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Discriminating the Presence of the Cerebral Aneurysm Using Shape Features Obtained from Medical Images of the Cerebral Vessel

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Abstract

Towards the establishment of the preventive medical care for the cerebral aneurysm, this paper proposes an SVM based method for building a discrimination function that classifies the presence or absence of the cerebral aneurysm using the cerebral blood vessel's shape features obtained from medical images such as MR images. Using the discrimination function, this paper explores how much each feature affects the onset of the cerebral aneurysm. This paper deals with the internal carotid artery (ICA). The blood vessel (ICA)'s shape features are extracted from medical images of 18 persons without cerebral aneurysm and 13 patients with a cerebral aneurysm. From the medical image, the cross sections and centerline of the ICA are obtained. The cross sections are divided into nine sections along the centerline. Shape features such as the cross sectional area, its circularity, curvature, torsion, length of the centerline and branch angles are obtained in each section; as a total, 113 features including the mean and variance of some features in each section are used for building the SVM. As a result of conducting the experiments, the accuracy for discriminating the presence/absence of the aneurysm by the SVM is 90.3%. In the obtained discrimination function, the coefficient values of the function can be considered how much the features affect the onset of the aneurysm. The features that could significantly cause the onset of the cerebral aneurysm are clarified, and the reasons why these features are significant are discussed.

Introduction

The number of Japanese people who died due to cerebrovascular in 2015 is 111,973, which resulted in the fourth largest mortality rate of 8.7% of the total death in Japan. Cerebral aneurysm is considered as one of the causes of cerebrovascular diseases. A cerebral aneurysm is a vascular lesion in which a part of the cerebral artery swells. According to angiography and autopsy, the existing rate of an intracranial aneurysm of the adults is 0.5 to 6% [1]. When the cerebral aneurysm ruptures and causes subarachnoid hemorrhage, the fatality rate ranges from 32 to 67 % [2]. Clipping surgery and coil embolization are the treatments for cerebral aneurysms, but both are expensive. However, the preventive medical care for cerebral aneurysms is still undeveloped.

Our research aims at establishing preventive medical care for cerebral aneurysms. If we can know the cause of the cerebral aneurysm, it is useful for the preventive medical care. There might be many approaches for this. The goal of this paper is to develop a discrimination function that can predict the onset of a cerebral aneurysm by applying some machine learning method to medical images such as MR images and can clarify the blood vessel's shape features that could significantly affect the onset of cerebral aneurysms.

Related works include research on analyses of cerebral vessel shapes [3-6]. However, most studies focus on dealing with shape features of cerebral aneurysms themselves, and analyzing cerebral vessel shape features excluding the cerebral aneurysm portion and without using machine learning methods. A study that deals with cerebral aneurysms and a machine learning method focuses on the detection of cerebral aneurysms [7], but does not predict the onset of cerebral aneurysms. On the other hand, there are studies for the prediction of the onset of cerebral aneurysms [8, 9]. They created shapes of blood vessels before the onset of cerebral aneurysms, and investigated blood flow factors that could affect the onset of cerebral aneurysms. Their work can contribute to the preventive medical care of the cerebral aneurysm, but does not deal with machine learning based analyses of brain blood vessels' shape features.

This paper proposes an approach that utilizes SVM (Support Vector Machine) for building a discrimination function that classifies patients with and without cerebral aneurysms. The discrimination function is a linear combination of brain blood vessels' shape features; therefore, the coefficients (weights) of each feature can be considered how much that feature affects the onset of the cerebral aneurysms. In this paper, the target vessel is the internal carotid artery, and the blood vessel's shape features are extracted from 18 healthy (without cerebral aneurysm) persons and 13 patients (with a cerebral aneurysm). The validity of the proposed approach is experimentally explored.

Approach

The diagram of the proposed approach is shown in Fig.1.

