Three-Dimensional Reconstruction of Fuzzy Medical Images Using Quantum Algorithm

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ABSTRACT In order to deal with the problems of poor anti-interference, low reconstruction clarity and large errors in the traditional medical image reconstruction methods, we proposed a fuzzy medical images three-dimensional (3D) reconstruction method using quantum algorithm. First of all, a feature matching model of fuzzy medical image was built. Secondly, this study decomposed the edge contour features by using the Gaussian mixture feature matching method, extracted the edge contour vectors of fuzzy medical image, and enhanced the information of fuzzy medical images by adopting the region edge sharpening. Thirdly, this study reorganized the 3D texture structure of images and reconstructed the sparse scattered points according to its texture and detail regions. Finally, we combined with the gray histogram of fuzzy medical images to achieve the adaptive pixel reconstruction of fuzzy medical images, and completed the 3D reconstruction of fuzzy medical images by employing the quantum algorithm. The results show that the proposed method is characterized by high matching degree of image features and balanced distribution of point clouds, and the self-similarity coefficient of the reconstructed texture can reach 0.994; in addition, the SINR value of the reconstruction result can be maintained around 100dB, and it has lower error rate than the traditional method, thereby improving the detection and recognition capability of medical images, and the algorithm has certain practical application.

INDEX TERMS Quantum algorithm, fuzzy medical images, three-dimensional reconstruction, characteristics of the reconstruction.

I. INTRODUCTION

Medical images have the characteristic of special shape. Therefore, there are usually phenomena such as low image contrast, frequent changes in tissue characteristics, and fuzzy regional and boundary features. In actual, due to insufficient equipment accuracy, the boundary of the medical image will be fuzzy, resulting in fuzzy medical images. With the development of 3D image processing technology, the image feature reconstruction method can be used to perform 3D reconstruction and feature recognition on medical images, establish a 3D reconstruction model of the fuzzy medical image, and effectively extract the detailed features of fuzzy medical images. On this basis, the method can identify the detailed features of fuzzy medical images and completed the 3D reconstruction and recognition of fuzzy medical images, which is beneficial to improve the 3D reconstruction and recognition capability of fuzzy medical images. Therefore, the research on 3D reconstruction method of fuzzy medical images is of great significance in detecting fuzzy medical image.

Quantum algorithm is a calculation method that combines quantum theory with computer technology [1]. It is essentially independent of quantum mechanics and does not depend on quantum physics at all, but combines the superposition and parallelism of quantum systems. Due to the uniqueness of quantum, the quantum algorithm shows obvious advantages in ensuring information security, increasing information capacity and extracting information features. In addition, these pure physical properties have greatly improved the parallel computing efficiency of the quantum algorithm. As a result, the quantum algorithm has been researched and applied by many scholars as soon as it was proposed, and it has produced certain results. At present, the quantum
algorithm has become an effective way to address the computing platform, and it is widely favored by scholars. Literature [2] conducted user recognition research using quantum computing, and proposed two fast IP address search algorithms, and increased the complexity of the search process, which complete user recognition by combining with the rapid computing capability of quantum computing. Literature [3] held that multi-party collaborative quantum computing was a problem to be further studied in the quantum field; the method assigned each party involved in quantum computing to a set of particles that completely covered each node and achieved multi-person collaboration, which effectively improved the monotony of each node corresponding to only one particle in the traditional method. Literature [4] proposed an improved quantum image description method, and extended the monochrome image to color images, which enriched the research object, provided the corresponding quantum extraction method, and verified the effectiveness of the algorithm on the computer. Literature [5] discussed the development of quantum computing at the junction of mathematics, physics and computer science, and achieved certain research results. Literature [6] suggested studying quantum programming with an object-oriented paradigm, and proposed the unary semantics of FJQuantum1, which was an object-oriented language used for inference and development of programs that processed quantum data and quantum operations.

Based on the existing research results of related quantum computing, this study introduced the quantum algorithm for fuzzy medical image 3D reconstruction, constructed a feature matching model, decomposed the edge contour features of images, and performs information enhancement; on this basis, reconstructed the sparse scattered points, and completed the 3D reconstruction of the fuzzy medical images based on the quantum algorithm. Through experiments, it is verified that the proposed method has good 3D image reconstruction capability.

1. This study introduces the quantum algorithm, makes use of the advantages of quantum algorithm for fuzzy medical image 3D reconstruction, and obtains a better reconstruction effect.

2. This study constructs the Gaussian mixture template feature matching model of fuzzy medical images, laying a foundation for subsequent feature decomposition and point cloud reconstruction.

3. This study linearly superimposes synthetic variables of fuzzy medical images in quantum space, so as to provide conditions for 3D reconstruction.

