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A Quantitive Description Method of Vascular basing on Unsupervised Learning towards Operation Skills Assessment of Endovascular Surgery

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Abstract **- In the field of rapidly developing endovascular technique and technology, accurate assessment of surgical operation is essential for improving the efficiency of endovascular surgery and the performance of endovascular surgery robots. Existing methods of assessment have taken into consideration of a variety of indicators such as path length of operation, operation time and so on. The indicators that have been considered all come from surgeon's operation itself. However, the characteristics of specific patients' blood vessels are not considered for objective assessment. So in this paper, operating difficulty of different blood vessels was described for operation through the aortic arch by machine learning k-means models. Then clustering results were verified with external and internal metrics. Based on this study, difficulty levels of blood vessels can be taken as an important indicator for surgeons' endovascular operation evaluation in the future research.**

Index Terms **– Endovascular surgery; Objective assessment; Description of vascular operation difficulty; Unsupervised machine learning**

I. INTRODUCTION

Endovascular surgery is widely adopted in various cardiovascular and cerebrovascular diseases on account of its advantages such as small trauma, simple operation, accurate interventional site and so on [1]. In this field, objective assessment of the surgeons ' skill is essential for evaluating the training effect of novice surgeon and further improving the efficacy of vascular interventional surgery[2]. In addition, the design and application of medical robotic systems for endovascular surgery also begin to appear and gradually develop [3]-[8], with previous research evaluating potential outcome benefits from application of robotic systems [9]-[10].

In recent years, there are lots of studies on evaluating skill of interventional surgery [11]-[14]. In the early days, assessment of surgical performance was aimed at evaluating the training effect of novice surgeons [15]. At that time, assessment relied on subjective qualitative evaluation by experienced experts or supervisors [16]. Later, structured human grading was proposed, such as Objective Structured Assessment of Technical Skills [17] which is a kind of qualitative scoring systems. These methods were the gold standard for performance evaluation at the time, even though they were somewhat subjective. Then simulator was used to extract some metrics like fluoroscopy times and the total procedure and simulator-recorded errors to evaluate surgical performance [18]. Using video fluoroscopy sequences was regarded as a method for skills assessment and the total path length correlated well with manually scored GRS with 21 participants of varying experience [19]. Non-dimensional jerk, number of sub-movements, average sub-movement duration and spectral arc length were proposed for assessment [20]-[21]. A framework was proposed for automated and objective performance evaluation by measuring contact force between catheter and the tissue [22] and movement pattern of operator at different skill levels [23]. Machine learning means have been applied for automatic assessment of physician performance in robotic-assisted minimally invasive surgery using metrics like path length, completion time, speed, depth perception, curvature and smoothness. A number of kinematic features (e.g. average speed, dimensionless jerk, average acceleration, procedure time) and the distance between the catheter tip to blood vessel wall are introduced to assess [24].

In the existing methods for evaluating surgical operation, various indicators are adopted, including path length, operation time, collision force, average velocity, acceleration, etc. However, these indicators are all extracted from the operation of surgeon. Blood vessels of different ages, genders and diseases patients are highly different. The condition of the blood vessels in a particular patient, such as the diameter of the blood vessels, the angle between the vessels at the bifurcation and the number of blood vessels, have significant influence on the surgical operation. Therefore, we should consider vascular conditions as a metric to evaluate surgical performance, which is where the research needs to be improved.

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In this paper, a vascular-difficulty classification model is established. Firstly, twenty different aortic arch vascular models are designed and features of vascular maps in the model are extracted, including path length, node number, bifurcation vessel diameter, etc. After that, unsupervised machine learning is employed to cluster vascular maps by these features and divide them into three categories. Finally, the clustering results are verified. Ten surgeons are asked to rate the operation difficulty of different blood vessel maps. Then, external and internal metrics of clustering effect evaluation in sklearn library are used to evaluate the results, which shows that the clustering results are effective and objective and proves that the Clustering Model is able to be used for grading vascular difficulty level.

Ⅱ. METHODS OF SIMULATION

In this section, the method of vascular path feature extraction is introduced. And the algorithm of unsupervised clustering model k-means is demonstrated and the method to evaluate the clustering results is presented.

A. Feature extraction of blood vessels

The establishment of vascular difficulty description model requires features of vessels. Our research will focus on operation of crossing the arch of aorta. Therefore, we will design multiple aortic arches for classification model and get vascular images.

