Computer-Aided Diagnosis of Cerebral Aneurysm Based on Fuzzy Expert System: MR Angiography Study

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Abstract

MRA (magnetic resonance angiography) is a commonly used method for diagnosing unruptured cerebral aneurysms. In this paper, we introduce a novel computer-aided diagnosis (CAD) system for the cerebral aneurysm using MRA images. The proposed CAD system automatically finds candidates of the cerebral aneurysm, and then evaluates a fuzzy degree belonging to aneurysm whose size is more than a user-specified size. To find the aneurysm candidates, the normal model, which has no aneurysm, is estimated by using the cerebral arteries segmented from MRA images. Then the candidates are characterized by four features; variance, hemi-sphericity, mean MR signal value, and directional gradient concentration. The system then estimates the fuzzy degrees by using a feature value map generated by reference datasets. In the experiments, the proposed system was applied to eight patients with cerebral aneurysms. The four patients were used to make reference datasets, and the four patients were used to test the ability of finding cerebral aneurysms. The experimental results showed that our system gave the highest fuzzy degree for the cerebral aneurysm among the candidates in all cases except one case with small aneurysm.

1. Introduction

Cerebral aneurysms occur in the blood vessels (usually arteries) in the brain. Finding the aneurysms before they rupture is essential for prophylaxes of the subarachnoid hemorrhage, the cerebral infarction and so on. Wilcock et al. showed that magnetic resonance angiography (MRA) reliably detected aneurysms greater than a diameter of 5 mm [1]. According to Wiebers et al.'s findings, mean diameter of ruptured aneurysm was 7.5 mm [2]. It has been reported that long-term risk of rupture for aneurysm whose size is more than 10 mm is between 1 % and 2 % [3]. In addition, the risk of rupture correlates with the aneurysm size [4]. Thus, it is important to detect cerebral aneurysm with respect to the size of the aneurysm.

Several studies have been conducted on a computer aided-diagnosis (CAD) of aneurysm. They can be classified into (1) blood vessel segmentation [5][6], (2) volume rendering [7], (3) evaluation of blood velocity [8], and (4) automated detection of aneurysm. Especially, there are the related methods for detecting aneurysms. Kawata et al. have proposed a method for detecting the abdominal blood vessel disease [9]. An automated method for detecting the retinal microaneurysm has been proposed [10]. As related study to our interest, automated polyp detection has been studied [11]. However, they have not been applied to detecting cerebral aneurysms in MRA images. Moreover, there is no work on a CAD system to assist radiologists in finding cerebral aneurysms using MRA images.

The aim of this paper is to develop a CAD system, which supports radiologists to find the cerebral aneurysm. Because aneurysm is unspecified in size, shape, or location, it is difficult to realize a fully automated detection system. Therefore, our method detects aneurysm candidates and assigns the fuzzy degree belonging to various size of aneurysm. The aneurysm candidates are found by using a normal model, which is composed of normal arteries of the given subject before the aneurysms occur. The normal model is constructed by using the cerebral arteries segmented from MRA images. Assigning the fuzzy degrees is carried out on a feature value map generated by reference datasets. In the experiments, the proposed system was applied to eight patients.

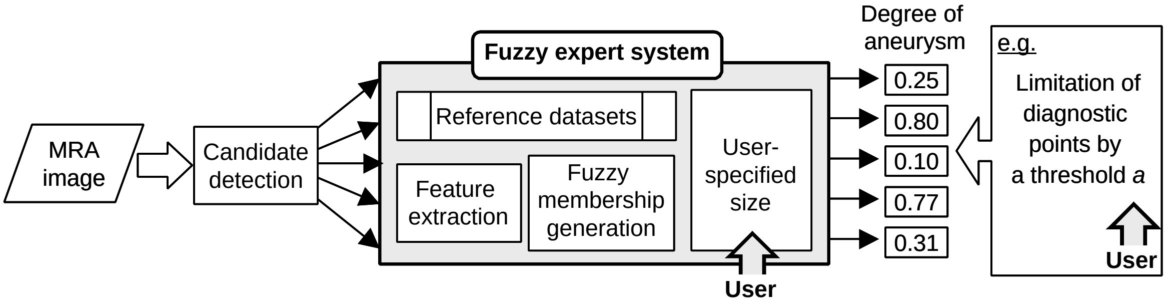


Figure 1. The proposed CAD scheme.

