EAI Endorsed Transactions
on Pervasive Health and Technology

Research Article EAI.EU

# Anatomical mining method of cervical nerve root syndrome under visual sensing technology

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## Abstract

INTRODUCTION: The gray resolution of anatomical image of cervical nerve root syndrome is low, that can not be mined accurately.
OBJECTIVES: Aiming at the defect of low gray resolution of anatomical images, an image mining method using visual perception technology was studied.
METHODS: According to the visual perception technology, the internal parameter matrix and external parameter matrix of binocular visual camera were determined by coordinate transformation, and the anatomical images of cervical nerve root syndrome were collected. The collected images are smoothed and enhanced by nonlinear smoothing algorithm and multi-scale nonlinear contrast enhancement method. The directional binary simple descriptor method is selected to extract the features of the enhanced image; Using K-means clustering algorithm, the anatomical image mining of cervical nerve root syndrome is completed by obtaining the initial clustering center and image mining.
RESULTS: Experimental results show that the information entropy of the images mined by the proposed method is higher than 5, the average gradient is greater than 7, the edge information retention is greater than 0.7, the peak signal-to-noise ratio is higher than 30 dB, and the similarity of the same category of images is greater than 0.9.
CONCLUSIONS: This method can effectively mine the anatomical images of cervical nerve root syndrome and provide an important basis for the diagnosis and treatment of cervical nerve root syndrome.

**Keywords:** Visual sensing technology; Cervical nerve root; Syndrome; Anatomical images; Mining method; K-means clustering

Received on 27 April 2022, accepted on 25 July 2022, published on 28 July 2022



doi: 10.4108/eetpht.v8i3.657

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## 1. Introduction

Image mining is an interdisciplinary subject in many fields, such as data mining, image analysis, computer vision, machine learning and so on. Image mining is an important method to extract feature vectors from images that can reflect the hidden content of images [1], so as to analyze the association of image feature vectors, realize image classification and analysis, and improve the applicability of images. At present, data mining methods are often used in structural data mining, and image data belongs to unstructured data [2]. Structured data is simply a database. It is easier to understand when combined with typical scenarios, such as enterprise ERP and financial system; Medical his database; Education all in one card; Government administrative examination and approval; Other core databases, etc. Compared with structured data, unstructured data is not suitable to be represented by two-dimensional tables in the database, including office documents in all formats, XML, HTML, various reports, pictures, audio and video information. Therefore, image mining technology is more difficult than structural data mining technology. Image mining technology has developed rapidly in recent years. Image mining has developed rapidly in many fields such as multimedia database and information retrieval [3], and it can promote the development and innovation of many fields. How to search the useful information that can reflect the characteristics of the original image from the image is the focus of image mining. Image mining needs to extract the implicit knowledge contained in the image and clarify the feature relationship between the images. Image mining needs to extract the effective features contained in the image [4], so that the mined image can meet the actual application needs of the image. Applying image mining to medical image processing is a necessary process for the rapid development of medical field. Image mining of medical images can effectively solve the problem of rich data in the medical field, but it is unable to mine the useful information contained in it [5]. Machine vision technology is applied to medical image processing to extract applied data information from images. Through machine vision sensing technology to improve medical quality [6], visual sensing technology has important practical significance for the further development of medical research.

Cervical spondylosis is an important disease that puzzles the public in recent years. The anatomy of cervical nerve root syndrome is an important way to study the neck and shoulder pain and upper limb muscle atrophy caused by cervical nerve entrapment [7]. It is of great significance for the treatment of cervical nerve root syndrome to clarify the main causes of cervical nerve root syndrome through the anatomy of cervical nerve root syndrome. The main judgment basis in this process is the anatomical image of the patient with cervical nerve root syndrome, so the related image processing methods have attracted extensive attention of scholars.

At present, there are many researches on visual sensing technology. Zhong et al. studied the full dynamic multi-mode visual sensor [8], which could be applied to image edge calculation and has high visual transmission performance; Lin et al. applied diffuser and mechanical control lens to optical sensing [9], which improved the clarity of visual sensing; Prakosa et al. applied laser sensing technology to automatic fluid displacement measurement, which broadened the application field of visual sensing technology [10]. Although the above methods have realized the in-depth research of visual sensing technology, they have not applied the visual sensing technology to the medical field, and have not verified the application performance of the above methods in the medical field. The gray resolution of anatomical image of cervical nerve root syndrome is low, so it can not be mined accurately. Therefore, in this paper, the anatomical mining method of cervical nerve root syndrome under visual sensing technology is studied, to collect the anatomical image of cervical nerve root syndrome by using visual sensing technology, mine the useful information contained in the anatomical image of cervical nerve root syndrome through image processing technology, and obtain the method of radical cure of cervical nerve root syndrome through image mining of cervical nerve root syndrome, so as to improve the application of visual sensing technology in the medical field.

