Classification of heterogeneity on multi-spectral transmission image based on modulation-demodulation-frame accumulation and pattern recognition

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ABSTRACT Multi-spectral transmission image provides a possibility for the detection of early breast cancer. However, in the process of acquiring multi-spectral transmission images, the recognition of heterogeneities has many difficulties due to the image blur caused by the scattering effect of light source in biological tissues and weak transmission signals. This paper proposes a combination method of modulation-demodulation-frame accumulation technique and pattern recognition to achieve heterogeneous classification. Firstly, the acquisition experiment of the phantom multi-spectral images is designed. Then, the signal-to-noise ratio (SNR) of the image is improved by the modulation-demodulation and frame accumulation technique, and the 14-dimensional feature information (firmness, angular second-order distance, contrast, gray-scale correlation, entropy, inverse gap, smoothness, dissimilarity, consistency, center of gravity, area, perimeter, long diameter of irregular image, short diameter of irregular image) of the heterogeneous region are extracted from the image with high SNR. Finally, the heterogeneous classification accuracy of different models is compared. The results show that: Compared with the classification accuracy of the traditional multi-spectral image classification models, Random Forest (RF) and Extreme Learning Machine (ELM) models have better classification effect when subdividing the four types of heterogeneity based on the data set of this paper. Among them, the RF and ELM models established by the dataset of four-wavelength combination have the best classification effect, and the classification accuracy rate reaches 100%, secondly, it is the three-wavelength combined model. The single-wavelength model has the worst classification effect. And the operating efficiency of ELM is significantly higher than RF. In conclusion, the image quality is improved by modulation-demodulation and frame accumulation technique. And compared with the classification accuracy of the traditional multi-spectral image classification models, the RF and ELM models established in this paper have better classification effect, which may promote the application of multi-spectral transmission imaging in early screening of breast tumors.

INDEX TERMS Multi-spectral transmission image, Modulation-demodulation and frame accumulation, Heterogeneous classification, Pattern recognition

I. INTRODUCTION
Breast cancer is a common disease in adult women, which is a serious threat to women's health and life [1]. In 2018, the China Cancer Center announced that the incidence of breast cancer in Chinese women was 11.2%, and the mortality rate was 9.2%, ranking first in the world [2]. Early detection of breast cancer is conducive to breast conserving treatment, and the cure rate of early stage patients is much higher than that of middle and late stage [3]. So early detection of breast cancer is critical.

Currently, imaging techniques for detecting breast cancer mainly include x-ray [4-6], ultrasound [7-9], magnetic resonance imaging (MRI) [10,11], computed tomography (CT) [12] and near-infrared transmission imaging [13-15]. However, due to x-ray radiation, it is detrimental to human biological tissues. Ultrasonic testing has different detection sensitivities for different populations, and it is difficult to guarantee the
standard of detection. The cost of MRI testing is too high to be promoted. In addition, the spatial distribution of early tumors in these images is ambiguous, making it difficult to identify heterogeneous regions. Considering the mammary gland is a transparent body without bone, and the tumor tissue contains a large number of new blood vessels and hemoglobin, there will appear a large shadow in the transmission imaging (in the tissue, uneven medium called heterogeneity [16]). Therefore, optical transmission imaging provides a feasible and simple method for early detection of breast cancer.

In optical transmission imaging, multi-spectral non-destructive optical testing has become a hot topic due to its advantages of real-time, non-invasive, safe, specific and sensitive and has been widely used in many fields [17-21], but there are few studies on the application of multi-spectral transmission images in the medical field. This is mainly due to the strong scattering effect of the incident light in the transmission process of biological tissue, which makes the signal in the multi-spectral transmission image weak and unable to obtain the rich characteristic information of heterogeneities. In recent years, the technique of modulation-demodulation (loading shaped signals) and frame accumulation has become one of the most effective methods to enhance low-light-level (LLL) diffuse reflection image signals. Among them, Li et al uses the combination method of frame accumulation and shaping signal technology to greatly enhance the SNR of the LLL image and improve the resolution of the image [22-24]. Therefore, this paper, for the first time, attempts to apply the combination method of modulation-demodulation and frame accumulation to the transmission images to improve the image quality.