4. The results of several groups of comparison experiments fully demonstrate the superior reconstruction performance of proposed method and contribute to the recognition and detection of medical images.

II. RELATED WORK
At present, some experts and scholars have put forward some mature research results in the field of fuzzy medical image 3D reconstruction, the literature [7] used the moving cube topology algorithm to reconstruct the CT image. By improving the basic topology to form 17 types of topology for reconstruction, the surface voids are reduced and the reconstruction effect is better. However, this method has poor adaptability for image reconstruction, and the recognition of fuzzy features is not high. Literature [8] proposed a multi-threshold 3D reconstruction method based on labeled medical image, so that the multi-threshold organs in fuzzy images were labeled as simple integers and the data storage was reduced. The method defined the voxel vertex index mode and isosurface intersection form of multi-threshold 3D Reconstruction, avoiding the triangular facet and vertex reuse when extracting multiple threshold features. At the same time, combined with fuzzy feature decomposition method, multi-scale structural feature decomposition on fuzzy images was performed, yet it did not provide much clarity for 3D reconstruction of medical images. Literature [9] proposed a fast 3D reconstruction method of multi-resolution cone-beam CT images based on wavelet transform, which performed wavelet transform of the corresponding scale on the acquired images. In this method, the wavelet coefficients of the corresponding scale were selected to perform cone-beam reconstruction, then the tomographic images were taken along the radial direction from the obtained low-resolution reconstruction data, and the corresponding wavelet inverse transform was realized to obtain a high-resolution 3D Image data. However, the method has poor anti-interference in medical image 3D reconstruction.

Literature [10] performed 3D reconstruction of CT images of abdominal organs, adopted an adaptive improved moving cube algorithm to segment the image, selected all voxels that intersect the threshold, and obtained point cloud information using the vertex index method of the general tree to complete the image reconstruction. But the reconstruction resolution is not high. Literature [11] studied fully automatic 3D reconstruction of medical images, and combined with the most advanced CNN positioning analysis images, and verified the effectiveness of the algorithm based on the case analysis. However, the algorithm fails to complete the feature matching. Literature [12] introduced a new and general 3D reconstruction algorithm. The algorithm used light field reconstruction theory to effectively construct a 3D SEM image in a large range, and achieved a dense 3D point cloud reconstruction through image capture, generation of polar plane images and image stitching. Although the algorithm’s deep reconstruction does not depend on matching correspondence and has a good effect, it is easily interfered by external environment.

Literature [13] proposed a semi-automatic method to accurately reconstruct the main inner ear structure. During the reconstruction process, an enhanced coupling level set method was developed. The method allows multiple image labeling at the same time without any overlap area. This method Post-processing the reconstructed geometry to improve the geometry of the basement membrane to truly represent the physiological dimensions, but the reconstruction
accuracy needs to be improved. Literature [14] designed a medical image segmentation classification system based on intuitionistic probability fuzzy c-means clustering and fuzzy SVM algorithm, which has a better image processing effect, but the data processing accuracy needs to be further improved.

Therefore, in order to solve the problems in the existing methods, this study proposed a fuzzy medical image 3D reconstruction method using the quantum algorithm. Through the extraction of edge contour features and the reconstruction of sparse scattered points, the proposed method provides favorable basic conditions for 3D reconstruction. In addition, the proposed method is characterized by good image 3D reconstruction effect, high feature matching degree, and balanced distribution of image reconstruction point cloud, and its reconstruction texture self-similarity coefficient can reach 0.994. The higher the clarity, the stronger the anti-interference; the SINR value is kept around 100dB, with small reconstruction error, and the algorithm has good practical applicability.

III. FUZZY MEDICAL IMAGE FEATURE MATCHING AND DECOMPOSITION OF EDGE CONTOUR FEATURES

In order to realize the 3D reconstruction of fuzzy medical images, it is necessary to linearly superimpose the composite variable of fuzzy medical image in the quantum space using the extraction of edge contour feature quantity and information enhancement processing, and complete the image 3D reconstruction by using the quantum space operation.

A. FUZZY MEDICAL IMAGE FEATURE MATCHING MODEL

First of all, the feature matching model of fuzzy medical image was constructed, the purpose of which is to improve Gaussian mixture feature matching, realize the decomposition of edge contour features, and thus extract the edge contour feature vector. Therefore, this study combined the fuzzy feature recognition method to perform feature reconstruction and 3D feature recognition of fuzzy medical images, established the edge contour feature detection model, and performed the block detection and regional fusion processing of fuzzy medical images.