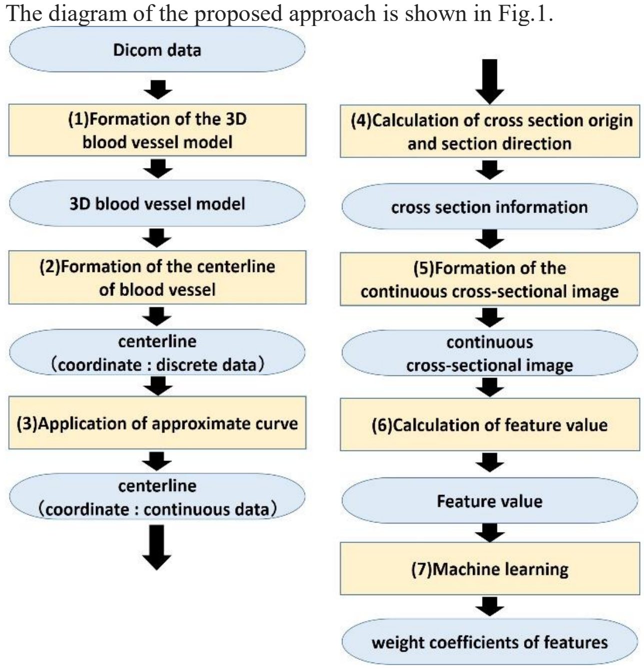

Figure.1 *Diagram of our method*

First, continuous cross-sectional images of a cerebral blood vessel are generated from DICOM data, which are obtained from medical images such as MRI and X-ray images. Next, we compute feature values in the continuous cross-sectional images and their centerlines of a cerebral blood vessel, where the feature values are not computed in the blood vessel's portion in which a cerebral aneurysm exists. Finally, the cerebral vessel's shape features are processed by SVM so that the features that are useful for discriminating with and without a cerebral aneurysm are clarified.
The outline of the processes from (1) to (7) in Fig. 1 is described as follows.

(1) A region with a signal value greater than the threshold of DICOM slice is regarded as a cerebral blood vessel, and 3D model of a cerebral blood vessel is generated in the world coordinate system.
(2) Using Antiga's method [10], a set of the center points of the vessel is generated.
(3) Since the coordinates of the centerline (the set of the center points) of (2) are discrete, a 3D curve is fitted to obtain a continuous centerline.
(4) Using Masahiko's method[11-13], the cross-sectional images are generated. In order to generate each cross-sectional image perpendicular to the cerebral blood vessel, the cross-sectional origin and cross-sectional direction are calculated. The cross-sectional origin is set at a regular interval on the continuous centerline. At each origin, the normal vector obtained by applying first-order derivative to the continuous centerline is determined as the cross-sectional direction. A 2D grid is defined in the world coordinate system, where the normal to the grid is Z-axis, and the grid spans the X-Y plane. The 2D grid is rotated and translated so that the grid's normal and 2D plane coincide with those of each cross section. Fig.2 shows the schematic of the generation of cross section.

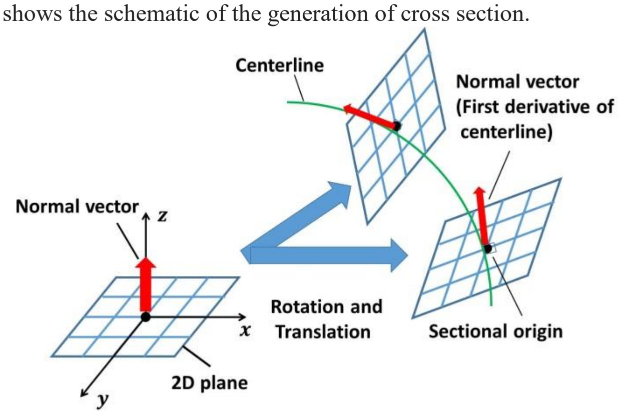

Figure.2 *Generation of cross section perpendicular to the centerline*

(5) Since grid points in grid cross sections and grid points in 3D DICOM data do not match, interpolation is performed by cubic convolution interpolation. Then, the signal values of DICOM data are stored in the grid cross section to generate continuous cross sectional images, as shown in Fig.3.

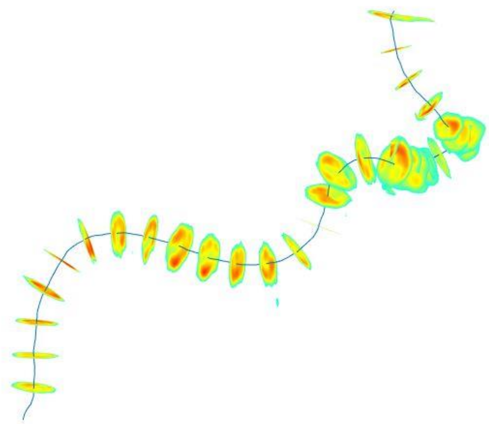

Figure.3 *Continuous cross sectional images of the cerebrovascular*

(6) The blood vessel's shape feature values are calculated from the continuous cross sectional images and the centerline. In this paper, we calculate (a) the areas of the cross sections of the cerebral vessel, (b) the circularities of the cross sections of the cerebral vessel cross, (c) the angle between the branched cerebral vessels, (d) the curvature and torsion of the centerline, (e) the length of the centerline. More specific method for calculating each feature value is as follows.