In addition, in the multi-spectral transmission imaging process, the optical properties of different tissues at different wavelengths are different, which is beneficial to the classification of heterogeneities. Although the spatial structure of the early tumor tissue is similar to that of the normal tissue, the characteristic of the above multi-spectral image provides a good idea for identifying early tumor tissue in the image. And as a powerful technique to analyze and extract unique information from multi-spectral image, feature information-based classification has been an active research topic in recent years. Many classification algorithms have been developed to perform multi-spectral image classification. For example, support vector machines (SVM) [25,26], linear discriminant analysis (LDA) [27,28], low-rank representation (LRR) [29-31], sparse representation (SR) [32-34] and multinomial logistic regression (MLR) [35] are well-known image classification methods. Among them, Gao et al used the multiple kernel learning method to fuse different features of samples to improve the classification accuracy of SVM in multi-spectral images [36]. Wang et al proposed a novel LDA to obtain all representative subspaces by adaptively, which improved the classification accuracy of different objects in multi-spectral images [37]. Wang et al proposed a local and structural-regularized LRR for multi-spectral image classification, which overcomes the limitations of multi-dimensional image feature extraction [38]. Gao et al improved SR to improve the precision of classification result by incorporating the neighboring information of the test pixel [39]. So, multi-spectral transmission image provides a possibility for the detection of early breast cancer.

In this paper, we combine the method of enhancing the LLL image signal with the model of pattern recognition to achieve effective classification of different heterogeneous tissues in multi-spectral transmission images. Different from the traditional multi-spectral image classification method mentioned above, which adaptively extracts image feature information, we extract the feature information of the heterogeneities on the different wavelength images from three aspects of spatial feature, texture feature and shape feature as the classification basis of the heterogeneities. And considering the nonlinearity among experimental data, we use the traditional pattern recognition method to classify the heterogeneous tissues. The traditional pattern recognition is divided into supervised classification and unsupervised classification. Different heterogeneities are used to simulate tumor masses, and the categories of heterogeneities are known. Therefore, we mainly study the methods of supervised classification pattern recognition. The methods commonly used in supervised pattern recognition include RF with multi-layer neural networks and ELM with single-layer neural network. RF, first proposed by Breiman, is widely used in data processing, text classification and other fields because of its advantages such as simple implementation, strong anti-overfitting ability, parallel processing and good ability to deal with nonlinear modeling problems [40]. In order to solve the problem that multi-neural networks consume a lot of time in the process of classification optimization algorithm, Huang proposed a single hidden layer feed-forward neural network ELM algorithm, which has the characteristics of simple model design, fast operation speed and high generalization performance, and has good performance in multi-label learning [41]. Finally, the SNR and gray resolution of the images are improved through the technique of modulation-demodulation and frame accumulation. And the 14-dimensional feature information of the heterogeneous region are extracted from the image with high SNR for pattern recognition. The results show that compared with the accuracy of traditional multi-spectral image classification models (SVM, LDA, LRR, SR and MLR), the RF and ELM we established both have a better classification effect when subdividing 4 heterogeneities under the data set of this paper, which promotes the application of transmission multi-spectral imaging in early screening of breast cancer.

II. RELATED TECHNOLOGY

A. MODULATION-DEMODULATION AND FRAME ACCUMULATION TECHNOLOGY

In the process of multi-spectral transmission imaging, the distribution of light intensity may be affected due to the influence of the external environment and the scattering effect of heterogeneities themselves, resulting in weak signal and low definition of transmission images. Therefore, this paper needs to perform certain pre-processing experiments on the obtained transmission images. Among them, the weak signal in the image includes two meanings: one is that the absolute value of the signal light intensity is low, and the other is that the SNR and resolution of the signal are low. The modulation-
B. TARGET CLASSIFICATION

Pattern recognition, also known as pattern classification, is divided into supervised classification and unsupervised classification from the perspectives of problem processing nature and problem solving method. This paper focuses on the study of supervised classification methods, mainly comparing the classification effects of RF with multi-layer neural network and ELM with single-layer neural network. Simultaneously, in order to prove the validity of the supervised classification models (RF and ELM) established in this paper, we compare them with the traditional multi-spectral image classification models.