Assuming that the pixel feature distribution set of the fuzzy medical image is $S_i (i = 1, 2, \ldots, n)$, this study performed 3D reconstruction using the texture distribution of fuzzy medical images, and constructed the Gaussian mixture model of fuzzy medical images in the $D$-dimensional space; combined with the traditional Gaussian mixture model, the weak edge texture set of the fuzzy medical image was obtained. Therefore, the target contour fitting feature distribution [15] of the obtained fuzzy medical image is expressed as:

$$P = S_i g \left( \frac{u - \Delta u}{\sigma} \right)$$

where, $P$ is the target contour fitting feature distribution set of the fuzzy medical image, $\Delta u$ is the feature component of the weak edge texture 3D reconstruction in the fuzzy medical image, $\Delta u$ represents the change amount of the weak edge texture features of fuzzy medical images during the reconstruction process, $g$ represents the intensity of pixel feature distribution of fuzzy medical images in the gradient direction, and $\sigma$ is the rotation operator in fuzzy medical images. According to the regular distribution of texture of fuzzy medical image and target contour fitting features, this study performed 3D reconstruction to obtain the distribution of regional edge feature distribution of fuzzy medical image as follows:

$$C((f, d)P)k$$

where, $C$ is the edge feature distribution set of the fuzzy medical image area. $(f, d)$ represents the statistical feature distribution set of pixel feature points of fuzzy medical images in the $d$ direction, and $k$ represents the number of single Gaussian models in the mixed Gaussian model. On this basis, this study matches the fuzzy features of fuzzy medical images, and constructs the feature matching model $M$ of fuzzy medical images as follows:

$$M = k \sum_{i=0}^{n} S_i C$$

The feature matching model of fuzzy medical image was obtained. It is shown in Figure 1.

B. DECOMPOSITION OF EDGE CONTOUR FEATURES

Based on the fuzzy medical image feature matching model obtained above, this study extracted the edge contour feature vector of fuzzy medical images and used the region edge sharpening method to perform information enhancement processing on fuzzy medical images. At the same time, combined with the method of mixed fractal, the local fitting of fuzzy medical image was carried out, and the information enhancement was performed on weak edge images [16], [17]. After the surface errors were adjusted during 3D reconstruction based on the similarity between random pixels, the output of the feature vector estimate $S$ of fuzzy medical images can be obtained as follows:

$$S = \phi M - l$$

where, $\phi$ represents the similarity coefficient between random pixels, and $l$ represents the distance of the surface error measurement of feature vectors. The R, G, and B color components were extracted in the fuzzy medical images, and the
texture distribution set of the fuzzy medical image was correspondingly $A = \{A_r, A_B, A_R\}$. Three-dimensional reconstruction template of the fuzzy medical images was obtained in the segmentation topology, and the feature matching set of the sharpening template of the fuzzy medical image was constructed. Suppose the given image has $m$ pixels, and the description feature of the pixel is $w_m$, the statistical distribution set $T$ [18], [19] of the 3D reconstruction point cloud of fuzzy medical images in the background region $y_1$ and the foreground region $y_2$ is as follows:

$$ T = \exp \left( \frac{Sw_m}{2\sigma^2} \right) \frac{A}{\text{dist}(y_1, y_2)} $$

(5)

where, $\text{dist}(y_1, y_2)$ is the Euclidean distance function [20].

In the 3D reconstruction point cloud statistical distribution set $T$ of fuzzy medical images, the weak edge features of the fuzzy medical image were extracted inside the extended contour edge of the curve to decompose fuzzy medical images, and then the output result of fuzzy medical image edge contour feature decomposition is as follows:

$$ I = \frac{\alpha(1 - T)}{t} $$

(6)

where, $I$ is the feature decomposition vector of the edge contour of the fuzzy medical image. $\alpha$ is the fitting degree of fuzzy medical images, and $t$ is the sampling interval of fuzzy medical images. In this study, the edge contour feature vector of fuzzy medical images was extracted, and the regional edge sharpening method was used to perform information enhancement processing of fuzzy medical images.

**IV. OPTIMIZATION OF FUZZY MEDICAL IMAGE 3D RECONSTRUCTION**

**A. SPARSE SCATTERED POINT RECONSTRUCTION OF FUZZY MEDICAL IMAGES**

In this study, the Gaussian mixture template feature matching model of fuzzy medical image was constructed above. Based on the Gaussian mixture feature matching method for edge contour feature decomposition of fuzzy medical images, this study carries out the fuzzy medical image 3D reconstruction.