## 2. Materials and methods

### 2.1. Anatomical image acquisition of cervical nerve root syndrome based on visual sensing technology

The binocular vision camera is selected to collect the anatomical image of cervical nerve root syndrome, and the binocular vision camera uses the visual sensing technology to collect the image information. Binocular vision camera needs to calibrate the measurement system to obtain the parameters of image acquisition. The internal and external parameters of binocular vision camera are obtained through the calibration of binocular vision camera. The imaging model of binocular vision camera is established. The imaging model of binocular vision camera is the simplification of optical imaging geometric relationship. Binocular vision sensing technology requires high sensor stability and accuracy of binocular vision camera.

$s$ and $c$ are used to represent the object distance and distance of the anatomical image of cervical nerve root syndrome; $Q$ and $f$ represent points in space and lens focal length, respectively. The lens optical center of binocular vision camera is represented by pinholes. The point $Q$ in space is projected to the imaging plane by using the lens optical center of binocular vision camera to form an inverted image point $q$ . $\left(X_w, Y_w, Z_w\right)$ and $\left(x, y, z\right)$ are used to represent the world coordinate system and the coordinate system of binocular vision camera respectively; $\left(X, Y\right)$ and $\left(u, v\right)$ respectively represent the physical coordinate system of anatomical image of cervical nerve root syndrome and the coordinate system of anatomical image of cervical nerve root syndrome; $O$ and $Q$ represent the optical center of the camera and random points in three-dimensional space respectively, $q$ represents the intersection of the camera imaging plane and the connecting line between $Q$ and $O$. The coordinate system conversion is used to complete the conversion between the imaging point $q$ and the object point $Q$, and the internal and external parameters of the binocular vision camera are obtained.

#### 2.1.1 Conversion from image coordinate system to physical coordinate system

The anatomical image of cervical nerve root syndrome collected by binocular vision camera is stored in the computer in the form of $M \times N$ matrix. The position of point $O_1$ in the anatomical image coordinate system of cervical nerve root syndrome is represented by $(u_0, v_0)$, and the physical dimensions of the point in $X$-axis and $Y$-axis are represented by $dX$ and $dY$ respectively. In the anatomical image of cervical nerve root syndrome, the conversion relationship between random pixels in coordinate system $(u, v)$ and coordinate system $(X, Y)$ is as follows:

$$\begin{cases} u = u_0 + \dfrac{X}{dX} \\ v = v_0 + \dfrac{Y}{dY} \end{cases} \tag{1}$$

### 2.1.2 Transformation from physical coordinate system to camera coordinate system

In the linear imaging model of binocular vision camera, when point $q$ is the connecting line between camera optical center $O$ and object point $Q$ and the intersection $OQ$ of camera imaging plane, binocular vision camera projects in the way of central perspective projection [11]. $OO_1$ is used to represent the focal length $f$ of the binocular vision camera, and the similar triangle scale transformation is used to obtain the relationship between the camera coordinate system and the physical coordinate system of the anatomical image of cervical nerve root syndrome. The expression of coordinate transformation is as follows:

$$s\begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = Q \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \tag{2}$$

In formula (2), $Q$ and $s$ represent perspective projection matrix and scale factor respectively.

### 2.1.3 Transformation of camera coordinate system to world coordinate system

$(X_w, Y_w, Z_w, 1)^T$ and $(x, y, z, 1)^T$ represent the homogeneous coordinates of the point $Q$ in the anatomical image of cervical nerve root syndrome in the two coordinate systems respectively, and the expression of coordinate transformation can be obtained as follows:

$$\begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} \tag{3}$$

In formula (3), $T$ and $R$ represent translation matrix and rotation matrix respectively.

Using the transformation of the above coordinate system relationship, the relationship between the final imaging plane coordinate and the three-dimensional space coordinate is obtained. Based on the above formula, the transformation expression of the relationship between the imaging plane coordinate $(u, v)$ of point $Q$ in the anatomical image of cervical nerve root syndrome and the $(X_w, Y_w, Z_w)$ coordinate of the world coordinate system is as follows:

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} a_x & 0 & u_0 & 0 \\ 0 & a_y & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} R & T \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} = K_2 K_1 X_w \tag{4}$$

In formula (4), $a_x$ and $a_y$ represent the scale factors of $u$-axis and $v$-axis respectively, and $K_2$ and $K_1$ represent the external parameter matrix and internal parameter matrix of binocular vision camera respectively. Through the above process, the internal parameter matrix and external parameter matrix of binocular vision camera are obtained to realize the anatomical image acquisition of cervical nerve root syndrome based on visual sensing technology.