2. Materials

MRA images used in this study were acquired using a Genesis Signa 1.5 tesla MRI scanner (General Electric Medical Systems). The image acquisition method was 3-D time-of-flight (TOF) angiography with a repetition time (TR) of 25.0 msec and an echo time (TE) of 6.9 msec. A field of view was 160 mm. A matrix was 512 by 512, and the thickness of the slice was 1.2 mm. The dimension of the given voxel was $0.3125 \times 0.3125 \times 0.6$ mm^3. Each of the volume data was composed of about 100 separated and volumetric slices taken from the axial plane. The intensity value for all voxels of all intracranial structure ranged between 0 and 4095. The subjects were eight volunteers with aneurysms. MRA datasets used in this experiment was converted into cubic voxels, that is, filled between axial slices by linear interpolation.

3. Methods

The risk of rupture of the aneurysm depends on its size. We propose a system to help radiologists find cerebral aneurysms whose size is greater than an arbitrary size that the radiologists want to find. The proposed CAD scheme is illustrated in Figure 1. This CAD system finds aneurysm candidates from MRA images of a given subject. For each candidate, the degree of aneurysm is assigned in the range of 0 to 1 by a fuzzy expert system. One means that the aneurysm candidate is completely the cerebral aneurysm. In the example illustrated in Figure 1, the system finds five aneurysm candidates, and assigns fuzzy degree for each candidate. Thus, users can diagnose only the aneurysm candidates with respect to the fuzzy degrees. This makes the users easily find the aneurysm because it is not necessary to observe the whole cerebral arteries. And the number of points to diagnose can be limited. For example, the number of points to diagnose can be controlled by changing a threshold value. That is, the users diagnose the aneurysm candidates whose fuzzy degree is higher than the threshold. In addition, the system estimates the fuzzy degrees belonging to the aneurysm whose size is more than an arbitrary size decided by the user. For example, when the user tries to find the aneurysms whose size is greater than 3.0 mm, our system gives the low fuzzy degree for the aneurysm whose size is smaller than 3.0 mm. In the following, we describe (1) finding of aneurysm candidates, (2) feature extraction, and (3) fuzzy expert system.

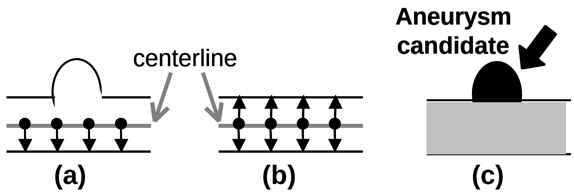


Figure 2. (a) Segmented arteries image and the centerline is described in the gray line. (b) The normal model by dilating the centerline. (c) Aneurysm candidate obtained by subtracting the normal model (a) from the segmented arteries (b).

3.1. Aneurysm candidates

We assume a normal model to extract aneurysm candidates. The normal model is composed of normal arteries of the given subject before the aneurysms occur. Thus, the normal model is generated for the individual subject. Finding the aneurysm candidate from an MRA dataset is performed with four steps. At the first step, arteries are extracted by means of an automated artery extraction method proposed by Kobashi et al. [5]. The method gives 3-D binary images in which the voxels of segmented arteries are 1 and the others are 0. The second step skeletonizes the 3-D binary image using Saito and Toriwaki's method [12], and then gives the centerlines of arteries. At the third step, the normal model is genelated using the centreline and radius of the arteries. Assume an example of constructing the normal model illustrated in Figure 2. For each voxel of the centrelines, we define the radius of the arteries to be the Euclidean distance from the voxel to the nearest background voxel as shown in Figure 2(a). So, in the case of the aneurysm, the normal radius before the aneurysm occurs can be approximated. Next, the centrelines are dilated so that the radius of centrelines becomes the approximated normal radius for each voxel of the centrelines as shown in Figure 2(b). We call the dilated centrelines as the normal model. Finally, aneurysm candidates are found by subtracting the normal model from the arteries segmented at the first step as shown in Figure 2(c).