RF is an integrated learning method based on Bagging, consisting of multiple unpruned decision trees. In a classification task, the categories of test samples are determined by the mode of the output category labels of these decision trees. Each decision tree and out of bag data (OOB data) in the RF are obtained by bootstrap resampling. The importance of the characteristic variables of the decision tree is calculated according to the Gini index [43]. Traditional multi-neural network algorithms need to set more network parameters. When solving the optimal solution, local optimal solutions may appear and the global optimal solution of the network cannot be obtained. In the ELM solution, only the number of hidden layer nodes needs to be set, and the global optimal solution can be solved by randomly initializing the weights and offsets. ELM solves the feedforward neural network with single hidden layer, which can be divided into two stages: random feature mapping and linear parameter solving.

III. EXPERIMENT

According to the characteristics of breast tissue, this paper designed the collection experiment of phantom. The 14-dimensional feature information of the different wavelength images is respectively extracted on the multi-spectral transmission images after the modulation-demodulation and frame accumulation processing. And the different heterogeneities are respectively classified by pattern recognition methods (RF and ELM) and traditional multi-spectral image classification models.

A. EXPERIMENTAL DEVICE

Fig.1 depicts a schematic of the experimental device. This experimental device is mainly divided into five parts: light source part, control part, image acquisition part, processing part and other parts. The light source part mainly includes: 4 wavelength LEDs (blue wavelength centered at 435nm, green wavelength centered at 546nm, red wavelength centered at 700nm and near-infrared wavelength centered at 860nm) and programmable DC regulated power supply (model: hspy-600). The control part uses the LED drive circuit of PT4115 to control the input of signal. The image acquisition part mainly includes: industrial camera (model: JHSM120f, camera frame rate: 54 frames/s and image resolution: 1280 × 960) and acquisition software (usbVideo). The processing part mainly adopts HP computer and MATLAB software to process related images. The other parts mainly include: blackout cloth and phantom. Phantom composition: a highly photometric PMMA (polymethyl methacrylate) rectangular container (the transmittance of the breast is higher than that of other human tissues) is used to hold the mixed solution of milk and water.
with different concentrations. According to the characteristics of strong transmissibility and tomographic distribution of breast tissue, potatoes and carrots are suspended in the solution as heterogeneities to simulate breast cancer [44].

B. IMAGE ACQUISITION

The original multi-spectral images are obtained on the experimental device that had been set up: milk solution + heterogeneous image. The specific experimental steps are as follows:

1. Set the parameters of camera and signal generator. The gain in the camera is set to 10, the exposure time is set to 101s, the acquisition rate is about 45 frames/s. And the frequency of the sinusoidal shaped signal in the signal generator is set to 4Hz.

2. Adjust and fix the distance between the light source and the phantom, the phantom and the camera separately, and set up the blackout cloth. Turn on the light source switch.

FIGURE 2. Phantom multi-spectral transmission images. (a) blue wavelength transmission image; (b) green wavelength transmission image; (c) near-infrared wavelength transmission image; (d) red wavelength transmission image.

FIGURE 3. Fourier transform diagram. (a) frequency coordinate position map; (b) frequency map.

FIGURE 4. Cycle diagram of the sinusoidal shaped signal
and the camera of the camera to get a sequence of images of the phantom.

(3) The four kinds of light sources loaded with the sinusoidal shaped signal are respectively irradiated with the phantom. The phantom included four heterogeneities (two potato pieces and two carrot pieces) of different sizes and thickness, and the experiment is carried out in groups. Each wavelength includes 6 groups, each group configured with different concentrations of solutions, a total of \( k = 24 \) groups.

(4) Excluding the images with large errors in each group, a total of \( n = 26880 \) original multi-spectral images are obtained, and Fig.2 are one frame of the original phantom images \( x_{ij}^l (l = 1, 2, \ldots, 1120; i = 1, 2, 3, 4; j = 1, 2, \ldots, 6) \) of the four wavelengths, respectively.