Assuming that the visual information reconstruction region of fuzzy medical images is $G$ and the distribution region of edge contour is $(x, y)$, this study performs the texture gradient decomposition and calculates all vector sets of fuzzy medical image, then the threshold for edge 3D reconstruction of fuzzy medical image [21], [22] is:

$$ Y = \frac{1}{z} \exp \left( \frac{d(x, y)}{G} \right) \times I $$

(7)

where, $z$ is a second-degree operator. In this study, the template feature distribution function of super-resolution reconstruction of fuzzy medical image was defined, the synthetic image and real image were fused, and the fuzzy medical image was detected in blocks [23], [24]. Assuming $j$ is the contrast enhancement value, this study used the quantum algorithm for 3D reconstruction according to the texture and detail distribution of fuzzy medical images. Therefore, the classic iteration of output quantum evolution [25] is:

$$ B = \frac{qG}{d} \times Y $$

(8)

where, $B$ is the image feature set. $q$ is the global fitting parameter, $c$ is the multi-dimensional convolution feature vector of fuzzy medical images, and $d$ is the transmission intensity of fuzzy medical images. In this study, the visual correlation detection model was constructed for fuzzy medical images, the gray histogram of fuzzy medical images was reconstructed, and the adaptive feature decomposition of the fuzzy medical image was combined with the fuzzy edge structure reorganization method. The process for reconstructing the sparse scattered point is as follows:

$$ G = B \exp \left( \frac{d(x, y)}{S} \right) $$

(9)

where, $G$ is the sparse and scattered point reconstruction model.

Based on the above analysis, the 3D reconstruction design of fuzzy medical image is carried out.

**B. THE IMPLEMENTATION OF THE PROPOSED ALGORITHM**

Input: Original feature data of fuzzy medical images;
Output: Fuzzy medical image 3D reconstruction results.

This study initialized the image feature data, combined fuzzy edge structure reorganization method for adaptive pixel reconstruction of fuzzy medical images, and adopted the quantum algorithm for 3D reconstruction of fuzzy medical images. The process is as follows:

1. The fuzzy medical images were reconstructed in the pixel region within the template region, and the statistical information fusion method was used to reconstruct the fuzzy medical image region. The distribution of 3D sparse scattered points is:

$$ H = \frac{G - S}{\delta} $$

(10)

where, $\delta$ represents the structural similarity of fuzzy medical images.

2. In the $4 \times 4$ sub-region imaged by fuzzy medical images, this study reconstructed the gray histogram of the fuzzy medical image to obtain the similarity $\mu$, and used the fuzzy scheduling center of the medical image as the pixel center to implement quantum operations. Accordingly, the quantum expansion model is:

$$ W = \frac{1}{\mu}(H + h)r $$

(11)

where, $h$ is the fixed amplitude of pixels in the pixel subset of fuzzy medical image, and $r$ is the statistical space vector of fuzzy medical image’s quantum space conversion.

3. The composite variable of fuzzy medical images was linearly superimposed in the quantum space, and the fuzzy...
FIGURE 2. Three-dimensional reconstruction process of fuzzy medical image.

Medical image 3D reconstruction model $M'$ was established in the local area of the $4 \times 4$ sub-block

$$M' = \frac{(W - G)e}{v}$$

where, $e$ is the principal eigenvalue of multi-sensor nodes, and $v$ is the distance between nodes. (4) End.

Based on the above analysis, this study achieved the 3D reconstruction of fuzzy medical images by using the quantum algorithm. It is shown in Figure 2.

V. EXPERIMENTAL ANALYSIS AND RESULTS

In order to test the practical application performance of fuzzy medical image 3D reconstruction method using quantum algorithm, this article designed the following simulation experiment for verification.

A. EXPERIMENTAL ENVIRONMENT AND DATA SET

This experiment is based on MATLAB platform and windows 10 system. The experimental data were obtained from Hypertrophic Cardiomyopathy (MRI) [26], Apical hypertrophic cardiomyopathy (MRI) [27], scmr (MRI) [28], ACDC(MRI) [29]and RVSC(MRI) [30]. Each data set is defined number as 1, 2, 3, 4, 5. Magnetic Resonance Imaging(MRI) medical heart data set was used for network training and testing. 10000 images were taken as training data set, and 5000 images as test set; The details of the experiment are introduced in detail: The matching template of fuzzy medical images is a $120^\times 120$ uniformly distributed template, and 200 pixels were randomly sampled for each image; the feature resolution of fuzzy medical images is $500 \times 500$, and the fuzzy similarity coefficient of fuzzy medical image 3D reconstruction was 0.55; Three-dimensional reconstruction objects were the left and right ventricles, and a total of 68 surface points were collected; Data sets were used to test the effect of the proposed method; Different indicators were selected to compare the difference between the proposed method and the existing methods, so as to verify the performance of the proposed method.