3.2. Feature Extraction

To characterize the aneurysm candidates, we introduce four features, *variance*, *hemi-sphericity*, *mean MR signal value*, and *directional gradient concentration*. Each feature value is normalized by

$$z_i = \frac{F_i - a_i}{s_i}; \quad (i = 1, \ldots, 4) \tag{1}$$

where F_i, a_i, and s_i are the ith extracted feature value, the average value and the standard deviation, respectively.

[Feature 1] ***Variance*****:** All voxels of the candidate are assigned the Euclidean distance from the voxel to the nearest voxel of normal model. The method then constructs Euclidean distance histogram of aneurysm candidate. Using the histogram, we define the *variance* of the histogram as a feature value. To demonstrate the effectiveness of this feature value, assume three candidates shown in Figure 3. In this example, the first candidate shown in (a-1) is the aneurysm that is called as true-positive (TP), the second and the third candidates shown in (b-1) and (c-1) are quasi aneurysms that are called false-positive (FP). In the case of the second candidate, *variance* is too small (b-2). This is due to errors of the normal model assumption. In contrast, in the case of the third candidate, *variance* is too large (c-3). This is due to an overextraction in the artery extraction process.

[Feature 2] ***Hemi-sphericity*****:** The shape of the aneurysm should be like a hemisphere. We define a feature of hemi-sphericity as:

$$HS = \sqrt[3]{\frac{V_C}{V_{CHS}}} \tag{2}$$

where V_C is the volume of the aneurysm candidate. V_{CHS} is the volume of a hemisphere, which circumscribes the aneurysm candidate.

[Feature 3] ***Mean MR signal value*****:** The voxels of aneurysm have similar intensity to the voxels of the arteries because aneurysm is a part of the arteries. Mean intensity value of the aneurysm candidate of interest is calculated as the third feature.

[Feature 4] ***Directional gradient concentration*****:** Generally, the shape of aneurysms appearing on the arteries wall is hemispherical. In the hemisphere, gradient vectors of the intensity map point toward the center of a sphere, which is estimated by using the hemisphere as shown in Figure 4. Therefore, we employ the *directional gradient concentration* (*DGC*) feature [11]. The *DGC* feature is computed by

$$DGC(p) = \frac{1}{2N}\sum_{i=1}^{N/2}\begin{cases}\left|e_i^{\max}(p) - e_{i+N/2}^{\max}(p)\right|; & e_i^{\max}(p), e_{i+N/2}^{\max}(p) > 0\\ e_i^{\max}(p) + e_{i+N/2}^{\max}(p); & \textit{otherwise.}\end{cases}, \tag{3}$$

$$e_i^{\max}(p) = \max_{R_{\min} \le n \le R_{\max}}\left\{\frac{1}{n - R_{\min} + 1}\sum_{j=R_{\min}}^{n}\cos y_{ij}(p)\right\},$$

where p is a voxel of the aneurysm candidate, and N is the number of the 3-D symmetric directions that is used for computing the response. The value $e_i^{\max}(p)$ is the maximum gradient concentration between $R_{\min}$ and $R_{\max}$. As illustrated in Figure 5, the angle $y_{ij}(p)$ is the angle between the direction vector $\overrightarrow{D_i}$ and a gradient vector $\vec{g}_j$ located at distance j from p. Also, $e_i^{\max}(p)$ and $e_{i+N/2}^{\max}(p)$ are computed from the opposite directions, $\overrightarrow{D_i}$ and $\overrightarrow{D_{i+N/2}}$. In comparison with the second feature, *hemi-sphericity*, this feature value gives the information about a hemisphere like based on the intensity values.

