\text{MAE}) \tag{16}$$

The comparison of PSNR value is shown in Table 2.

CONCLUSION

Thus, the Segmentation algorithm using traditional morphological filters is compared with fuzzy watershed transformation. Simulation results show that the Fuzzy Watershed Transformation algorithm avoids the over segmentation problem and produce better segmentation result on the basis of quality (PSNR) and consumes less execution time when compared to traditional morphological filters.

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