## 2.2. Anatomical image preprocessing of cervical nerve root syndrome

### 2.2.1 Image smoothing

The nonlinear smoothing algorithm is selected as the smoothing algorithm of the collected anatomical image of cervical nerve root syndrome. The algorithm comprehensively considers the texture discontinuity and local discontinuity of the anatomical image of cervical nerve root syndrome, and selects the average quantization method to complete the image smoothing. The image gray value expression is as follows:

$$E_{xy} = \left| I_{x+1,y} - I_{x-1,y} \right| \tag{5}$$

The anatomical image of cervical nerve root syndrome is based on the difference of pixel gray, and the image gray value is vulnerable to noise [12]. The neighborhood information of the pixels of the anatomical image of cervical nerve root syndrome can prevent the image from being affected by noise. Discontinuous quantitative texture is selected to normalize the gray mean and variance. The formula for normalizing the gray mean at pixel $(x, y)$ of the anatomical image of cervical nerve root syndrome is as follows:

$$\bar{\delta}_{xy}^2(E) = \frac{\delta_{xy}^2(E) - \delta_{\min}^2(E)}{\delta_{max}^2(E) - \delta_{\min}^2(E)} \tag{6}$$

$\lambda$ represents the threshold value of the smoothing algorithm, and the expression of the anatomical image of cervical nerve root syndrome obtained by smoothing is as follows:

$$\phi\left(\bar{\delta}_{xy}^2(E),\lambda\right)=\begin{cases}0 & \bar{\delta}_{xy}^2(E)<\lambda \\ \bar{\delta}_{xy}^2(E) & \bar{\delta}_{xy}^2(E)\geq\lambda\end{cases} \tag{7}$$

### 2.2.2 Anatomical image enhancement of cervical nerve root syndrome

The multi-scale nonlinear contrast enhancement method is selected to enhance the anatomical image of cervical nerve root syndrome. Due to the low contrast of the anatomical image of cervical nerve root syndrome, the multi-scale nonlinear contrast enhancement method has efficient enhancement performance to enhance the anatomical image of cervical nerve root syndrome.

The expression of anatomical image enhancement of cervical nerve root syndrome is as follows:

$$\hat{y}_j^i = L^i D_j^i b_{i,j}\left(\frac{y_j^i b_{i,j}}{D_j^i}\right) \tag{8}$$

In formula (8), $D_j^i$ and $L^i$ represent the maximum modulus of the scale coefficient in direction $j$ and scale $i$ and the gain constant monotonically decreasing with scale $i$ , respectively. The enhancement scale of anatomical image of cervical nerve root syndrome is controlled by parameter $b_{i,j}$ [13], and the calculation formula of parameter $b_{i,j}$ is as follows:

$$b_{i,j}=\frac{L^i}{\left(N^i\right)^2 D_j^i}\sum_x^{N^i}\left|y_j^i(x)\right| \tag{9}$$

In formula (9), $N^i$ represents the sub-band image size with scale $i$ in the anatomical image of cervical nerve root syndrome.

## 2.3. Feature extraction of anatomical image of cervical nerve root syndrome

The directional binary simple descriptor method is selected to extract the anatomical image features of cervical nerve root syndrome. This method is a feature point extraction method based on visual information. Directional binary simple descriptor method selects gray centroid method to solve the problem of lack of directionality in anatomical image feature extraction of cervical nerve root syndrome. When there is a difference between the extracted feature gray value and the image centroid gray value, there is an offset between the image centroid and corners [14]. The main direction of the extracted anatomical image features of cervical nerve root syndrome is determined by using the offset between the centroid and corner of the anatomical image of cervical nerve root syndrome.

The expression of gray moment of characteristic points in the anatomical image of cervical nerve root syndrome is as follows:

$$h_{\alpha\beta}=\sum_{x,y}x^\alpha y^\beta I(x,y) \tag{10}$$

In formula (10), $I(x,y)$, $\alpha$ and $\beta$ respectively represent the gray value of the anatomical image pixels of cervical nerve root syndrome and the judgment coefficient of the gray order of the image.

In the anatomical image of cervical nerve root syndrome, the expression of the centroid of the image block is as follows:

$$C=\left(\frac{h_{10}}{h_{00}},\frac{h_{01}}{h_{00}}\right) \tag{11}$$

After determining the centroid of the image block in the anatomical image of cervical nerve root syndrome, it is necessary to determine the direction of the feature points in the anatomical image of cervical nerve root syndrome [15]. The direction from the center of the feature point in the image block to the image centroid is the direction of the feature point in the anatomical image of cervical nerve root syndrome. The direction expression of feature points in the anatomical image of cervical nerve root syndrome is as follows:

$$\xi=\arctan\left(h_{01},h_{10}\right) \tag{12}$$

The directional binary simple descriptor method is sensitive to noise. The directional binary simple descriptor method uses the pixel average value to represent the gray value of a point, which can effectively avoid noise interference [16]. The binary string is obtained by BREF feature descriptor, and the feature points of anatomical image of cervical nerve root syndrome are described by binary string.