Many parameters are used in this study, including the number $k$ of single Gaussian models in the Gaussian mixture model. The similarity coefficient $\phi$ between random pixels. The surface error measurement distance $l$ of the feature vector. Fuzzy medical image fit degree $\alpha$. Fuzzy medical image sampling interval $t$. These parameter range are shown in Table 1.

| Parameter | Ranges |
|-----------|--------|
| $k$ | — |
| $\phi$ | [0,1] |
| $l$ | [0,1] |
| $\alpha$ | [0,1] |
| $t$ | [1,10] |

According to the table 1 parameters, the larger the number $k$ of a single Gaussian model in the Gaussian mixture model, the better the denoising effect of the proposed algorithm. The larger the value of $\phi$ and $\alpha$, the higher the self-similarity of the proposed algorithm image and the better the image fitting degree. $l$ is the error measurement distance, the smaller the value, the smaller the algorithm error.

B. EVALUATION CRITERIA

(1) Image 3D reconstruction effect

This study presented the initial reconstruction model of medical images, and showed the image 3D reconstruction effect of the proposed method with real pictures.

(2) Image feature matching degree

Equation (3) was used to calculate the image feature matching value and mark the matching points, and to compare the feature matching degree of different methods.

(3) Image reconstruction point cloud distribution balance and cloud reconstruction applicability

This study calculated the statistical distribution set of the image 3D reconstruction point cloud according to Equation (5), and reconstructed the point cloud distribution balance for different method images. On this basis, the heart image is reconstructed using point cloud data to verify the practical application of the algorithm;

(4) Reconstructing the texture self-similarity degree

The greater the self-similarity degree, the stronger the adaptive performance and recognition of the image 3D reconstruction method, and the better the reconstruction effect. Therefore, the self-similarity degrees of reconstructed
textures were compared through different methods. The calculation process is as follows.

\[ G = 1 - \frac{1}{2} \sum_{z} |g^p_z - g^q_z| \]  \hspace{1cm} (13)

where, \( G \) represents the self-similarity degree of the reconstructed texture, \( g^p_z \) represents the distribution region range of target texture characteristics after reconstruction in \( z \) grayscale, and \( g^q_z \) represents the range of the background texture characteristic distribution region after reconstruction in \( z \) gray scale.

(5) Signal to Interference plus Noise Ratio (SINR)

SINR is the ratio of the intensity of useful signals to the intensity of the interference signal in the received information. The larger the SINR value, the greater the intensity of useful signals, the higher the image clarity, and the stronger the anti-interference. The calculation process is as follows.

\[ \text{SINR} = 10 \log_{10} \left( \frac{P_1}{P_2} \right) \]  \hspace{1cm} (14)

where, \( P_1 \) and \( P_2 \) stand for the power value of effective signal and noise, respectively.

(6) Reconstruction error

By comparing the reconstruction errors of different methods, the researchers may judge the effect and anti-interference ability of image 3D reconstruction method. The reconstruction error is the difference between the position of the feature point and the actual position after reconstruction.

C. RESULTS AND DISCUSSION

(1) Image 3D Reconstruction Effect

According to the setting of the above experimental environment, this study constructed the Gaussian mixture template feature matching model of fuzzy medical images, and thus obtains the initial reconstruction model. It is shown in Figure 3.

According to the texture and detail region of medical images, this study reconstructed the 3D texture structure of images, reconstructed the sparse scattered points, and performed adaptive pixel reconstruction of the fuzzy medical image by combining with the fuzzy edge structure reconstruction method. It is shown in Figure 4.

After the reconstruction of the proposed fuzzy medical image 3D reconstruction method using the quantum algorithm, the feature resolution of initial fuzzy medical images has been greatly improved, and the increase in feature points and the prominent feature information can help quickly realize the 3D reconstruction of fuzzy medical images, which reflected the effectiveness of fuzzy medical image 3D reconstruction method using quantum algorithm.

(2) Comparison of Image Feature Matching Degree

Literature [7], Literature [10], Literature [11] and Literature [13] method and proposed method feature matching were described. In Figure 5, the long diagram indicates matching feature points. It is shown in Figure 5.

According to Figure 5. In Literature [7], the feature matching points of the algorithm are basically distributed below the image, but the matching effect of the feature points above the image is poor. The method in Literature [10] produces good image contour feature matching effect, but the center part of the image is poorly matched. In comparison, the methods in Literature [11] and Literature [13] have better overall matching effect. However, it can be clearly found from the figure that the image feature matching point of the proposed method has a large amount of data and a wide distribution, and the matching effect is superior to the method in Literature [11] and Literature [13]. In this study, the Gaussian mixture model was used to obtain the distribution of the edge feature distribution of fuzzy medical images, so better results would be yielded if the matching method was designed on this basis.

(3) Comparison of Image Reconstruction Point Cloud Distribution Balance and Cloud Reconstruction Applicability

In the process of image reconstruction, the larger the distribution range of the reconstructed point cloud, the better the balance. Therefore, this study validates the proposed method by reconstructing the point cloud distribution balance as an indicator. It is shown in Figure 6.