C. IMAGE PREPROCESSING

The multi-spectral transmission images obtained in this experiment are processed by the technique of modulation-demodulation and frame accumulation. The specific image processing steps are as follows:

(1) Perform a fast Fourier Transform (FFT) on images \( x_{ij}^l (l = 1, 2, \ldots, 1120; i = 1, 2, 3, 4; j = 1, 2, \ldots, 6) \), and extract the coordinate values corresponding to the frequency components of the four wavelengths, as shown in Fig.3.

(2) According to the frequency coordinate value determined above, the pixels of all the images of the four wavelengths are demodulated, and the demodulated images of all wavelengths are obtained.

(3) Read the demodulated images \( x_{ij}^l (l = 1, 2, \ldots, 1120) \) into MATLAB program respectively, find the sum of gray values of each frame, and draw 1120 gray value of images \( x_{ij}^l (l = 1, 2, 3, \ldots, 1120) \), as shown in Fig.4.

(4) Determine the number of image frames in a single sine wave period according to the curve shown in Fig.4. It can be seen from the figure that each sinusoidal shaped signal includes 11 frames images.

(5) Perform the frame-accumulate average for every 11 frames of images each group in the experiment, that is:

\[
x_{ij}^k = \frac{\sum_{l=1}^{11} x_{ij}^l}{f}
\]

\( i = 1, 2, 3, 4; j = 1, 2, \ldots, 6; l = 1, 2, \ldots, 1109; k = 1, 2, \ldots, 606; f = 11 \).

(6) According to formula (1), a total of \( n = 2424 \) frame accumulative multi-spectral images are obtained, in which each wavelength includes 606 images.

D. HETEROGENEOUS CLASSIFICATION

1) FEATURE INFORMATION EXTRACTION

In order to accurately extract the information in each heterogeneous region, each preprocessed image is reasonably cropped into four regions of uniform size without affecting the accuracy of the algorithm and image quality (each region includes one heterogeneity). Different from the traditional multi-spectral image classification methods mentioned above, which adaptively extracts image feature information, the relevant information of the image is extracted from the spectral features, the texture features and shape features.

Spatial feature extraction: The spatial relationship indicates that there is a certain spatial positional relationship and directional relationship among multiple objects in the image, such as the firmness of the image's adjacency relationship. Texture feature extraction: The gray-level co-occurrence matrix (GLCM) is used to extract the texture features of the image, which uses the probability in statistics to reflect the overall information of the image grayscale related directions and intervals. There are 8 commonly used texture feature parameters (angular second-order distance, contrast, gray-scale correlation, entropy, inverse gap, smoothness, dissimilarity and consistency). Shape feature extraction: Hough transform is used to detect the heterogeneous regional feature information of the image, which mainly includes five feature parameters (center of gravity, area, perimeter, long diameter of irregular image, short diameter of irregular image).

Among them, in order to precisely determine the region of the homogeneities, the heterogeneous feature region is obtained by using the Ostu threshold segmentation method for different wavelength images. In the process of obtaining mask images by Ostu threshold segmentation method, the coincidence degrees of different heterogeneous mask images and true knowledge map (the actual heterogeneous images were obtained before the experiment) are calculated as the discrimination basis for the selection of threshold values, so as to obtain the multi-wavelength mask images with the highest coincidence degree. Because the mask image needs to cover the target region of the sample as much as possible, it needs to have a high degree of coincidence with the actual target region of the sample to improve the accuracy of heterogeneity detection. According to comprehensive statistics, the coincidence degree of all multi-spectral mask images reached more than 96%, which was enough to cover the characteristic information of heterogeneity in the images. And the average threshold value and the mask image of different heterogeneities are obtained, as shown in Tab.I and Fig.5. The thresholds in Tab.I respectively represent the average thresholds of each group of the best heterogeneous mask images in different wavelength light sources, so as to ensure more accurate extraction of the feature information of the heterogeneous region. And as can be seen from Tab.I, the floating range of image segmentation threshold in the same wavelength is small, while the variation range between different wavelengths is large. Finally, a total of 9696 × 14 dimensional information is obtained for all wavelength images, and each wavelength includes 2424 × 14 samples.

2) DATA SET PRODUCTION

All wavelength heterogeneous feature information (9696 × 14) is made into a data set, which included a total of 14 data sets. ① Single wavelength test data set, a total of 4 groups. ② Two-wavelength combined test data set, a total of 6 groups. ③ Three-wavelength combined test data set, a total of 3 groups. ④ Four-wavelength combined test data set, a total of 1 group.