The formula for judging whether the image is a binary string is as follows:

$$\psi(\alpha;x,y)=\begin{cases}1, & \alpha(x)<\alpha(y)\\ 0, & other\end{cases} \tag{13}$$

In the above formula, $\alpha(x)$ represents the gray value of transverse point $x$ in the image block $\alpha$ of the anatomical image of cervical nerve root syndrome; $\alpha(y)$ represents the gray value of longitudinal point $x$ in image block $\alpha$ of the anatomical image of cervical cervical nerve root syndrome.

The binary string calculation formula is as follows:

$$f_n(\alpha)=\sum_{1\leq i\leq n}2^{i-1}\psi(\alpha;x,y) \tag{14}$$

The directional binary simple descriptor method sets the direction of feature points in the anatomical image of cervical nerve root syndrome as the main direction in the operation of brief feature descriptor [17]. It can define a random binary feature set of matrix $H$ with size $2n$ at pixel $(x_i,y_i)$ as follows:

$$H=\begin{bmatrix} x_1 & \cdots & x_n \\ y_1 & \cdots & y_n \end{bmatrix} \tag{15}$$

The transformation matrix is set as the rotation matrix $R$ with feature point direction $\varphi$ and the rotation transformation matrix $M$, and the matrix $M$ can be converted into a directed form as follows:

$$R_\varphi=\begin{bmatrix} \cos\varphi & \sin\varphi \\ -\sin\varphi & \cos\varphi \end{bmatrix} \tag{16}$$

The rotation transformation expression for feature extraction of anatomical image of cervical nerve root syndrome can be obtained as follows:

$$S_\varphi=R_\varphi H g_n(\alpha,\varphi) \tag{17}$$

The expression of BRIEF feature descriptor is as follows:

$$g_n(\alpha,\varphi)=f_n(\alpha) \tag{18}$$

Through the above process, the characteristics of the anatomical image of cervical nerve root syndrome are extracted.

## 2.4. Anatomical image mining of cervical nerve root syndrome

The K-means clustering algorithm is selected to complete the anatomical image mining of cervical nerve root syndrome according to the extracted anatomical image features of cervical nerve root syndrome. The method includes two steps: obtaining the initial clustering center and image mining.

The initial centroid of K-means clustering algorithm is determined by calculating the distance between the extracted feature vectors of anatomical image of cervical nerve root syndrome. The initial cardioid acquisition process of anatomical image mining of cervical nerve root syndrome is as follows:

(1) The number of clusters and cluster centers are represented by $K$ and $C$ respectively, and the set obtained by clustering is represented by $W=\{w_1,w_2,\cdots,w_K\}$. Let the number and dimension of features contained in the anatomical image feature database of cervical nerve root syndrome be $N$ and $M$ respectively, and the Euclidean distance $D_{ij}$ expression of random feature vectors $x_i$ and $x_j$ is as follows:

$$D_{ij}=\sqrt{(x_{i1}-x_{j1})^2+\cdots+(x_{iM}-x_{jM})^2} \tag{19}$$

The largest $D_{ij}$ is searched. When $D_{ij}=\max_{i,j}|D_{ij}|$ exists, the feature vectors $x_i$ and $x_j$ of the anatomical image of cervical nerve root syndrome are taken as the first two clustering centers of the initial clustering, which are represented by $c_1$ and $c_2$.

(2) The first two cluster centers of the anatomical image of cervical nerve root syndrome are obtained through the previous step, and the remaining cluster centers are the feature vectors with the maximum distance cumulative sum between the feature vectors in the feature vector set and the determined cluster centers [18]. In the anatomical image of cervical nerve root syndrome, the cumulative sum expression of the distance between the feature vector and the determined cluster center is as follows:

$$S_i=\sum_{j=1}^{k}\sqrt{(x_{i1}-c_{j1})^2+\cdots+(x_{iM}-c_{jM})^2} \tag{20}$$

Searching for the largest $S_i$, when $S_i=\max_i|S_i|$ exists, the feature vector $x_i$ at this time is the next cluster center. Repeat the above process until all cluster centers of anatomical image mining of cervical nerve root syndrome are obtained.

$T$ is used to represent the maximum number of iterations of the clustering algorithm, and the clustering criterion function is introduced to improve the clustering accuracy of anatomical images of cervical nerve root syndrome. When the clustering criterion function $\Phi(t)$ reaches the preset threshold, the clustering is completed and the iteration is terminated. The clustering criterion function $\Phi(t)$ is expressed as follows:

$$\Phi(t)=\sum_{j=1}^{K}x\in w_j\left|x-c_j\right|^2 \tag{21}$$

In formula (21), $c_j$ and $\Phi(t)$ respectively represent the center of category $w_j$ and the sum of square errors of all elements in the anatomical image of cervical nerve root syndrome when the number of iterations is $t$.