According to Figure 6. Under different experimental test data, the image reconstruction point cloud of the proposed method is more evenly distributed in the coordinate range, the reconstruction point cloud has a wide distribution range, and the overall distribution shows a good balance. However, the reconstructed point cloud distribution of other literature method is uneven and the distribution range is small, which cannot describe image features well. It can be seen that the image reconstruction point cloud of the proposed method has a balanced distribution, which provides a good basis for the decomposition of edge contour features.

In order to verify the practical application of the proposed algorithm, sparse point clouds are reconstructed from test data sets, and three-dimensional point cloud images of heart surface are obtained based on balanced distribution point cloud data. It is shown in Figure 7.
Combined with the gray histogram of fuzzy medical image, adaptive pixel reconstruction is carried out on MATLAB platform, and the three-dimensional reconstruction of fuzzy medical image is completed by quantum algorithm. The reconstruction results are shown in Figure 8.

(4) Comparison of Self-similarity of Reconstruction Texture

The self-similarity of the image texture reconstructed by different methods was tested, and the test results were obtained. It is shown in Table 2.

According to the results of Table 2, the texture self-similarity coefficient of Literature [7] is between 0.606-0.690, the texture self-similarity coefficient of
Literature [10] is between 0.432-0.750, and the texture self-similarity coefficient of Literature [11] is between 0.706-0.757, the texture self-similarity coefficient of the Literature [13] is between 0.532-0.592, while the texture self-similarity coefficient of the proposed method is between 0.946-0.994.

On different data sets, the texture self-similarity coefficients of the methods in Literature [7], Literature [10], Literature [11] and Literature [13] are always lower than the proposed method. The maximum texture self-similarity coefficient can reach 0.994 in this study. Therefore, the proposed fuzzy medical image 3D reconstruction method using the quantum algorithm has a higher image quality after reconstruction. The reasons are that the fuzzy medical image 3D reconstruction method designed in this study combines with the quantum computing process, and linearly superimposes the image composite variable by establishing a quantum expansion model, thereby improving the reconstruction effect. The similarity coefficient \( \phi \) between random pixels reaches the highest value.

(6) Comparison of SINR

In this article, many parameters such as \( k \), \( \phi \), \( \alpha \) and \( l \) are used in proposed algorithm, and each parameter has a certain influence on the SINR value of the algorithm, as shown in Figure 9.

According to Figure 9. The values of parameters \( k \), \( \phi \) and \( \alpha \) increase in a given range. The SINR value of the proposed algorithm will increase accordingly, and the parameter \( l \) will decrease, and the SINR value of the algorithm will also decrease, which indicates that these parameters have a certain influence on the algorithm. But the range of influence is small, and the range of SINR value change is less than 5.

To fully demonstrate the performance of the proposed algorithm, the maximum values of parameters \( k \), \( \phi \) and \( \alpha \) are 1 respectively. The minimum value of \( l \) is 0. Under this optimal parameter setting, the comparison results of SINR after reconstruction by different methods are shown in Figure 10.

According to the results of Figure 10. Under different data set conditions. The SINR values reconstructed by different methods will also change accordingly. The SINR values reconstructed using the methods in Literature [7], Literature [10], Literature [11] and Literature [13] are relatively close and basically remain between 80-90dB. In contrast, the SINR value reconstructed using the proposed fuzzy medical image 3D reconstruction method using the quantum algorithm is always the highest among the five algorithms, and the SINR value of reconstruction results maintains around 100dB, demonstrating that the proposed method outputs the most valid information in the results and the highest clarity in the reconstruction results. The reasons are that based on extracting the edge contour feature vector of fuzzy medical images, the proposed fuzzy medical image 3D reconstruction method using the quantum algorithm realizes the enhancement processing of image information through the area edge sharpening method, and makes the image texture and detail region clearer, at the same time, the number \( k \) of a single Gaussian model in the mixed Gaussian model gradually increases, which is beneficial to reduce image noise, thereby improving the SINR value.

| Data sets | The proposed method | Literature [7] method | Literature [10] method | Literature [11] method | Literature [13] method |
|-----------|---------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| 1         | 0.946               | 0.606                 | 0.432                 | 0.706                 | 0.532                 |
| 2         | 0.967               | 0.635                 | 0.545                 | 0.712                 | 0.550                 |
| 3         | 0.978               | 0.676                 | 0.634                 | 0.724                 | 0.565                 |
| 4         | 0.987               | 0.680                 | 0.641                 | 0.735                 | 0.589                 |
| 5         | 0.994               | 0.690                 | 0.750                 | 0.757                 | 0.592                 |
In order to further test the effectiveness of the proposed fuzzy medical image 3D reconstruction method using the quantum algorithm, the following comparative experiment was designed to test the reconstruction error of different methods when performing fuzzy medical image 3D reconstruction. It is shown in Figure 11.