To promote the possibility of multi-spectral transmission images in early breast cancer detection, the wavelength combination process is sequentially arranged in the order of blue light, green light, near-infrared light and red light. Data
sets of different wavelengths are randomly divided into training sets and test sets. Since the data set in this paper is small, the ratio is set to 4:2 according to the traditional division ratio of the machine learning field. In the solution, the heterogeneities are divided into 4 types: two pieces of potato and two pieces of carrot of different sizes and thicknesses.

3) MODEL DEBUGGING

The sample data is normalized during the model debugging process. In order to find the optimal model, different combinations of heterogeneous feature information (single wavelength, two wavelengths, three wavelengths and four wavelengths) of four wavelengths are input into the network for training, and each set of data sets is trained 100 times. According to the classification results of RF and ELM models, the number of optimal decision trees and neurons in the models are determined respectively, and the best detection model for different heterogeneous classifications is obtained. Finally, the classification accuracy, correlation coefficient $R^2$, root mean square error (RMSE) and running time of the RF and ELM models are obtained. The results are shown in Tab.IV.

### RESULTS AND ANALYSIS

After the multi-spectral transmission image is processed by the modulation-demodulation and frame accumulation technique, the SNR is significantly enhanced and the gray level is significantly increased, as shown in Fig.6. And it can be seen from the figure that the gray level of the processed images increases significantly, which makes the heterogeneous regions in all wavelength images more prominent. And compared with the traditional multi-spectral image classification model, the RF and ELM models established in this paper achieve better classification accuracy.

(1) Modulation-demodulation and frame accumulation technique significantly improves the quality of the phantom image. The results are shown in Tab.II. It is found that by calculation that the peak signal-to-noise ratio (PSNR) of the image before and after frame accumulation is positive, which indicates that the gray level of the image significantly increases after preprocessing. The image SNR after frame accumulation has been improved to a certain extent, which will be conducive to the extraction of regional feature information of heterogeneity in the image.

(2) Heterogeneous classification results: Based on the modulation-demodulation and frame accumulation technique.
FIGURE 6. Gray level comparison chart before and after image preprocessing. (a) blue light image; (b) green light image; (c) near infrared light image; (d) red light image. a2-d2 are the original phantom images of 4 different wavelengths, and a3-d3 are the pre-processed images. And a1-d1 and a4-d4 are the gray histogram distribution of a2-d2 and a3-d3 respectively.

TABLE II

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR/dB</th>
<th>SNR1/dB</th>
<th>SNR2/dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blue wavelength</td>
<td>45.2904</td>
<td>3.4615</td>
<td>3.4708</td>
</tr>
<tr>
<td>Green wavelength</td>
<td>39.3314</td>
<td>7.3430</td>
<td>9.3843</td>
</tr>
<tr>
<td>Near infrared wavelength</td>
<td>50.4308</td>
<td>4.9463</td>
<td>5.4157</td>
</tr>
<tr>
<td>Red wavelength</td>
<td>40.4887</td>
<td>5.9977</td>
<td>6.6183</td>
</tr>
</tbody>
</table>

Note: SNR1 represents the SNR of the original image. SNR2 represents the SNR of the preprocessed image.

which has improved the quality of multi-spectral images, the data sets of different combined wavelengths are trained in RF and ELM models respectively to obtain the best classification model for identifying different heterogeneities. As shown in Fig.7, RF and ELM determine model parameters (number of decision tree and neurons) according to classification accuracy respectively. It can be seen from the figure that by changing the number of decision trees in RF and the number of neurons in ELM respectively, it can be found that the overall classification accuracy of the model keeps improving with the increase of the number of decision trees(neurons).After reaching a certain classification accuracy rate, the classification accuracy no longer changes, and the optimal number of decision trees(neurons) in the best model is obtained. The results are shown in Tab.IV. Meanwhile, in order to verify the validity of the models we established, we compare its classification
(1) The importance of feature is as follows: 

\[ \text{IMP}(i) = \sum_{n=1}^{N} \text{Gini}(n) \] 