The clustering criterion function is used to improve the quality of clustering results of anatomical image mining of cervical nerve root syndrome. The lower the clustering criterion function is, the lower the clustering error is [19]. At this time, the anatomical image mining of cervical nerve root syndrome has high clustering quality.

The K-means clustering algorithm is used to cluster the anatomical images of cervical nerve root syndrome. The specific process is as follows:

(1) The number of $K$ clustering centers obtained is used as the clustering center of anatomical image mining of cervical nerve root syndrome. The number of eigenvectors of clustering is recorded by vector $Z$ with dimension $K$, and set $t=1$, $Z=(0)^T$, $\Phi(1)=0$.

(2) The distance from the remaining feature vector of the anatomical image of cervical nerve root syndrome to the cluster center is calculated [20], and the remaining

feature vector is divided into the class closest to the vector.

$d_{ij}$ represents the distance from the random eigenvector $x_i$ to the centroid $c_j$. When $d_{ij} = \min|d_{ij}|$ is satisfied, the feature vector $x_i$ is divided into the class whose heart is $c_j$. According to the above process, all the feature vectors of the anatomical image of cervical nerve root syndrome are divided into corresponding categories.

(3) The cluster center is updated.

For the random category $w_i$ of anatomical image of cervical nerve root syndrome, the updating formula of clustering center $c_i$ of the anatomical image category of cervical nerve root syndrome is as follows:

$$c_i = \frac{1}{z_i}\sum x \in w_i(x) \tag{22}$$

(4) The value of clustering criterion function is calculated.

The clustering threshold $\varepsilon$ of anatomical image mining of cervical nerve root syndrome is set as 0.01. When $|\Phi(t)-\Phi(t-1)<\varepsilon|$, the clustering is terminated and the algorithm ends; Otherwise, the number of iterations is set to $t=t+1$. When $t \geq T$, the algorithm is terminated; Otherwise, return to step (2) until the clustering iteration termination condition is met.

Through the above anatomical image mining process of cervical nerve root syndrome, the clustering results of anatomical images of cervical nerve root syndrome are obtained. According to the clustering results of anatomical images of cervical nerve root syndrome, cervical nerve root syndrome is analyzed as an important basis for the diagnosis and treatment of cervical nerve root syndrome.

## 3. Results

### 3.1. Experimental environment

Two DH-SV1580 medical cameras with the pixels of $2560 \times 1920$ are selected to establish a binocular stereo vision system to collect anatomical images of cervical nerve root syndrome. The baseline length of binocular vision sensing technology is 220mm. Using the established binocular stereo vision system to collect the whole process of the anatomy of cervical nerve root syndrome, this method preprocesses the collected anatomy of cervical nerve root syndrome, and uses the preprocessed image to realize the anatomical image mining of cervical nerve root syndrome.

### 3.2. Analysis of experimental results

#### 3.2.1 Pretreatment result analysis

The anatomical images of cervical nerve root syndrome collected by binocular stereo vision system are randomly selected. The anatomical image acquisition results of cervical nerve root syndrome are shown in Figure 1.

**Figure 1.** The results of anatomical image acquisition of cervical radiculopathy

The method in this paper is used to smooth and enhance the collected anatomical images of cervical nerve root syndrome. The results of the preprocessed anatomical images of cervical nerve root syndrome are shown in Figure 2.

**Figure 2.** The results of preprocessing of anatomical images of cervical radiculopathy

Through the comparison of the experimental results in Figure 1 and Figure 2, it can be seen that after the two preprocessing methods of image smoothing and image enhancement are carried out on the anatomical image of cervical nerve root syndrome collected by binocular stereo vision system, the clarity of the anatomical image of cervical nerve root syndrome is effectively improved, the image edge is clear, and many detailed information can be displayed intuitively, which provides the basis for the anatomical image mining of cervical nerve root syndrome. After preprocessing the anatomical image of cervical nerve root syndrome, the gray value fluctuation of the image is small, the noise of the anatomical image of cervical nerve root syndrome is effectively processed, and the gray value is relatively smooth. The method in this paper can effectively enhance the pixels of the anatomical image of cervical nerve root syndrome, avoid the interference of noise, and make the enhanced anatomical image of cervical nerve root syndrome retain high smoothing performance.

### 3.2.2 Calibration accuracy analysis

The image acquisition performance of binocular stereo vision system determines the accuracy of anatomical image mining of cervical nerve root syndrome. The calibration accuracy of anatomical images of cervical nerve root syndrome collected by binocular stereo vision system is statistically analyzed. In this paper, the binocular stereo vision system is used to take images at different angles and positions, and the vernier caliper is used to obtain the actual position of the target point of the anatomical image of cervical nerve root syndrome. The actual coordinates of the target point in the anatomical image of cervical nerve root syndrome are compared with the spatial coordinates of the image. The comparison results are shown in Table 1.