(a) Each cross sectional image is binarized. A pixel with a value equal to or larger than the threshold value is considered to correspond to a cerebral blood vessel. The total number of pixels included in the cross sectional area of the cerebral blood vessel is obtained as the area of the cross section of the vessel.
(b) The circularity of each cerebral vessel cross section is computed by Eq. (1).

$$(Circularity) = \frac{4\pi(Area)}{(Perimeter)^2} \quad (1)$$

In Eq. (1), the area is obtained by (a); the perimeter is calculated from the sum of the differences in the center coordinates of the boundary pixels of the blood vessel's cross section.
(c) The angles of the cerebral vessel's branch are calculated by the coordinates of three points A, B and C on the centerline (Fig.4), where the sphere with radius r is centered at O; A, B and C are the points at which the sphere and centerline cross. The three angles ∠AOB, ∠BOC, and ∠AOC are computed.

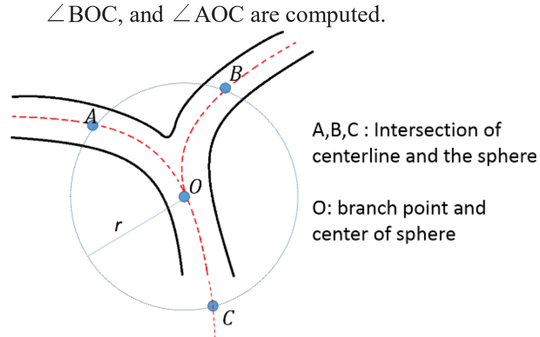

Figure.4 *The cerebral vessel branch part*

(d) Using Masaharu's method[14],the curavature and torsion of the centerlines are calculated. Eq.(2) shows the curvature κ and torsion τ in the spline curve(centerlines);P(t) =(x,y,z).

$$\kappa = \frac{1}{s'^2}\sqrt{(x'')^2 + (y'')^2 + (x'')^2}$$
$$\tau = \frac{1}{k^2 s^6}\begin{vmatrix} x' & y' & z' \\ x'' & y'' & z'' \\ x''' & y''' & z''' \end{vmatrix} \qquad (2)$$

Where, x′, x′′′, x′′′ is first,second,third derivative of x with respect to t. The same is true for y and z. s' is expressed by Eq.(3)

$$s' = \sqrt{(x')^2 + (y')^2 + (z')^2} \qquad (3)$$

(e) The sum of the Euclidean distances between adjacent points on the centerline is obtained as the length of the centerline.

(7) The total number of the features of this paper is 113. Machine learning is performed for the 113 calculated feature values. As a learning model, this paper uses the linear SVM, which is suitable for two-class classifications. Eq. (4) shows the discrimination function of the SVM.

$$f(x) = \omega \cdot x + b \qquad (4)$$

Where, ω is a weighting coefficient of each feature, x is a standardized feature value, and b is a bias term. Then identification is done by f (x) taking positive or negative values. Therefore, the larger the absolute value of the weighting coefficient, the larger the difference between the healthy people and patients.

Evaluation

About experiment condition

Table.1 shows details of the DICOM data used for the experiments and Table.2 shows experiment environment.

Table.1 Details of the DICOM data

	Healthy	Patient	
Cases	18	2	11
Modality	MR	MR	XA

Table.2 About experiment environment

PC	Dell XPS 8700
OS	Windows8.1
CPU	Intel® Core™ i7-4790@3.60GHz
Memory	16GB
Programming Language	MATLAB

