

Research Article **Detection Method of Three-Dimensional Echocardiography Based on Deep Learning**

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In order to improve the detection and recognition ability of 3D echocardiography, a method of 3D echocardiography detection based on depth learning is proposed. The information conduction model of three-dimensional echocardiography is constructed. The edge pixel feature matching method is used to extract the key information of echocardiography, and the information compensation method is used to repair the missing area of three-dimensional echocardiography information. The feature decomposition and information fusion of 3D ultrasonic imaging are carried out by using five stage wavelet decomposition method, and the feature reconstruction and adaptive template matching of 3D echocardiography are processed by depth learning algorithm, modeling and detecting the rationality of three-dimensional echocardiography. The simulation results show that this method has better detection performance; the accuracy of detection and recognition is high, which is more reasonable in the application of 3D echocardiography repair and detection recognition.

1. Introduction

With the development of ultrasound technology and the advent of real-time three-dimensional echocardiography, the defects of two-dimensional echocardiography and static and dynamic three-dimensional echocardiography are overcame, and the operation is simple and the imaging is fast. By collecting the actual ventricular data, it can accurately measure the actual volume of the heart and calculate the cardiac function parameters. It is reported that RT3DE can be used in in vitro models and animal experiments to measure ventricular volume and has a significant correlation with magnetic resonance imaging (MRI) [1], so it has been widely used in clinic. At the same time, CT imaging technology is also developing continuously. MSCT imaging technology can reconstruct the scanned data, calculate the ventricular volume size according to the diastolic and systolic images, and calculate the cardiac function parameters according to the relevant data [2].

Traditionally, the parameters of left ventricular function are analyzed by multislice spiral CT and real-time threedimensional echocardiography. It is found that both of the two methods could accurately measure the parameters of cardiac function, and the parameters of LVEF and LVMM are compared between the two groups. The difference is not statistically significant (P > 0.05). It is believed that multislice spiral CT is accurate and reliable in evaluating left ventricular function and is highly correlated with echocardiography [3]. The parameters of left ventricular function are measured by real-time three-dimensional echocardiography and multislice spiral CT scanning. Multislice spiral CT and real-time three-dimensional echocardiography can accurately evaluate left ventricular function, but multislice spiral CT can be used to examine coronary angiography and understand the lesions of coronary artery and vein. Therefore, it is necessary to study an effective three-dimensional echocardiographic detection method and apply it to clinical practice, combined with multislice spiral CT to examine the coronary artery, and

to understand the coronary artery at the same time, so as to evaluate the value of multislice spiral CT (MSCT) and realtime three-dimensional echocardiography (RT3DE) in measuring left ventricular function [4–6].

In this paper, a three-dimensional echocardiographic detection method based on depth learning is proposed. The information conduction model of three-dimensional echocardiography is constructed. The edge pixel feature matching method is used to extract the key information of echocardiography, and the information compensation method is used to repair the missing area of three-dimensional echocardiography information. The feature decomposition and information fusion of 3D ultrasonic imaging are carried out by using the 5-stage wavelet decomposition method, and the feature reconstruction and adaptive template matching of 3D echocardiography are processed by depth learning algorithm, modeling and detecting the rationality of three-dimensional echocardiography.

2. Information Conduction Model and Image Preprocessing in Three-Dimensional Echocardiography

2.1. Three-Dimensional Echocardiographic Information Conduction Model. By constructing the information conduction model of three-dimensional echocardiography, the information collection and feature extraction of threedimensional echocardiography are carried out. In the collection of three-dimensional echocardiography, it is necessary to use ultrasound beam scanning three-dimensional echocardiography. The reflected ultrasonic wave is reflected to the output port of the ultrasonic wave, and the pixel features are arranged in different order and the three-dimensional ultrasonic imaging is obtained [7]. In the information reconstruction of three-dimensional echocardiography, the size of the modeling feature region is 16 * 16. The threedimensional echocardiography of each M * N is divided into ((M/16) + 1) * ((N/16) + 1) rectangular blocks, as shown in Figure 1.