In endovascular surgery, the shape of blood vessels varies from different patients. Different anatomical shapes of blood vessels lead to different operating difficulties in endovascular surgery. Referring to surgeons' experience, if distance between target vessel and descending aorta is farther, the operation of this target vessel is more difficult. In addition, the vessel radius and inclination angle of the target vessel at bifurcation of aortic arch are also important factors affecting doctor's operation. Number of vascular bifurcation in vascular pathway also affects operation difficulty. Therefore, according to the factors affecting vascular operation difficulty in actual surgery, eligibled features of the aortic arch were selected.

According to images of the blood vessel, canny operator will be adopted to extract the contour of blood vessels based on OpenCV library. Centerline of blood vessels will be extracted by means of morphological corrosion and expansion. After obtaining the vascular contour and centerline, AutoCAD software will be used to extract vascular features according to these two kind of image, including path length, number of vessel bifurcations, vessel diameter at the bifurcation point, angle of vessel centerline at the bifurcation point, distance between the two bifurcations and other indicators. These indicators will be used for unsupervised training in the following step.

B. Unsupervised learning: k-means clustering

In medical industry, there is no gold standard for grading the difficulty of blood vessels. It is inaccurate for surgeons to judge the difficulty grade only with the naked eye and experience. Therefore, this study will adopt the unsupervised learning method to cluster the difficulty of blood vessels according to the extracted characteristics of vessels.

Unsupervised learning is the process of solving various problems in pattern recognition based on training samples of unknown (unlabeled) categories. This paper will adopt the k-means algorithm in unsupervised learning. K-means clustering is a vector quantization method, deriving from signal processing, which is a common cluster analysis method of data mining. And it is the most popular algorithm using iterative optimization techniques.

The K-means algorithm is to put N data points of an I-dimensional space into K clusters. The mean vector $m^{(k)}$ of each cluster parameterize this cluster. Data points will be represented by $\{x^{(n)}\}$ in which superscript n goes from 1 to the counting value of data points N. Each vector x has I components x_i. It will be an assumption that the space where x in is a actual space. We will assume that there have a metric that defines distance between points, for instance

$$d(x,y)=\frac{1}{2}\sum_i (x_i-y_i)^2 \tag{1}$$

To begin K-means algorithm (equation (1)), the K cluster means $\{m^{(k)}\}$ are initialized in one way or another, such as to make the value of random. The K-means is a two-step iterative algorithm. In the first step of assignment, calculate the distance between each data point and each seed cluster center and assign each data point to the mean vector nearest to it. The second step is to update, the clustering center will be recalculated according to the existing means of the data points in the clustering .

K-means algorithm is shown as follows:

1) Initialization. Make the value of K cluster means $\{m^{(k)}\}$ to random.
2) Assignment. Calculate the distance between each data point and each seed cluster center and assign each data point to the mean vector nearest to it. We express our guess for the cluster $k^{(n)}$ that the point $x^{(n)}$ belongs to by $\hat{k}^{(n)}$.

$$\hat{k}^{(n)}=\arg\max_k \{d(m^{(k)},x^{(n)})\}\,. \tag{2}$$

Another alternative representation of assigning points to each cluster center are indicator variables $r_k^{(n)}$. When we do assignment, $r_k^{(n)}$ is set to one if mean k is nearest to data point $x^{(n)}$; otherwise $r_k^{(n)}$ is set to zero.

Fig.1. One of aortic arch models.

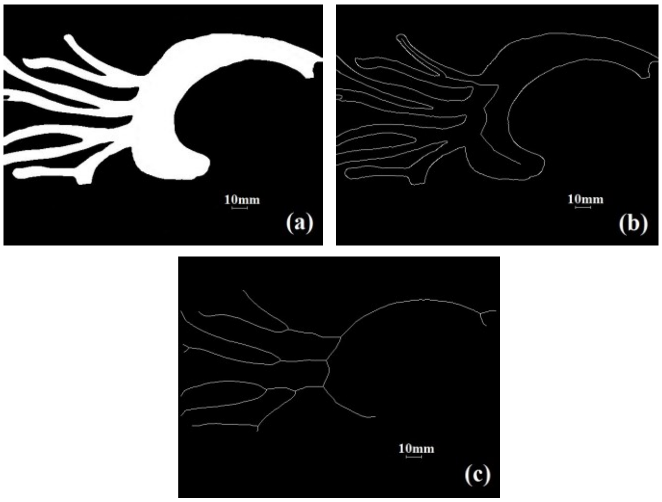

Fig.2. The processing of the aortic arch images. (a) The binary image, (b) The contour, (c) The centreline.

$$r_k^{(n)} = \begin{cases} 1 & if \quad \hat{k}^{(n)} = k \\ 0 & if \quad \hat{k}^{(n)} \neq k. \end{cases} \tag{3}$$

3) Update. The model means parameters are adjusted to match the sample means of the data points that they are responsible for.

$$m^{(k)} = \frac{\sum_n r_k^{(n)} x^{(n)}}{R_{(k)}} \tag{4}$$

where $R_{(k)}$ is the total responsibility of mean k,

$$R_{(k)} = \sum_n r_k^{(n)} . \tag{5}$$

4) Repeat steps 2) and 3) to assign and update until the assignment do not change.