As shown in Table 1, 18 MR images of 18 healthy persons (one image per one person) without a cerebral aneurysm and 13 images (two MR images and 11 X-ray images) of 13 patients (one image per one person) with a cerebral aneurysm are collected. Among brain vessels, this paper conducts experiments on ICA (Internal Carotid Artery). We generate 140 continuous cerebral vascular cross sections of the ICA for each person and calculate the feature values. As shown in Fig.5, the 140 cross sections are divided into nine sections in the direction of blood flow of ICA. As can be seen in Fig. 5, the nine sections are obtained as a result of dividing the ICA in two manners: sections 1 to 5 are obtained by dividing the entire ICA in a non-overlap manner; sections 6 to 9 correspond to areas with large curvature values. Sections 6 to 9 are considered to reflect more local features than sections 1 to 5. In each of the nine sections, the mean and variance of each feature value are obtained. Table.3 lists the feature values used for the experiments. Since the torsion takes positive and negative values, the absolute value of the torsion is also added to the feature value. The branch angles are computed at the branching points from ICA to MCA (Middle Cerebral Artery) and ACA (Anterior Cerebral Artery). Out of 13 patients, 12 cases have an aneurysm at the branch of ICA and Pcom, and one case has an aneurysm in section 4.

Table.3 The feature values used for the experiments

		Section ID number									
		1	2	3	4	5	6	7	8	9	all
Feature Value	Area-mean	○	○	○	○	○	○	○	○	○	○
	Area-variance	○	○	○	○	○	○	○	○	○	○
	Circularity-mean	○	○	○	○	○	○	○	○	○	○
	Circularity-variance	○	○	○	○	○	○	○	○	○	○
	Curvature-mean	○	○	○	○	○	○	○	○	○	○
	Curvature-variance	○	○	○	○	○	○	○	○	○	○
	Torsion-mean	○	○	○	○	○	○	○	○	○	○
	Torsion-variance	○	○	○	○	○	○	○	○	○	○
	Absolute value of torsion-mean	○	○	○	○	○	○	○	○	○	○
	Absolute value of torsion-variance	○	○	○	○	○	○	○	○	○	○
	Length of centerline	○	○	○	○	○	○	○	○	○	○
	Branch angle of ICA and MCA										○
	Branch angle of MCA and ACA										○
	Branch angle of ACA and ICA										○

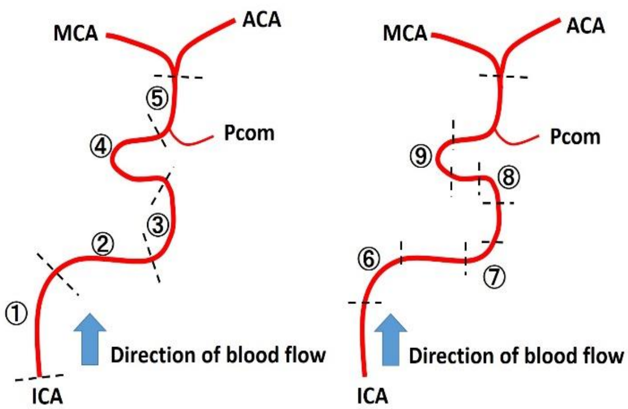

Figure.5 *Nine divided sections of the internal carotid artery*

Result

A learning model is constructed with linear SVM, and the model accuracy is estimated by 31-fold cross validation method. Table.4 shows the confusion matrix. According to Table.4, the discrimination accuracy is 90.3%. Eq.(5) shows the discrimination function of the separating hyperplane obtained by the SVM. In Eq. (5), x_i is a standardized feature value, and β_i is a weight for each feature value. In Eq. (5), $f(x) = 0$ corresponds to the separating hyperplane; $f(x) > 0$ corresponds to the space for "with aneurysms"; otherwise, "without aneurysms". Larger the magnitude of the absolute value of β_i is, the more x_i influences on the discrimination.

Table.4 The confusion matrix (Accuracy:90.3%)

		Predicted	
		Healthy	Patient
Actual	Healthy	17	1
	Patient	2	11

$$f(x) = \sum_{i=1}^{n} \left(\frac{x_i}{12.30}\right)\beta_i - 0.3347 \qquad (5)$$

Table.5 shows the top five and last five of the absolute values of the coefficient β_i of the feature x_i obtained by the experiments.

According to Table.5, the 1st and 4th ranked features are obtained from the sections 9 or 4, and these section are the section immediately before the cerebral aneurysm position. This implies that features from sections close to the aneurysm could affect the discrimination significantly.

The mean of torsion has the largest weight and it takes positive value, which could mean that the blood vessel is likely to cause an aneurysm if that section has large torsion values. The reason for this can be considered that the blood flow gets complicated due to different torsions (twists) in that section.