The most similar matching block is selected to reconstruct the 3D feature of the image to be repaired, and the information conduction pixel set of the interior of each subblock is obtained. By using the similarity between the dark primary color blocks and the blocks to be repaired in threedimensional echocardiography, the points on the boundary are determined, and the priority characteristics of information conduction are matched. Gradient smoothing is needed for the relative elements of adjacent blocks in threedimensional ultrasound imaging. The affine invariant moment feature extraction is carried out with the affine invariant kernel function of 3 * 3. The affine invariant moment has the rotation translation and the scale invariance [8]. Therefore, the feature mining can be carried out through the template matching of the image, and the image processing template can be determined by the template size. The texinformation of three-dimensional ture structure echocardiography is G(x, y; t), and the intuitionistic fuzzy set of texture subspace of three-dimensional echocardiogra-



FIGURE 1: Three-dimensional echocardiographic rectangular segments.

phy is defined as conduction function:

$$p(x,t) = \lim_{\Delta x \to 0} \left[\sigma \frac{u - (u + \Delta u)}{\Delta x} \right] = -\sigma \frac{\partial u(x,t)}{\partial x}.$$
 (1)

Assume that the edge information of the threedimensional echocardiography along the gradient direction is shown as follows:

$$G_{x}(x, y; t) = \frac{\partial u(x, y; t)}{\partial x}.$$
 (2)

The traversal characteristics of the sharp changes of image features in the scene are obtained, and the information flow density vector of 3D echocardiographic texture structure is obtained as follows:

$$p(x, y; t) = -\sigma \nabla u(x, y; t) = -\sigma G(x, y; t)$$

= $-\sigma [G_x(x, y; t)i + G_y(x, y; t)j],$ (3)

Here, i, j are unit direction vectors, based on the visual significance of a target in the detection recognition process, a three-dimensional echocardiography structure texture information conduction model is constructed, the rare degree in the whole scene is obtained [9], and the global rare degree of the three-dimensional echocardiography is obtained by adopting zero uniform traversal. Based on the analysis, the state equation of the three-dimensional echocardiography texture information conduction model is described as follows:

$$\begin{cases} f(x_1, x_2) = r_1 x_1 \left(1 - \frac{x_1}{N_1} - \sigma_1 \frac{x_2}{N_2} \right) = 0, \\ g(x_1, x_2) = r_2 x_2 \left(1 - \sigma_2 \frac{x_1}{N_1} - \frac{x_2}{N_2} \right) = 0. \end{cases}$$
(4)

Here, r_1 and r_2 are the local and global salient feature sets, and σ_1 represents the mean value of the image features. Based on the above 3D echocardiographic information conduction model, a 3D echocardiographic information conduction model is constructed. The information collection and feature analysis of three-dimensional echocardiography are realized, which provides an accurate data basis for three-dimensional echocardiography modeling [10].

2.2. Prioritv Determination of Three-Dimensional Echocardiography Reconstruction. In the information conduction model, edge pixel feature matching method and 3D echocardiography are used to determine the priority of information missing region repair. The subspace structure model of three-dimensional echocardiography is designed to calculate the priority coefficient of the block to be reconstructed and update the edge pixel of the threedimensional echocardiography [11]. The multidimensional search method of subspace feature information is adopted. The information points of three-dimensional echocardiography are searched by gray scale until there are no edge pixels. The mean value of feature is used as pheromone in subspace structure block, and the global rare degree feature of three-dimensional ultrasonic imaging is decomposed. equation of The iterative characteristic decomposition is described as follows:

$$u^{(n+1)}(x,y) = u^{(n)}(x,y) + \delta u_1^{(n)}(x,y),$$
(5)

$$u_1^{(n)}(x,y) = M\Delta_s u^{(n)}(x,y) + N\Delta_t u^{(n)}(x,y;d).$$
(6)

The size of the 3D echocardiography to be reconstructed is assumed to be $m \times n$, and the size of the characteristic scale block Ψ_p is $s \times s$. By means of edge pixel feature matching, the depth learning algorithm is used to determine the priority of unknown pixel points in 3D echocardiography. The priority sort of pixels meets

$$P\left(\left|\overline{x_T} - K\right| < \frac{\lambda_{\chi}\sigma}{\sqrt{N}}\right) \approx \frac{2}{\sqrt{2\pi}} \int_0^{\lambda_{\chi}} e^{-(1/2)t^2} dt = 1 - \chi.$$
(7)

Here, $\overline{x_T}$ is the mean value of the local contrast window of the 3D echocardiography, χ is the significance weight, and H is the global rare degree coefficient.