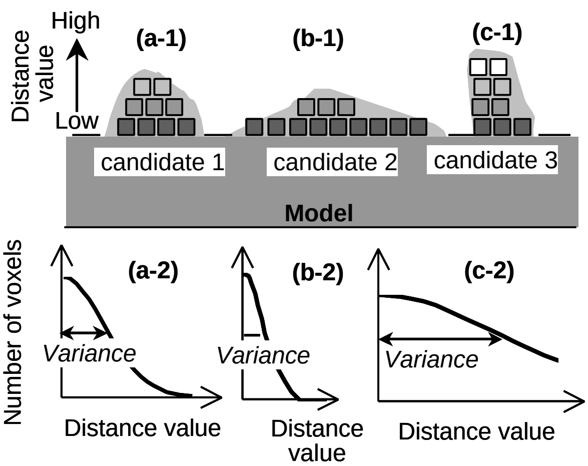


Figure 3. (a) TP candidate. (b) FP candidate due to overextraction. (c) FP candidate due to errors of the normal model assumption.

3.3. Fuzzy expert system

In this section, we propose a fuzzy expert system. The

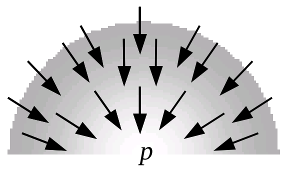


Figure 4. An example of gradient vector distribution in a hemispherical density.

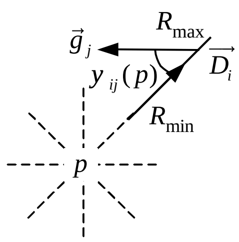


Figure 5. The angle between $\overrightarrow{D_i}$ and $\vec{g}_j$ for computation of in each direction.

fuzzy degrees are given by evaluating the similarity of the candidate to the reference datasets.

The reference datasets, which are constructed by an expert preliminary, are a set of feature values, the size, and the labeled instance (TP or FP) of the aneurysm candidates. The instance, TP, means an expert instructs that the candidate is the aneurysm. In contrast, the instance, FP, means the expert instructs the candidate is NOT the aneurysm. In the following, we call the reference datasets of TP and FP are TP object and FP object, respectively. The reference datasets are obtained from MRA images by candidate detection, feature extraction, and instance labeling. The instance of each candidate is given by the expert. Note that there are various sizes of TP objects.

For each candidate, a fuzzy degree belonging to each TP object is calculated as below. First, Euclidian distance values from the feature vector of the candidate to that of each reference data are computed. For explanation of estimating the fuzzy degree, consider a feature vector map of the reference data illustrated in Figure 6. This is an example of the feature map in the case of 2-D space. In this figure, the values d_{T1}, …, $d_{\mathrm{T}n}$ (n: the number of TP objects) are the distances to each TP object, and d_{F} is to the nearest FP object. Using the distance values, we estimate a fuzzy degree belonging to the ith TP object, m_{T1}, …, $m_{\mathrm{T}i}$, (i = 1, …, n) by:

$$m_{\mathrm{T}i} = \frac{1}{1+e^{-c_1(r_{\mathrm{T}i}-0.5)}}, \quad r_{\mathrm{T}i} = \frac{d_{\mathrm{F}}}{d_{\mathrm{F}}+d_{\mathrm{T}i}}, \tag{4}$$

where c_1 is a parameter that controls fuzziness (c_1 = 10 is used in this experiment). Figure 7 gives an example of Eq. 4. As shown in this figure, if the distance from the candidate to the ith TP object is $d_{\mathrm{T}i}$, the fuzzy degree is $m_{\mathrm{T}i}$. That is, the shorter distance gives the higher fuzzy degree. By applying Eq. 4 for all TP objects, we can obtain fuzzy degrees belonging to for each TP object.