After clustering results are obtained, clustering availability needs to be evaluated. The evaluation methods of clustering effectiveness can be roughly divided into two types [25]. In regard to external metrics [26]-[27], the clustering results will be compared with a reference model after the completion of clustering. On the contrary, internal metrics directly examine the clustering results without using any reference models [28]. The following of metrics will be used in following study. CH (Calinski-harabaz Index), the smaller the covariance of the data within the categories and the larger the covariance between the categories, the clustering result the better. So in this way, the calinski-harabasz score will be higher. RI (Rand index)[29] calculates the similarity between sample predicted value and real value, and value range of RI is [0, 1]. The rand index needs to be given the actual category information C, assuming that K is clustering result. And a represents the elements logarithm of same classes in C and K, whereas b represents it of different classes. After that the rand index is:

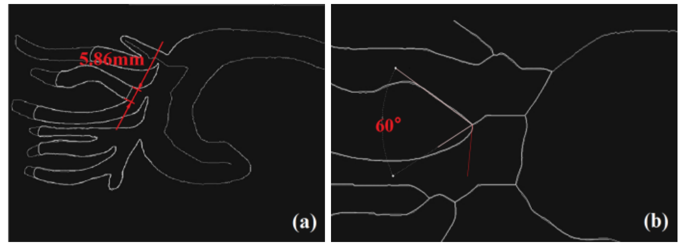

Fig.3. Vessel diameter (a) and angle (b) measuring by AutoCAD.

$$RI = \frac{a+b}{C_2^{n_{samples}}} , \tag{6}$$

where $C_2^{n_{samples}}$ is the total element logarithm which may be composed in data set. RI is within value range of [0, 1]. The larger the value, the stronger consistency of the clustering result with the actual value.

Homogeneity refers to the fact that each cluster contains only a single class of samples. Integrity (Completeness) refers to the same category samples are classified into the same cluster. It is one-sided to consider the uniformity or completeness alone, so the weighted average v-measure of the two indicators is introduced. If $\beta > 1$, the measure is more integrated. $\beta < 1$, the measure is more uniform.

$$v_\beta = \frac{(1+\beta)\cdot h \cdot c}{\beta \cdot h + c} , \tag{7}$$

where h stands for homogeneity, c stands for completeness.

III. Experiment

A. Feature extraction

Twenty different aortic arch models are designed, as shown in Fig.1. Blood vessel images are acquired from models by camera. After that, grey processing, binarization and threshold segmentation are performed on the blood vessel images. Finally, we extract the contour of the aortic arch with canny operator and obtain the images of vascular centreline by morphological closed operation and thin operation. Results as shown in Fig.2.

In the next part, we use AutoCAD software to extract features of aortic arch. AutoCAD is a ltd. CAD (computer - aided design) and drafting software application. It can be adopted directly to read the curve length, angle, diameter and other information in vascular contour and centreline.

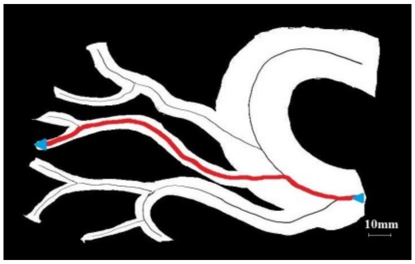

Fig.4. Vascular pathway selected for experiment using k-means model.

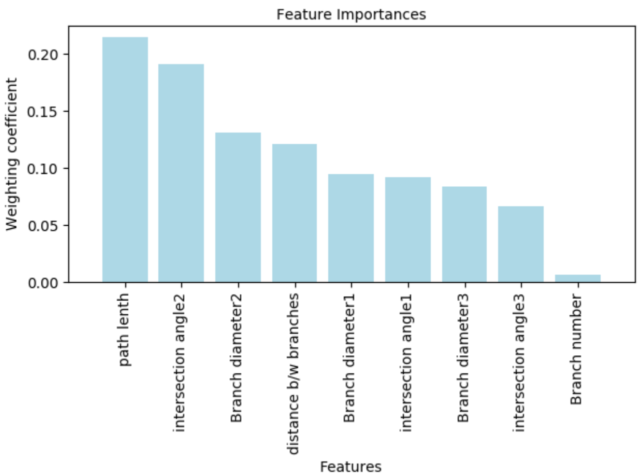

Fig.5. Important ranking of different features of blood vessels.

