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Breast tumors recognition based on edge feature extraction using support vector machine

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ABSTRACT

Nowadays, it is important for the detection of ultrasound images of breast tumors. In this paper, a new ultrasonic image feature extraction algorithm combining edge-based features and morphologic feature information is proposed, which has good effect on benign and malignant identification of breast tumors. This paper mainly studies three features (Sum of maximum curvature, Sum of maximum curvature and peak, Sum of maximum curvature and standard deviation) according to the shape histogram of ultrasound breast tumors from a local perspective. Based on the results of SVM classifier, it was found that the edge-based features have higher classification accuracy. The recognition system would perform better when morphologic features (Roughness, Regularity, Aspect ratio, Ellipticity, Roundness) were incorporated, compared with the control group whose input only with morphologic features. The results show that edge-based features can well describe breast tumors in ultrasound images, and have the potential to be used in breast ultrasound computer-aided design.

1. Introduction

The statistic report in 2017 shows that the average age of breast cancer patients in China is 48.7 [1]. Breast cancer has become a common disease among women in the current society [2]. Both the breast cancer's morbidity and mortality are higher than that of other female malignant tumors. Clinical studies have shown that early detection and effective treatments can greatly improve the survival rate of female patients. However, there was no obvious symptoms in the initial when the patient got the cancer, which makes the detection difficult. Therefore, how to discover the lesion area of breast as early as possible so as to improve the cure rate of breast cancer has become a very important topic in the medical field.

Ultrasound imaging is a convenient, low-cost, effective, real-time, non-radiation imaging tool, which has been widely used in clinical breast cancer detection [3,4]. In breast tumor diagnosis, the breast ultrasound computer-aided diagnosis (CAD) has been becoming more and more important. It performs better in image preprocessing, segmentation, feature extraction and selection, and tumor classification, including the objective evaluation results, the classification accuracy, and the diagnostic sensitivity [5,6]. The extraction of different features is crucial in breast ultrasound CAD. Over the past years, research prevailingly concerned the morphologic feature extraction and texture feature extraction [7–9]. Texture features mainly reflect the surface properties of objects through pixels' gray distribution and their surrounding spatial neighborhoods' properties like the clarity, thickness and depth of the image texture.

Some studies believed that the morphologic feature is effective in distinguishing benign tumors from malignant ones [10–12]. The contour of benign tumors is relatively smooth and well-defined, while the malignant have much more irregular contours and corner points. In the commonly used data system (BI-RADS) and sonographic breast imaging reporting in clinic, breast ultrasound images are described from three aspects: background echo texture, mass and calcification. Background echo texture and calcification can be described by gray level information and texture information, while breast masses can be described by extracting shape, orientation, edge and boundary features.

Based upon this observation, a great number of shape features have been developed [13,14]. Atteneave had a research on corner detection based on morphologic features. He found the image of malignant tumor had high curvature on the contour. In addition, many important information about the object shape is contained in the corner points [15]. According to the

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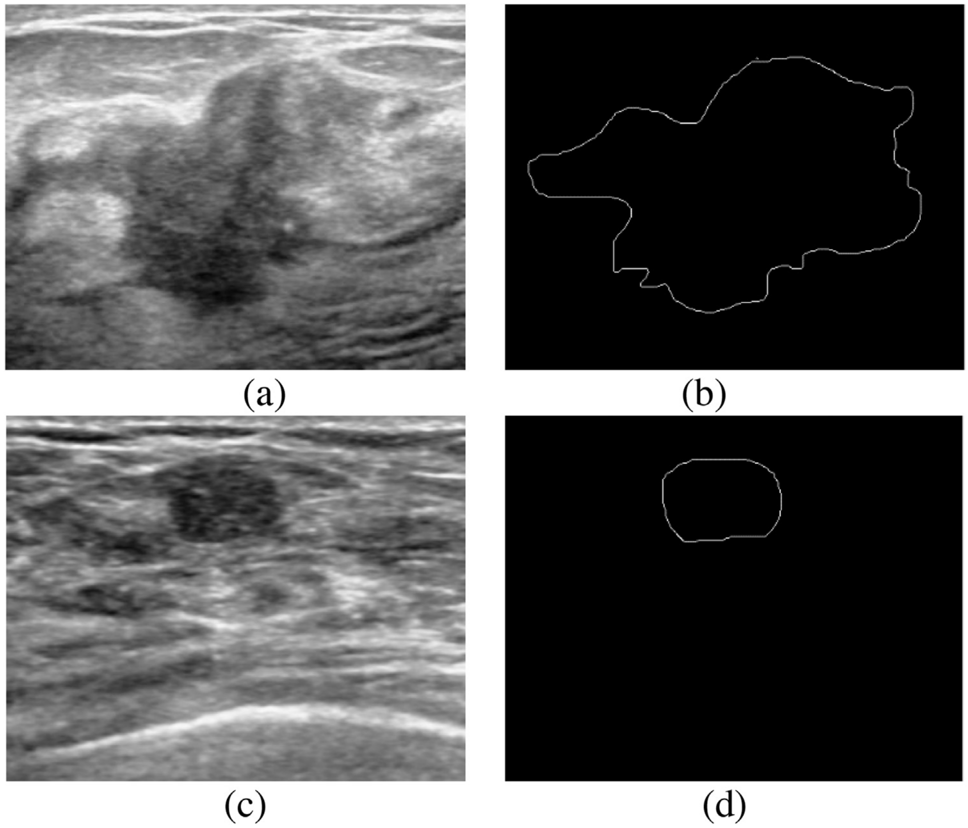