Using the fuzzy degrees, a membership function illustrated in Figure 8 is given by:

$$f_{\mathrm{T}}(D) = f_{\mathrm{T1}}(D) \cup f_{\mathrm{T2}}(D) \cup \cdots \cup f_{\mathrm{T}i}(D),$$
$$f_{\mathrm{T}i}(D) = m_{\mathrm{T}i} \cdot \exp\left(\frac{-\left(D-D_{\mathrm{T}i}\right)^2}{b^2}\right), \tag{5}$$

where $D_{\mathrm{T}i}$ is the size of the ith TP, and b is a parameter for fuzziness (b = 30 in this experiment). This membership function gives a change of fuzzy degree according to the size of aneurysm. Thus, using the membership function, we can obtain a fuzzy degree belonging to an arbitrary size of the aneurysm.

Finally, this system calculates a fuzzy degree, m_{aneurysm}, belonging to the aneurysm whose size is greater than a user-specified size. For a candidate of interest, the aneurysm degree m_{aneurysm} is given by:

$$m_{\mathrm{aneurysm}} = \max\left(f_{\mathrm{T}}(D) \times g(D)\right),$$
$$g(D) = \begin{cases} \exp\left(\dfrac{-(D-D_{\mathrm{object}})^2}{b^2}\right); & 0 \le D \le D_{\mathrm{object}} \\ 1; & D_{\mathrm{object}} < D \end{cases}. \tag{6}$$

where D_{object} is a size specified by the users. The example is illustrated in Figure 9. The difference between this

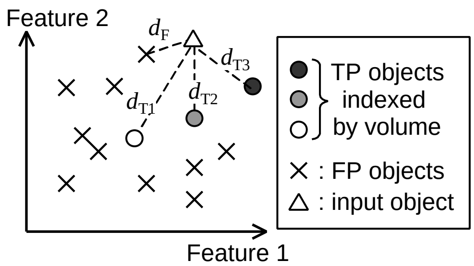


Figure 6. An example of the feature values map of the reference data.

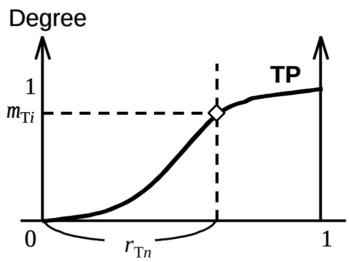


Figure 7. The degree of the *i*th TP.

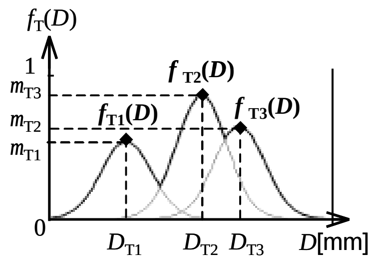


Figure 8. The membership function of the degree of TP.

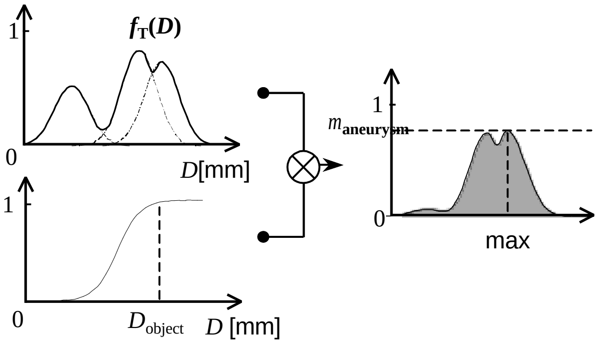


Figure 9. The aneurysm degree.

Table 1

(a) The TP feature values.

TP#	*Variance*	*Hemi-Sphericity*	*Mean MR value*	*DGC*
1	4.20	0.771	199.2	0.144
2	6.40	0.904	182.5	0.143
3	11.4	0.661	194.5	0.141
4	11.9	0.703	175.8	0.139

(b) Normalization parameters.