3. Three-Dimensional Echocardiography **Detection Algorithm**

3.1. Characteristic Decomposition and Information Fusion of Three-Dimensional Echocardiography. On the basis of constructing the information conduction model and determining the priority of the reconstruction of three-dimensional echocardiography, the reasonable modeling design of threedimensional echocardiography is carried out. In this paper, a three-dimensional echocardiographic rationality modeling method based on depth learning is proposed [12]. The characteristic decomposition and information fusion of 3D ultrasonic imaging are carried out by using the 5-stage wavelet decomposition method. The structure similar features of 3D echocardiographic detection and recognition image are obtained by the 5-stage wavelet decomposition of 3D echocardiography:

$$ws(X, Y) = \frac{2\left|\sum_{i=1}^{N} c_{x,i} c_{y,i}\right| + K}{\sum_{i=1}^{N} \left|c_{x,i}\right|^{2} + \sum_{i=1}^{N} \left|c_{y,i}\right|^{2} + K}.$$
(8)

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The results of feature decomposition and information fusion are expressed as follows:

$$l(X, Y) = \frac{2u_x u_y + C_1}{u_x^2 + u_y^2 + C_1},$$
(9)

$$c(X, Y) = \frac{2\sigma_x \sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2},$$
 (10)

$$s(X, Y) = \frac{\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3}.$$
 (11)

Here, σ_{xy} is the edge information covariance and C_1 , C_2 , and C3 are the global rarity constants. The feature reconstruction and adaptive template matching of 3D echocardiography are processed by depth learning algorithm [13].

3.2. 3D Echocardiography Reconstruction and Detection Recognition. On the basis of the characteristic decomposition and information fusion of three-dimensional ultrasound imaging using the five-stage wavelet decomposition method, the depth learning is carried out to realize the rational modeling of three-dimensional echocardiography, and the depth learning algorithm is adopted [14]. The parameters of WSSIM are calculated for the wavelet structure similarity of two or 3D echocardiography:

WSSIM =
$$[l(X, Y)]^{\alpha}[c(X, Y)]^{\beta}[ws(X, Y)]^{\gamma}$$
. (12)

After the multiscale decomposition of the global rarity, the two-directional subband energies in the information conduction model of the detection and recognition imaging are obtained as follows:

$$E_{HL_i} = \sum_{j} \left(c_j^{HL_i} \right)^2,$$

$$E_{LH_i} = \sum_{j} \left(c_j^{LH_i} \right)^2.$$
(13)

By using the depth learning algorithm, the threedimensional echocardiography is firstly convolution with the Gauss kernel function of different scales [15], and the reconstruction output of the three-dimensional echocardiography is obtained as follows [16, 17]:

$$\omega_{HL_i} = \frac{E_{HL_i}}{E_{HL_i} + E_{LH_i} + E_{HH_i}},\tag{14}$$

$$\omega_{LH_{i}} = \frac{E_{LH_{i}}}{E_{HL_{i}} + E_{LH_{i}} + E_{HH_{i}}},$$
(15)

$$\omega_{HH_i} = \frac{E_{HH_i}}{E_{HL_i} + E_{LH_i} + E_{HH_i}}.$$
 (16)

The probability of each pixel variance in the whole image is calculated. The depth learning algorithm is used to measure the salience of the feature points of three-dimensional

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FIGURE 2: Three-dimensional echocardiographic results.