(2) If the node set of feature as node segmentation attribute in the \( k \)-th decision tree is \( N \), the importance of feature in this decision tree can be obtained from equation (3):

\[ \text{IMP}_{i,k} = \sum_{n=1}^{N} \text{IMP}_{i,n}^{\text{Gini}} \] 

(3) If there are \( K \) trees in RF, the importance of feature \( x_i \) in the whole RF can be calculated by equation (4):

\[ \text{IMP}_{i}^{\text{Gini}} = \frac{1}{K} \sum_{k=1}^{K} \text{IMP}_{i,k}^{\text{Gini}} \] 

(4) Where: \( \text{IMP}_{i}^{\text{Gini}} \) represents the average change of Gini index of the \( i \)-th feature on all RF decision tree nodes; \( I_{G}(n) \) represents the exponential change of node \( n \); \( I_{G}(n) \) and \( I_{G}(n) \) represent respectively the change of Gini index before and after distributing the data on node \( n \) to its left and right sub-nodes \( n_l \) and \( n_r \); \( \text{IMP}_{i,k}^{\text{Gini}} \) represents the importance of the \( i \)-th characteristic variables in the \( k \)-th decision tree (the set of nodes where the node partitioning attribute is \( N \)); \( \text{IMP}_{i}^{\text{Gini}} \) represents the importance of the \( i \)-th characteristic variable in the whole RF.

As shown in Table III, the importance of all characteristic variables in the model establishment process is obtained based on Gini index. It can be seen from the table that in the model prediction process, the importance of characteristic variables based on Gini index is as follows:

1. The importance of feature \( x_i \) on node \( n \), that is, the Gini index change before and after the data on node \( n \) is divided into its left and right sub-nodes \( n_l \) and \( n_r \), is shown in equation (2):

\[ \text{IMP}_{i,n}^{\text{Gini}} = I_{G}(n) - I_{G}(n_l) - I_{G}(n_r) \] 

2. The specific analysis process of the importance of characteristic variables based on Gini index is as follows:

- **Firmness**: The green mark indicates the factor with the highest weight of the variables in the different wavelength combinations.
- **Angular**: The red mark indicates the highest weight of the same factor in different wavelength combinations.

### Table III

<table>
<thead>
<tr>
<th>Variable</th>
<th>Image a</th>
<th>Image b</th>
<th>Image c</th>
<th>Image d</th>
<th>Image ab</th>
<th>Image ac</th>
<th>Image ad</th>
<th>Image bc</th>
<th>Image bd</th>
<th>Image cd</th>
<th>Image abc</th>
<th>Image abd</th>
<th>Image bcd</th>
<th>Image abcd</th>
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<tbody>
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<td>0.162</td>
<td>0.112</td>
<td>0.164</td>
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<td>0.174</td>
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<td>0.142</td>
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<td>0.165</td>
<td>0.146</td>
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<td>0.133</td>
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<td>0.014</td>
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<td>0.013</td>
<td>0.015</td>
<td>0.009</td>
<td>0.012</td>
<td>0.034</td>
<td>0.025</td>
<td>0.018</td>
<td>0.022</td>
<td>0.019</td>
<td>0.028</td>
<td>0.016</td>
</tr>
<tr>
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<td>0.004</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>0.002</td>
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<td>0.007</td>
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<td>0.005</td>
<td>0.004</td>
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<tr>
<td>Long</td>
<td>0.006</td>
<td>0.026</td>
<td>0.017</td>
<td>0.001</td>
<td>0.013</td>
<td>0.012</td>
<td>0.010</td>
<td>0.021</td>
<td>0.023</td>
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<td>0.019</td>
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<tr>
<td>Short</td>
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<td>0.010</td>
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<td>0.015</td>
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<td>0.029</td>
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<td>0.019</td>
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</table>

Note: ① The green mark indicates the factor with the highest weight of the variables in the different wavelength combinations. ② The red mark indicates the highest weight of the same factor in different wavelength combinations.
The overall classification of RF and ELM is ideal. The classification effect of the combined wavelength is better than the single-wavelength classification effect, and the four-wavelength combination classification effect is optimal. With the increase of wavelength, the classification accuracy of the models (RF and ELM) is gradually improved.