According to the results of Figure 11. Under different data set, the reconstruction errors of different fuzzy images 3D reconstruction methods will change accordingly. The reconstruction error of the method in Literature [10] is less than the proposed fuzzy medical image 3D reconstruction method using the quantum algorithm only at the beginning, while the reconstruction error of the methods in Literature [7], Literature [11] and Literature [13] is always greater than the proposed method. Literature [7] has the largest error, which can be as high as 1.7 mm, while the maximum reconstruction error of the proposed method is not higher than 0.9 mm.

The comparison results show that, compared with the results of other Literatures, the proposed method has smallest reconstruction error, which proves that the proposed method has higher reconstruction accuracy, and the reconstruction process is less interfered by the external environment.

VI. CONCLUSION
Three-dimensional reconstruction and recognition ability of fuzzy medical images can be improved by establishing the fuzzy medical image 3D reconstruction model and extracting the detailed feature vector of fuzzy medical images. For this purpose, a fuzzy medical image 3D reconstruction method using quantum algorithm was proposed. Then, this study decomposed the edge contour features by using the Gaussian mixture feature matching method, extracted the edge contour vectors of fuzzy medical image, and enhanced the information of fuzzy medical images by adopting the region edge sharpening. In addition, this study combined with medical images in blocks, combined the fuzzy edge structure reorganization method for adaptive feature decomposition of fuzzy medical images, and linearly superimposed the composite variable of fuzzy medical images. In this way, this study achieved the adaptive pixel reconstruction of fuzzy medical images by combining with the fuzzy edge structure reorganization method, and completed the 3D reconstruction of fuzzy medical images by employing the quantum algorithm. The result shows that the method used for 3D reconstruction of fuzzy medical images has better effect. Image reconstruction point cloud distribution is balanced, the method’s maximum texture self-similarity coefficient can reach 0.994, the SINR value of the reconstruction result can be maintained around 100 dB, and the maximum reconstruction error of the method is not higher than 0.9 mm. Therefore, the proposed method demonstrates a strong application advantage. In the future, the proposed fuzzy medical image 3D reconstruction method using quantum algorithm will be further optimized, with the purpose of achieving a breakthrough in terms of reconstruction timeliness.

REFERENCES
[1] X. Hong, L. Panchi, and L. Binxu, “Quantum scrambling algorithm for color images,” Signal Process., vol. 33, no. 1, pp. 10–17, 2017.
[2] Z. Wanning and L. Zihao, “User identification algorithm based on quantum computing,” Acta Electronica Sinica, vol. 46, no. 1, pp. 24–30, 2018.
[3] T. Yuling, F. Tianfeng, and Z. Xiaoxi, “Multi-person cooperative quantum computing based on redundant patterns,” J. Phys., vol. 68, no. 11, pp. 35–41, 2019.
[4] X. Hong, L. Panchi, and L. Binxu, “Improved quantum image watermarking algorithm,” Signal Process., vol. 33, no. 2, pp. 135–143, 2017.
[5] E. C. Rowell and W. Zhengan, “Mathematics of topological quantum computing,” Bull. Amer. Math. Soc., vol. 55, no. 2, pp. 183–238, 2018.
[6] S. D. S. Feitosa, J. K. Vizzotto, E. K. Piveta, and A. R. Du Bois, “A monadic semantics for quantum computing in an object oriented language,” Sci. Comput. Program., vol. 173, pp. 37–55, Mar. 2019.
[7] L. Yimin, “3D reconstruction of CT images based on MC-E algorithm,” Comput. Eng. Des., vol. 40, no. 10, pp. 2959–2963, 2019.
[8] H. Xiao, Z. Yang, S. Jiang, and Z. Huang, “Multi-threshold 3D reconstruction algorithm based on labeled medical images,” Comput. Eng. Sci., vol. 39, no. 10, pp. 1870–1876, 2017.
[9] H. Min, “Fast three-dimensional reconstruction algorithm of multi-resolution cone-beam CT images based on wavelet transform,” J. Electron. Inf. Technol., vol. 39, no. 10, pp. 2347–2441, 2017.
[10] H. Lingyan, “3D reconstruction based on improved moving cube algorithm,” Chin. Med. Imag. Technol., vol. 35, no. 6, pp. 925–929, 2019.
[11] J. Torrents-Barrena, G. Piella, N. Masoller, E. Gratacos, E. Ixarch, M. Ceresa, and M. A. Gonzalez Ballester, “Fully automatic 3D reconstruction of the placenta and its peripheral vasculature in intrauterine fetal MRI,” Med. Image Anal., vol. 54, pp. 263–279, May 2019.
[12] W. Ding, Y. Zhang, H. Lu, W. Wan, and Y. Shen, “Automatic 3D reconstruction of SEM images based on nano-robotic manipulation and epipolar plane images,” Ultramicroscopy, vol. 200, pp. 149–159, May 2019.
[13] A. I. Sakellarios, N. S. Tachos, G. Rigas, T. Bubas, G. Ni, F. Böhmke, and D. I. Fotiadi, “A validated methodology for the 3D reconstruction of cochlea geometries using human microCT images,” Meas. Sci. Technol., vol. 28, no. 5, May 2017, Art. no. 054001.
[14] C. L. Chowdhary, M. Mittal, K. P., P. A. Pattanaik, and Z. Marszalek, “An efficient segmentation and classification system in medical images using intuitionist possibilistic fuzzy C-Mean clustering and fuzzy SVM algorithm,” Sensors, vol. 20, no. 14, p. 3903, Jul. 2020, doi: 10.3390/s20143903.
[15] X. Yu, “GPU-based adaptive medical CT image reconstructions,” J. Signal Process. Syst., vol. 91, no. 3, pp. 1–18, 2018.
[16] L. Luping and W. Yongge, “Models and algorithms for CT image reconstruction from incomplete angles,” J. Beijing Univ. Aeronaut. Astronaut., vol. 43, no. 4, pp. 823–830, 2017.
[17] J. Zhan, J. Teng, and Y. Bai, “Improving sparse compressed sensing medical CT image reconstruction,” Autom. Control Comput. Sci., vol. 53, no. 3, pp. 281–289, May 2019.
[18] Y. Chunlei, “An image saliency detection scheme based on quantum mechanism,” J. Quantum Electron., vol. 34, no. 3, pp. 305–315, 2017.