Therefore, we use it to obtain the vascular features mentioned in the previous section from the vascular contour and the centreline, composing the vascular feature data set. The process of obtaining vessel diameter and angle from this software is as shown in Fig.3. Each aortic arch has 8 vascular paths, and there are twenty aortic arcades of different shapes. Through feature extraction, we can obtain 9 different features composing feature vectors of each vascular path. A total of 160 feature vectors in the data set will be used for unsupervised training in the next step.

B. Data preprocessing, clustering training and evaluation

The extracted features may be irrelevant or redundant, which increases the time of model training and reduces the accuracy of the model. In addition, collinearity features which are highly correlated with each other, will lead to poor generalization ability of data sets due to their high variance and low interpretability. Therefore, before unsupervised training, feature data are pre-processed and feature selection is carried out.

We sort the importance of features using the random forest method and adopt the identify-collinear function of feature selection in Python to calculate the correlation between various features. Combining results of importance ranking and correlation detection of features, we eliminate features with low importance and high correlation.

After feature selection, feature data is standardized for improving performance of this algorithm. Unsupervised k-means method is adopted to train the data set and we set k value as 3. After repeated iterative operations, the clustering results are obtained. To verify the clustering results, ten expert doctors are asked to grade the difficulty of vascular path operation. The Calinski - Harabaz Index metrics/Rand Index metrics/Homogeneity/Completeness/weighted average of the V - measure metrics are considered to analyse clustering results.

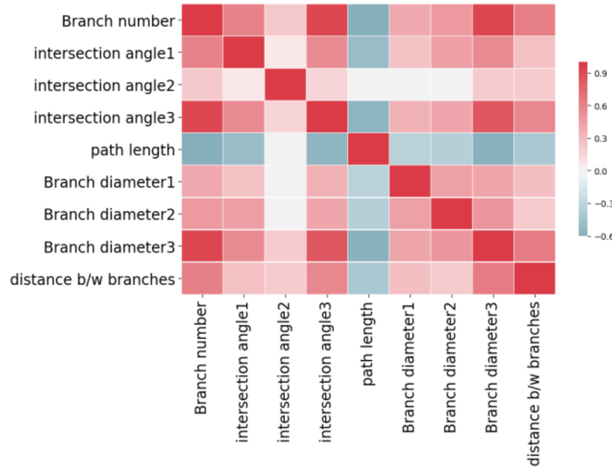

Fig.6. Feature correlation coefficient thermal diagram.

TABLE I

FEATURES WITH CORRELATION GREATER THAN 0.8.

Corr_feature 1	Corr_feature 2	Corr_value
Branch number	Intersection angle3	0.922269
Branch number	Branch diameter3	0.934286
Intersection angle3	Branch diameter3	0.841193

Finally, the k-means model is used to determine the operation difficulty of a specific vascular pathway within the aortic arch. As shown in Fig.4, the vascular pathway marked red is selected for experiment. Obviously, doctors cannot accurately judge the operation difficulty of this vascular pathway by observing it with naked eyes. So k-means model in this paper is adopted to judge its operation difficulty. Feature vector of this vascular pathway is obtained by feature extraction method above. The clustering centre coordinate value obtained by k-means model in the previous step is used to calculate the distance between the clustering centre and the feature vector. Then feature vector is assigned to the nearest clustering centre to obtain the final operation difficulty of this vascular pathway.

IV. RESULTS AND DISCUSSION

A. Feature selection results

Before the training, 9 kinds of vascular features are extracted and processed. The importance of each feature to the classification is obtained by the random forest method.

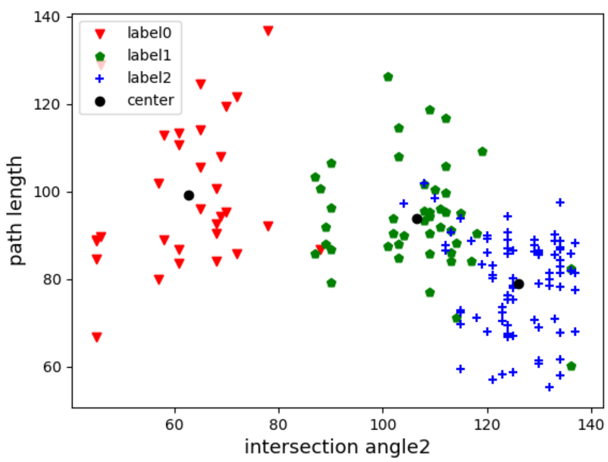

Fig.7. Scatter Diagram of K-means clustering results (k=3).