	Variance	*Hemi-Sphericity*	*Mean MR value*	*DGC*
a	4.91	0.608	154.6	0.135
s	5.15	0.173	24.22	0.008

fuzzy degree, m_{aneurysm}, and the fuzzy membership function defined above is that m_{aneurysm} gives a fuzzy degree belonging to the aneurysm whose size is greater than a given by a user, and the membership functions give a fuzzy degree belonging to the aneurysm for each size.

4. Results and discussion

We applied the proposed method to MRA datasets of eight patients with aneurysms. The four MRA datasets were used to make reference datasets, and the another four MRA datasets were used to test the ability of finding cerebral aneurysms. 22 reference datasets were obtained from four MRA datasets by candidate detection and feature extraction. The reference data consisted of 4 TP objects and 18 FP objects. Table 1 tabulates the feature values of TP objects and the normalization parameters. Table 1 showed that the feature values of TP objects were obtained within a constraint range.

The MRA datasets of the four patients (subject 1, 2, 3, and 4) for testing were analyzed by the proposed system. Figure 10 shows a part of results of candidate detection for subject 1. In this case, three candidates including one aneurysm (candidate 3) and two mis-findings (candidates 1,2) were obtained. The membership function f_T for each candidate is shown in Figure 11. As shown in these figures, we found that the f_T of the aneurysm (candidate 3) was higher than that of the other mis-finding (candidates 1,2). Figure 12 shows the maximum fuzzy degree distribution of all aneurysm candidates for each subject. The ground-truth aneurysms in the candidates were given by a radiologist for evaluation. The fuzzy degree of the ground-truth aneurisms are denoted by a white allow in the maximum fuzzy degree distribution. In this result, our system gave the highest fuzzy degree for the ground-truth aneurysms among the candidates in all cases except the subject 2. In the case of subject 2, the fuzzy degree of the ground-truth aneurysm was poorly estimated because the number of the reference datasets used in this experiment is very small and there is no reference dataset corresponding to the aneurysm in the subject 2.

Figure 13 shows the aneurysm candidates whose fuzzy degree is the highest in the candidates for subject 1 and 4. The size to derive the resultant fuzzy degree was set at 4 mm. The aneurysm candidates with the highest fuzzy degree were equal to the ground-truth aneurysms given by the radiologist. The size of the candidate in subject 1

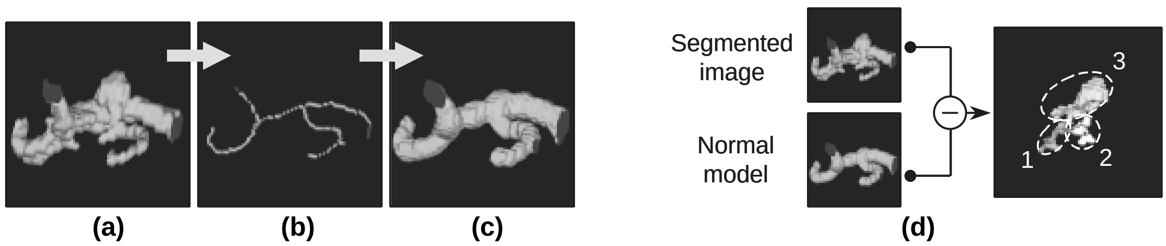


Figure 10. (a) Segmented arteries. (b)Skeletonized image. (c) Normal model. (d) Three aneurysm candidates were found.