FIGURE 11. Comparison of 3D reconstruction error of fuzzy medical image.
C. Ying, Z. Peng, and L. Ye, “Low-light-level image super-resolution reconstruction based on iterative projection photon localization algorithm,” J. Electron. Imag., vol. 27, no. 1, pp. 1–11, 2018.

A. A. Abd El-Latif, B. Abd-El-Atty, M. S. Hossain, M. A. Rahman, A. Alamri, and B. B. Gupta, “Efficient quantum information hiding for remote medical image sharing,” IEEE Access, vol. 6, pp. 21075–21083, 2018.

S. Zhu, L. Wang, and S. Duan, “Memristive pulse coupled neural network with applications in medical image processing,” Neurocomputing, vol. 227, pp. 149–157, Mar. 2017.

Z. Li, X. Zhang, H. Müller, and S. Zhang, “Large-scale retrieval for medical image analytics: A comprehensive review,” Med. Image Anal., vol. 43, pp. 66–84, Jan. 2018.

F. Li, X. He, Z. Wei, Z. Mu, and M. Li, “Super-resolution image reconstruction based on an improved maximum a posteriori algorithm,” J. Beijing Inst. Technol., vol. 2, no. 2, pp. 81–84, 2018.

L. Lin, W. Yang, C. Li, J. Tang, and X. Cao, “Inference with collaborative model for interactive tumor segmentation in medical image sequences,” IEEE Trans. Cybern., vol. 46, no. 12, pp. 2796–2809, Dec. 2016.

R. Chard, R. Madduri, N. T. Kononis, K. Chard, K. L. Duffin, C. E. Ordoñez, T. D. Uram, J. Fleischauer, I. T. Foster, M. E. Papka, and J. Winans, “Scalable pCT image reconstruction delivered as a cloud service,” IEEE Trans. Cloud Comput., vol. 6, no. 1, pp. 182–195, Mar. 2018.

Hypertrophic Cardiomyopathy (MRI). Accessed: Sep. 2020. [Online]. Available: https://medpix.nlm.nih.gov/case?id=dc0e0559-e5f0-4fbe-82be-3b610ce7a9b2

Apical Hypertrophic Cardiomyopathy (MRI). Accessed: Sep. 2020. [Online]. Available: https://medpix.nlm.nih.gov/case?id=3c2e17b0-b807-4232-ba63-76b57434fa5

SCMR (MRI). Accessed: Sep. 2020. [Online]. Available: https://www.cardiacatlas.org/studies/scmr-consensus-data/

ACDC (MRI). Accessed: Sep. 2020. [Online]. Available: https://www.creatis.insa-lyon.fr/Challenge/acdc/index.html

RVSC (MRI). Accessed: Sep. 2020. [Online]. Available: http://pagesperso.litislab.fr/cpetitjean/mr-images-and-contour-data/

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