Importance ranking is shown in the Fig.5.

Afterwards, the identify-collinear function of feature selection in Python is used to calculate the correlation between various features. The correlation coefficient threshold is set as 0.8 to screen out features with high correlation, as shown in the TABLE I. The correlation of features is visualized by thermal diagram, as shown in the Fig.6. The legend is the correlation coefficient. The redder the color, the greater the correlation between features.

Feature importance sorting results show that the contribution of Branch number expressing the characteristics of vascular path is only 0.006805. Contribution of Branch diameter3, intersection angle3, Branch diameter1, intersection angle1 expressing the characteristics is not more than 0.1.

According to the correlation form, correlation between Branch number and Branch diameter3, intersection angle3 is more than 0.9. Features with high correlation lead to the redundancy. Combining the above two results, we decided to eliminate Branch number and Branch diameter3, intersection angle3 these three vascular features for feature selection.

B. Clustering results and verification

After data standardization processing, k-means clustering training is carried out. The training results are shown in Fig.7, where the black center is clustering center and three labels are three classes. In addition, Intersection angle1 and path length are the features with the highest contribution degree. So the two features are selected as horizontal and vertical coordinates respectively.

The evaluation of clustering results based on external and internal measurement is shown in the following TABLE II.

According to the scatter diagram of clustering results, we find that difficulty level of vascular path is divided into three levels with good effectiveness. The selected clustering center is reasonable. In addition, the CH score was 114.58 which indicating that the covariance within the categories of clustering was small, while the covariance between the

TABLE II
EVALUATION METRICS FOR CLUSTERING RESULTS

Evaluation metrics	Results
Calinski-Harabaz Index	114.5854
Rand Index[0, 1]	0.79506
Homogeneity	0.70388
Completeness	0.69741
V - measure	0.70064

categories was large. In other words, vessels with similar characteristics are well grouped together and closely related. RI value range is [0, 1]. And our RI value of 0.795 is close to 1, indicating the high similarity between sample predicted value and the real value. Considering completeness of homogeneity, the result is 0.7 which indicating that each cluster contains only samples of a single category in the clustering result and samples of the same category are classified into the same cluster with high degree. All of the above evaluation results show that the clustering effectiveness reaches a high level and can be applied to the grading application of vascular difficulty level.

Experimental results show that operation difficulty of vascular pathway in Fig.4 is at the third level. This result can be used as an indicator to evaluate the operation of doctors in future research.

V. CONCLUSIONS

In the Endovascular surgery, evaluation of a surgeons ' operation procedure is essential. However, the current research in this field is still immature, and the most important thing is that we have not been considering the individual differences of each patient's vascular. Patients with different ages, genders and diseases have significant differences in blood vessels, which is also one of the important factors affecting surgeons' operation.

Therefore, this study aimed at the deficiency of surgery operation evaluation and analyzed the operation difficulty of different blood vessels. The purpose of this paper is to add this metric in the future study on the evaluation of surgeons' operation and make the evaluation more scientific and reasonable. Firstly, a variety of different aortic arch vascular models were designed to prepare training data for the clustering model. Next, multiple features of vascular pathways were extracted using AutoCAD software. The random forest method and the method of calculating feature correlation were used to select features. Then, based on the results of feature selection, k-means unsupervised model was used to cluster different blood vessels. We got three different types of vessels. Finally, we evaluated the effectiveness of k-means clustering. Various evaluation metrics, both internal and external, were adopted. The results showed that the clustering results are well and can be employed to further evaluate the operation of interventional surgery doctors.

This research makes up for the lack of patient vascular information in the evaluation of surgeons' interventional operation. However, this research is preliminary for operation through the aortic arch. The complete vascular information in interventional surgery can be comprehensively evaluated in future studies. In addition, this study only preliminary analyze one of the important evaluation indexes for evaluating surgeons' operation. Operation of doctors across the aortic arch in combination with other evaluation indicators will be evaluated in the following. Furthermore, the operation skills of expert doctors will be quantified to facilitate the evaluation of interventional surgery training. And it will be make possible for the interventional surgery robot to learn the skills of the surgeon.

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