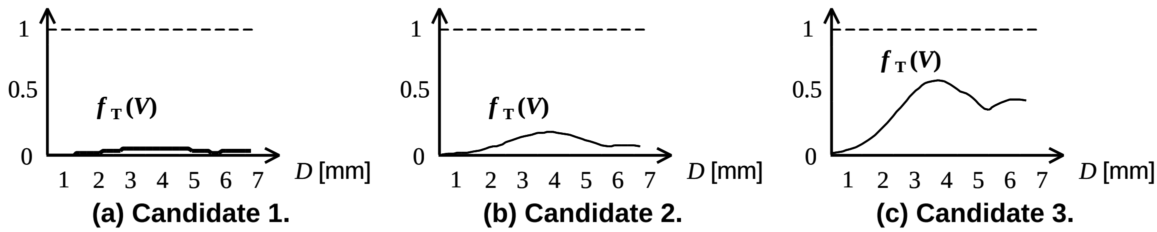


Figure 11. The membership function f_T. (a) and (b) are the FP candidates. (c) is the TP candidate.

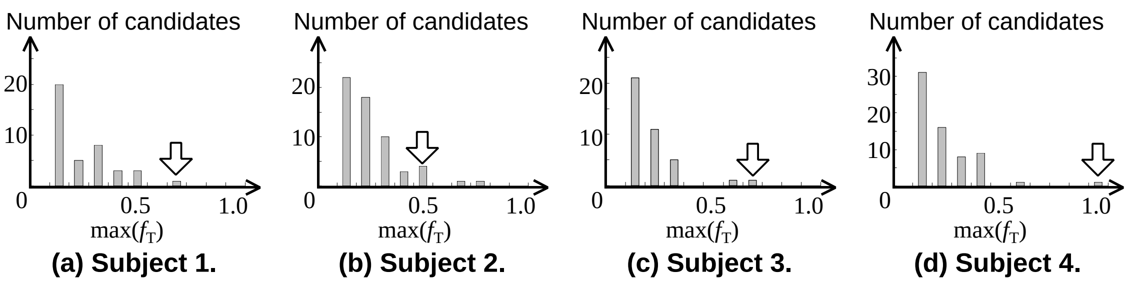
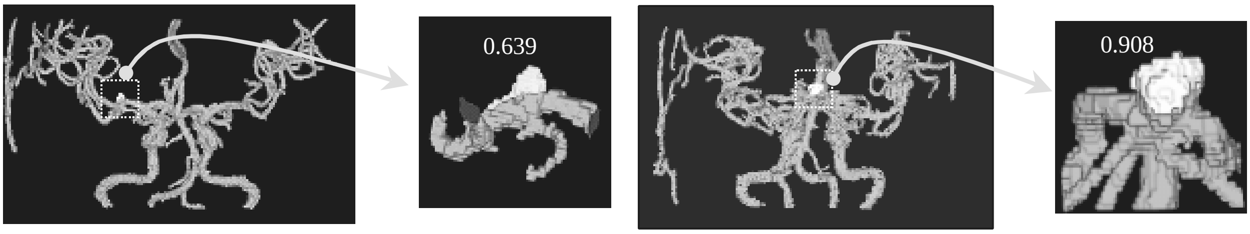


Figure 12. Fuzzy degree distribution of aneurysm candidates.



(a) Subject 1 (b) Subject 4.

Figure 13. Illustration of the detection of aneurysm.

and 4 are 4.1mm and 6.0mm, respectively. These results indicate that the proposed system gave high fuzzy degrees for the aneurysm in spite of little number of the reference datasets. The accuracy will be more improved with an increase in the number of the reference datasets.

5. Conclusions

We have proposed a novel CAD system for finding aneurysms using MRA images. The CAD system estimates a fuzzy degree belonging to aneurysms whose size is greater than a user specified size by using reference datasets. The experimental results confirmed that high fuzzy degrees were given for the ground-truth aneurysms. Thus, the proposed system strongly assists radiologists to find the cerebral aneurysm from the MRA images but the radiologists investigates the all sectional images or all points of the arteries. The feature of the proposed system is that it can be applied to entire cerebral arteries independent of the shape, and can limit the aneurysm candidates on the size of user's demand. It should be noted that our method is efficient to assist diagnosis of cerebral aneurysm. It remains us to evaluate the proposed system using the large number of subjects.

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