Table 1. Comparison of actual coordinates and image coordinates

| arget point number | Image coordinates/mm | | | Actual coordinates/mm | | |
|---|---|---|---|---|---|---|
| | X-axis | Y-axis | Z-axis | X-axis | Y-axis | Z-axis |
| 1 | 23 | 169 | 177 | 24 | 170 | 178 |
| 2 | 42 | 584 | 175 | 41 | 595 | 176 |
| 3 | 598 | 315 | 256 | 598 | 316 | 257 |
| 4 | 152 | 56 | 137 | 151 | 57 | 138 |
| 5 | 254 | 285 | 385 | 253 | 286 | 386 |
| 6 | 115 | 195 | 294 | 116 | 196 | 295 |
| 7 | 291 | 485 | 584 | 291 | 486 | 595 |
| 8 | 348 | 346 | 264 | 349 | 345 | 263 |
| 9 | 418 | 247 | 184 | 417 | 248 | 184 |
| 10 | 294 | 185 | 369 | 295 | 186 | 368 |

The experimental results in Table 1 show that the method in this paper uses binocular stereo vision system to collect anatomical images of cervical nerve root syndrome through visual sensing technology. The binocular stereo vision system established by this method can achieve efficient calibration, and the target point of the anatomical image of cervical nerve root syndrome is indirectly close to the actual target point. The difference between the three-dimensional point distance of the anatomical image of cervical nerve root syndrome and the actual distance is less than 1mm. In order to ensure the accuracy of image mining, it is necessary to carry out multiple smoothing and enhancement on this basis, so as to extract features with smaller error until the error is less than 2 μm. So as to ensure the final anatomical image mining accuracy of cervical nerve root syndrome.

### 3.2.3 Analysis of useful information

Information entropy is an important evaluation index to measure the amount of useful information contained in the anatomical image of cervical nerve root syndrome. Without considering the noise contained in the anatomical image of cervical nerve root syndrome, the higher the information entropy of the anatomical image of cervical nerve root syndrome is, it means that the anatomical image of cervical nerve root syndrome contains more useful information. The information entropy expression of anatomical image of cervical nerve root syndrome is as follows:

$$E = \sum_{i=0}^{L-1} p_i \log_2 p_i \tag{23}$$

In formula (23), $p_i$ and $L$ respectively represent the ratio of all pixels with gray value $i$ in the anatomical image of cervical nerve root syndrome to the pixels contained in the anatomical image of cervical nerve root syndrome and the number of gray levels of the image to be mined.

The method in this paper is used to mine the anatomical image of cervical nerve root syndrome. The information entropy of the mined image is completed and compared with the methods in reference [8] and reference [9]. The statistical results are shown in Figure 3.

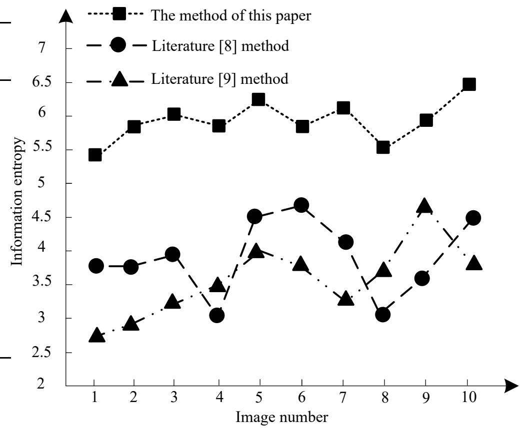


**Figure 3.** Information entropy comparison

As can be seen from the comparison results in Figure 3, the method in this paper uses visual sensing technology to mine the anatomical image of cervical nerve root syndrome, and the information entropy of the image is significantly higher than that of the other two methods. The information entropy of the anatomical image of cervical nerve root syndrome mined by the method in this paper is higher than 5, while the information entropy of the anatomical image of cervical nerve root syndrome mined by the methods of reference [8] and reference [9] is lower than 5. The comparison results show that this method can effectively preserve the useful information in the anatomical image of cervical nerve root syndrome, and avoid removing the useful information of the image while removing the image noise during image preprocessing. This method can effectively retain the useful information contained in the anatomical image of cervical nerve root syndrome, make the anatomical image of cervical nerve root syndrome play the greatest value and have high applicability.