Since the weight of the branch angle of MCA and ACA, the second ranked, is positive, if its angle gets bigger, the aneurysm is formed more likely. Fig.6 shows the branch angle of MCA and ACA of healthy person and patients. As can be seen in Fig.6, the angle of the patient is larger than that of a healthy person. But, the branch angle on the downstream side of the aneurysm position is unlikely to be a cause of aneurysm development. Therefore, since the knowledge that the cerebral aneurysm is more likely to develop in the elderly[15] and most of the healthy subjects used in this experiment were young people, it is considered that the branching angle is the shape of the blood vessel influenced by aging .

Table.5 The absolute values of the weighting coefficients of the features obtained this time

Rank	Feature	Section	Weighting Coefficient
1	Torsion-mean	⑨	0.8881
2	Branch angle of MCA and ACA		0.7816
3	Circularity-variance	all	0.7277
4	Area-mean	④	-0.7014
5	Curvature-mean	③	0.7012
⋮			
109	Area-variance	②	-0.02355
110	Circularity-mean	①	-0.008100
111	Curvature-variance	⑥	-0.005520
112	Length of centerline	⑦	0.005355
113	Curvature-variance	⑨	0.004329

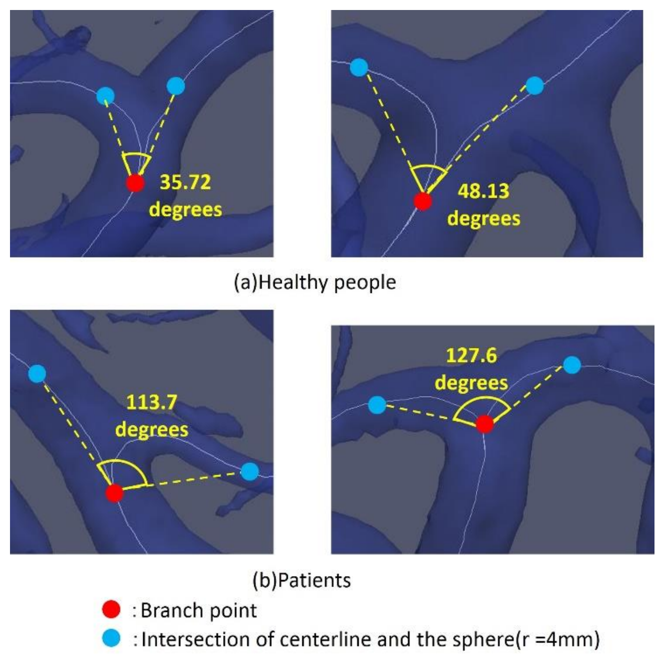

Figure.6 *Nine divided sections of the internal carotid artery*

Since the weight of the mean of area, the 4th ranked, is negative, if the diameter of the blood vessel gets smaller, the aneurysm is formed more likely. The reason for this could be that a narrow blood vessel (with a small diameter) causes large wall shear stresses, which could damage the wall of the blood vessel.

According to the 3rd and 5th features, when the shape of the cerebral blood vessel collapses or turns, there is a tendency to develop an aneurysm.

Also, as can be seen in Table 4, the weight values of the five bottom ranked (109 to 113th ranked) are almost zero. Some features in some sections do not affect the discrimination almost at all.

Conclusion

This paper has proposed an SVM based method for building a discrimination function that classifies patients with and without cerebral aneurysms using the cerebral blood vessel's shape features obtained from medical images such as MR images. Using the discrimination function, this paper has explored how much each feature affects the discrimination. The target vessel is the internal carotid artery (ICA), and the blood vessel's shape features are extracted from 18 healthy (without cerebral aneurysm) persons and 13 patients (with a cerebral aneurysm). From the medical image, the cross sections and centerline of the ICA are obtained, and the cross sections are divided into nine sections along the centerline. Shape features such as the cross sectional area, its circularity, curvature, torsion and branch angles are obtained in each section; as a total, 113 features including the mean and variance of each feature in each section are used for building the SVM. The experimental results are summarized as follows. The discrimination accuracy is 90.3%. From the obtained discrimination function, the features that could significantly cause the onset of the cerebral aneurysms are clarified, and the reasons why these features are significant are discussed.

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