FIGURE 3: Comparison of 3D echocardiographic detection performance.

echocardiography [18, 19]. The structural similarity features of the image are calculated in the high frequency subband of wavelet [20]:

$$WSSIM_{H_{i}} = \omega_{HL_{i}} \cdot WSSIM_{HL_{i}} + \omega_{LH_{i}} \cdot WSSIM_{LH_{i}} + \omega_{HH_{i}} \cdot WSSIM_{HH_{i}}.$$
(17)

The wavelet structure similarity of three-dimensional echocardiography is calculated, which is described as FWSSIMI:

$$FWSSIM(X, Y) = \frac{\omega_{LL} \cdot WSSIM_{LL} + \sum_{i=1}^{5} \left(\omega_{H_i} \cdot WSSIM_{H_i}\right)}{\omega_{LL} + \sum_{i=1}^{5} \omega_{H_i}}.$$
(18)

On the basis of above processing, the 3D echocardiographic modeling and detection recognition are realized [21].

4. Simulation Experiment and Result Analysis

In order to verify the effectiveness of this algorithm, different types of three-dimensional echocardiography are used to reconstruct the simulation. The test platform is Pentium (R) 4 CPU 3.00 GHz, 1 GB memory in windows XP system. MATLAB simulation software is used to design the algorithm. Firstly, the information transmission model of threedimensional echocardiography is constructed, and the information characteristic sampling and information fusion of three-dimensional ultrasonic imaging are realized. According to the simulation environment and parameter setting, 3D echocardiography is performed, and the imaging results are shown in Figure 2.



FIGURE 4: Changes of indicators in the same environment on cardiogram images.



FIGURE 5: Cardiogram detection indicators in different detection environments.

According to the analysis (Figure 2), the result of threedimensional echocardiography using this method is better, the characteristic fusion degree is higher, and the peak signal-to-noise ratio is higher. The accuracy of threedimensional echocardiography is tested by different methods, and the comparison of detection performance is obtained as shown in Figure 3.

The analysis of Figure 3 shows that the accuracy of threedimensional echocardiography using this method is better.

The weighted low frequency coefficient is $\omega_{LL} = 3.78$ of 3D ultrasonic wavelet decomposition, and the high frequency coefficients of echocardiography are as follows: $\omega_{H_1} = 1.00$, $\omega_{H_2} = 3.75$, $\omega_{H_2} = 7.20$, $\omega_{H_4} = 3.48$, and $\omega_{H_5} = 3.21$. Search step size N = 4; 3D echocardiographic image sample block matching template is 9×9 . The size of the windows is 3 *

3.5 * 5.9 * 9.17 * 17. Changes of indicators in the same environment on cardiogram images is shown in Figure 4.

The characteristic decomposition and information fusion of 3D ultrasonic imaging are carried out by using the 5-stage wavelet decomposition method. The structure similar features of 3D echocardiographic detection and recognition image are obtained by the 5-stage wavelet decomposition of 3D echocardiography. Cardiogram detection indicators in different detection environments are shown in Figure 5.

The feature decomposition and information fusion of 3D ultrasonic imaging are carried out by using the five-stage wavelet decomposition method, and the feature reconstruction and adaptive template matching of 3D echocardiography are processed by a depth learning algorithm, modeling and detecting the rationality of three-dimensional echocardiography.

5. Conclusions

In this paper, a method of 3D echocardiography detection based on depth learning is proposed. The information conduction model of three-dimensional echocardiography is constructed. The edge pixel feature matching method is used to extract the key information of echocardiography, and the information compensation method is used to repair the missing area of three-dimensional echocardiography information. The feature decomposition and information fusion of 3D ultrasonic imaging are carried out by using the fivestage wavelet decomposition method, and the feature reconstruction and adaptive template matching of 3D echocardiography are processed by a depth learning algorithm, modeling and detecting the rationality of three-dimensional echocardiography. The simulation results show that this method has better detection performance, and the accuracy of detection and recognition is high, which is more reasonable in the application of 3D echocardiography repair and detection recognition. This method has good application value in the detection and clinical application of echocardiography.

Data Availability

All author information is available from the author.

Conflicts of Interest

None of the authors have any conflicts of interest.

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