(4) In the classification effect of different wavelength combinations, RF is superior to ELM. (5) In the model classification running time, ELM is shorter than RF, and the difference of time amount is large. (6) Under the premise of small difference in overall classification accuracy, ELM's operation efficiency is significantly higher than RF.

$$R^2 = 1 - \frac{\sum_{i=1}^{m} \hat{y}_i - y_i}{\sum_{i=1}^{m} (y_i - \bar{y})^2}$$  \hspace{1cm} (5)

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2}$$  \hspace{1cm} (6)

Where $m$ represents the number of test samples; $\hat{y}_i$ represents the predicted value of the test sample; $y_i$ represents the actual value of the test sample; $\bar{y}$ represents the actual value.
average value of the test sample. The average classification accuracy of different models is shown in Tab.V. It can be seen from the table that compared with the RF and ELM models established by multi-spectral transmission images before preprocessing, the classification accuracy of all wavelength combination RF and ELM models established by multi-spectral transmission images after preprocessing is significantly improved, which indicates the effectiveness of the proposed method to enhance image quality. And as can also be seen from the table that in the models of single wavelength and four wavelength combination, the traditional SVM classification effect is the best, reaching 89.51 and 99.90, respectively. In the models of the two and three wavelength combination, the traditional MLR classification is the best, reaching 97.14 and 99.12, respectively. However, compared with the combination of different wavelengths, the RF and ELM models established after the preprocessed of multi-spectral transmission images in this paper have better classification effect, and the RF and ELM models have better overall classification effect.

Analysis of experimental results: The image preprocessed by the modulation-demodulation and frame accumulation technique, it is found that the SNR of the image is improved to a certain extent, which makes the heterogeneities in the image more prominent and the extracted feature information more perfect. With the same error rate and iteration times, RF's classification accuracy is slightly higher than ELM, while ELM is slightly superior in classification speed. Therefore, ELM operates slightly more efficiently than RF. And compared with the accuracy of traditional multi-spectral image classification models, the RF and ELM we established have better classification effect.

V. CONCLUSION
In this paper, combined with the characteristics of breast tissue, multi-spectral transmission image acquisition experiment is designed. The image quality is improved by modulation-demodulation and frame accumulation technique, and the heterogeneous classification is studied by pattern recognition (RF, ELM) and traditional multi-spectral image classification models (SVM, LDA, LRR, SR and MLR). Firstly, in the process of acquiring multi-spectral transmission images, sinusoidal signals with frequency of 4HZ are used as carrier signals to enhance the information degree of the image. Then, in image preprocessing, the PSNR and SNR of the image are improved through the modulation-demodulation and frame accumulation technology. The result shows that the PSNR of the image before and after frame accumulation is positive, which indicates that the gray level of the image significantly increases after preprocessing. And the image SNR after frame accumulation has also been improved to a certain extent, which will obtain more abundant feature information of the image heterogeneous region. Finally, in the aspect of heterogeneous classification, the different wavelength combination data sets of phantom feature information are trained as the training sample, and the heterogeneous classification accuracy of different models is compared. The results show that compared with the classification accuracy of the traditional multi-spectral image classification models, RF and ELM models have better classification effect. Among them, the RF and ELM models established in the data set of four-wavelength combination have the best classification effect, and the classification accuracy is up to 100%, secondly, it is the three-wavelength combined model. And the single-wavelength model has the worst classification effect. And, in terms of model operation efficiency, ELM is significantly higher than RF. In summary, the technique of modulation-demodulation and frame accumulation has improved the gray resolution of images. And compared with the classification accuracy of the traditional multi-spectral image classification models, the RF and ELM models established in this paper have better classification effect. In addition, potatoes and carrots are selected as heterogeneities to simulate breast cancer according to the characteristics of strong transmissibility and tomographic distribution of breast tissue, which may be limited by other unknown conditions, but provides a good idea for the detection of heterogeneity in breast tissue. Through further research, the improved method can be adapted to more complex situations and even clinical applications. It is expected that this method can promote the clinical application of multi-spectral transmission imaging in early screening of breast tumors in the future.

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CONFLICT OF INTEREST
The authors declare that they have no conflict of interest.

REFERENCES