### 3.2.4 Image quality analysis

Average gradient is another important evaluation index to measure image quality. The average gradient is measured by the mutation degree of gray value between adjacent pixels of the image. When the average gradient of the anatomical image of cervical nerve root syndrome is higher, the anatomical image of cervical nerve root syndrome contains more anatomical details of cervical nerve root syndrome, indicating that the higher the quality of the anatomical image of cervical nerve root syndrome is, the higher the definition of the anatomical image of cervical nerve root syndrome is. The average gradient is calculated as follows:

$$AG = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} \sqrt{\frac{\Delta F_x^2 + \Delta F_y^2}{2}} \tag{24}$$

In formula (24), $\Delta F_x$ and $\Delta F_y$ represent the first-order difference value of the gray value of the adjacent pixel points in the horizontal and vertical directions of the pixel point $(x, y)$ respectively, and $M \times N$ represents the image size.

According to the statistics, the anatomical images of cervical nerve root syndrome are mined by the method in this paper, and the average gradient of the anatomical images of cervical nerve root syndrome is counted. The comparison statistical results of the average gradient are shown in Figure 4.

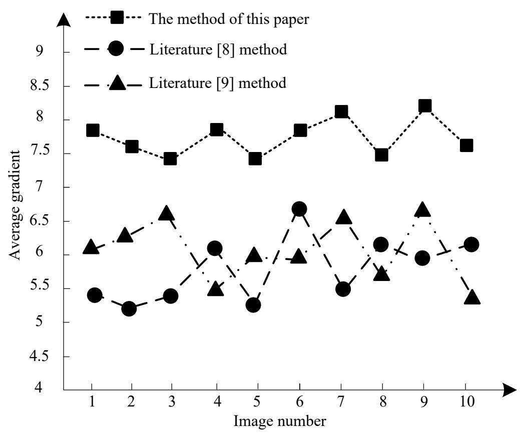


**Figure 4.** Average gradient comparison

As can be seen from the comparison results in Figure 4, the method in this paper uses visual sensing technology to mine the anatomical image of cervical nerve root syndrome, and the average gradient of the anatomical image of cervical nerve root syndrome is significantly higher than that of the other two methods. The average gradient of anatomical images of cervical nerve root syndrome mined by this method is higher than 7; The average gradient of anatomical images of cervical nerve root syndrome mined by the methods of reference [8] and reference [9] is less than 7. The comparison results verify that the method in this paper can effectively retain the detailed information in the anatomical image of cervical nerve root syndrome, make the anatomical image of cervical nerve root syndrome play the greatest value, and avoid the practical application of the anatomical image of cervical nerve root syndrome due to the loss of detailed information.

### 3.2.5 Edge texture detail richness analysis

The richness of edge texture details in anatomical images of cervical nerve root syndrome is measured by edge intensity and edge information retention. The method in this paper is used to mine the anatomical image of cervical nerve root syndrome. The edge intensity, edge intensity retention value and edge direction retention value of the anatomical image of cervical nerve root syndrome are two edge information retention parameters. The statistical results are shown in Figure 5.

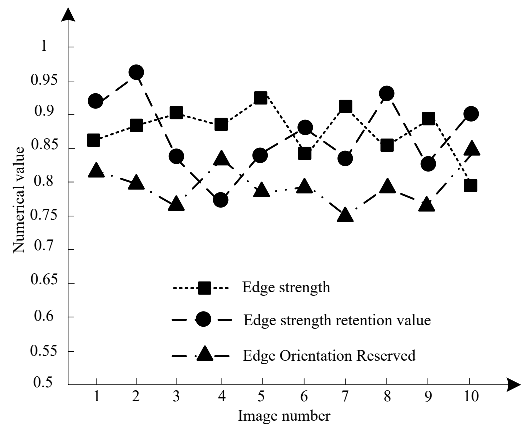


**Figure 5.** Retention of edge information

According to the experimental results in Figure 5, the edge intensity and edge information retention of the anatomical image of cervical nerve root syndrome mined by the method in this paper are higher than 0.7. The experimental results show that using this method to mine the anatomical image of cervical nerve root syndrome can effectively retain the edge information of the anatomical image of cervical nerve root syndrome. The edge texture and other details of the anatomical image of cervical nerve root syndrome are extremely rich, which can effectively improve the application of the anatomical image of cervical nerve root syndrome. The method in this paper mining anatomical images of cervical nerve root syndrome can maximize the visual information in the anatomical images of cervical nerve root syndrome, retain practical details, and improve the quality of anatomical images of cervical nerve root syndrome.

### 3.2.6 Peak signal-to-noise ratio analysis

The peak signal-to-noise ratio is an important index to measure the image quality. The peak signal-to-noise ratio of the anatomical image of cervical nerve root syndrome mined by the method in this paper is counted, and the method in this paper is compared with the methods in reference [8] and reference [9]. The statistical results are shown in Figure 6.

The experimental results in Figure 6 show that the peak signal-to-noise ratio of the anatomical images of cervical nerve root syndrome mined by the method in this paper is higher than 30dB. The experimental results effectively verify that this method can mine the anatomical images of cervical nerve root syndrome, and the image quality is high. The peak signal-to-noise ratio of the anatomical image of cervical nerve root syndrome mined by this method is significantly higher than that of the other two methods. It is effectively verified that the visual sensing technology used in this method has high processing performance for the anatomical image of cervical nerve root syndrome. The method in this paper can realize the effective processing of the anatomical image of cervical nerve root syndrome and complete the accurate mining of the anatomical image of cervical nerve root syndrome.

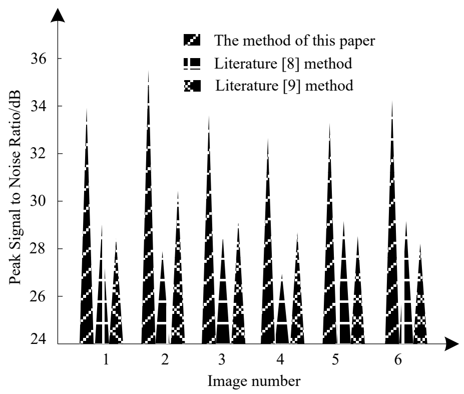


**Figure 6.** Comparison results of peak signal-to-noise ratio

### 3.2.7 Similarity analysis of similar image mining

In order to verify the clustering performance of the method in this paper on anatomical images of cervical nerve root syndrome, the similarity of images of the same category in the image mining results when this method is used to mine anatomical images of cervical nerve root syndrome is counted, and this method is compared with the methods of reference [8] and reference [9]. The statistical results are shown in Figure 7.

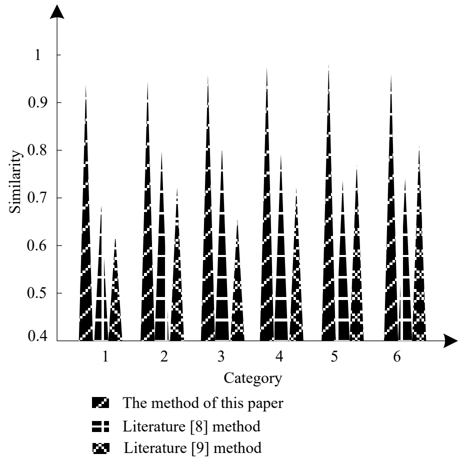


**Figure 7.** Image mining similarity results of the same category

According to the experimental results in Figure 7, the anatomical images of cervical nerve root syndrome are mined by the method in this paper. In the mining results, the similarity of images of the same category is more than 0.9; The similarity of the same category of images is lower than 0.8. The experimental results show that the mining performance of the method in this paper is significantly higher than that of the other two methods. This method has higher performance of anatomical image mining of cervical nerve root syndrome, improves the application performance of anatomical image of cervical nerve root syndrome, and contributes to the good application of anatomical image of cervical nerve root syndrome.

## 4. Discussion

The effective mining of anatomical images of cervical nerve root syndrome provides an effective application basis for the treatment of cervical nerve root syndrome. In this paper, visual perception technology is applied to the anatomical image mining of cervical nerve root syndrome, which improves the visual effect of the anatomical image of cervical nerve root syndrome, effectively suppresses the noise of the anatomical image of cervical nerve root syndrome, retains the useful information contained in the image, realizes the effective enhancement of the image, and makes the anatomical image of cervical nerve root syndrome collected by visual perception technology play the greatest role. The main reason is that this paper uses visual perception technology to mine the anatomical images of cervical nerve root syndrome, so as to obtain the useful information contained in the anatomical images of cervical nerve root syndrome. Enhance the collected anatomical images of cervical nerve root syndrome, and solve the defect that the content of cervical nerve root syndrome is too complex to accurately mine the anatomical images. Through image smoothing and enhancement processing, remove the noise contained in the anatomical image of cervical nerve root syndrome, solve the defect of local contrast enhancement or smooth de noise amplification in the process of image enhancement, enhance the detailed information contained in the anatomical image of cervical nerve root syndrome, and accurately excavate the edge information and useful information of the anatomical image of cervical nerve root syndrome.

## 5. Conclusion

In this paper, visual perception technology is applied to the anatomical mining of cervical nerve root syndrome, and the extracted image features are used for image mining to realize the effective application of the anatomical image of cervical nerve root syndrome. The experiments show that the information entropy, average gradient and edge information retained by the proposed method are higher than 5, 7 and 0.7 respectively, and the edge information of the anatomical image of cervical nerve root syndrome is preserved completely. And the peak signal-to-noise ratio of the mined image is higher than 30 dB, which has better mining quality and reduces noise interference. Therefore, this method can make the anatomical image of cervical nerve root syndrome achieve the expected application effect, and meet the needs of obtaining the anatomical image information of cervical nerve root syndrome. The image mining results can be used as an important basis for doctors to treat cervical nerve root syndrome, and have high application value.

### Acknowledgements.
The paper is supported by Foundation of Hunan Educational Committee with No.20C0374.

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