Fig. 1. Breast cancer ultrasound image and sketched ROI image: (a) malignant tumor ultrasound image; (b) malignant tumor sketched ROI image; (c) benign tumor ultrasound image; (d) benign tumor sketched ROI image.

morphological characteristics of malignant tumors, such as corners and differential lobules, the benign and malignant tumors can be distinguished by quantifying the curvature of the margin.

In most cases, two steps are included in the existing edge-based feature detecting algorithms [16]. At every point along the contour, the first step is to get the smoothed version of curvature. The second step is to detect whether the maximum curvature is beyond the threshold and record its location as corners if it meets the former requirement. In this paper, we firstly fitted the ellipse by least square method and acquired the histogram of difference values between fitted values and curvature values at every point. Secondly, we connected all the values in the histogram to get the curve of the shape histogram and calculated smoothed version of the curvature. Finally, different edge-based features (Sum of maximum curvature, Sum of maximum curvature and peak, Sum of maximum curvature and standard deviation) from smoothed version of curvature were studied and all parameters were used in the classification.

As the input of support vector machine (SVM), the edge-based features of an ultrasonic breast tumor image to recognize the tumors could achieve acceptable accuracy in tumor classification [17–19]. Incorporating morphologic features (Roughness, Regularity, Aspect ratio, Ellipticity, Roundness) into different classification system would achieve different performances [20–23]. In the control group, the input with only morphologic features in SVM could have lower accuracy. Compared with other methods of feature extraction, the feature fusion algorithm we proposed in this paper has a high accuracy of description, that is, the feature fusion algorithm can achieve higher classification accuracy. The experiments verify the rationality and effectiveness of this method as well.

2. Material and methods

2.1. Experimental data and pretreatment

The experimental dataset is a series of breast ultrasonic images and its corresponding tumor grade and biopsy results and experienced doctors (each with more than 3 years). The images were obtained from the ultrasound diagnostic instrument (VINNO 70, Feino Technology Co., Ltd., Suzhou), a total of 192 cases (Fig. 1 for 2 cases), including 71 pictures of malignant tumors and 121 pictures of benign tumors. The probe emission frequency varied from 5 MHz to 14 MHz. This research protocol was approved by the ethics committee. All subjects signed the written informed consent.

As shown in Fig. 1(a) and 1(c), the long axis length of the tumors are 2.27 cm and 0.706 cm, respectively. Pretreatment is based on irregular feature regions selected by doctors (shown in Fig. 1(b) and (d)), so we used binary converting to process these images. Different types of characteristics were extracted from the sub-images and then used for tumor classification. The algorithm was implemented on Matlab 7.1.

2.2. Feature extraction

2.2.1. Edge-based features extraction

Tumor target segmentation is performed on breast tumor ultrasound images after pretreatment. Based on the coordinates of the pixels on the tumor edge, the elliptic curve shown in Fig. 2 (yellow line) fitted the tumor target's shape by the least square method.

A series of rays from the centroid of the ellipse was set. The rays began with the long axis of the ellipse and rotated in a counterclockwise direction. Each ray emitted at an angle of 5.7 degrees and connected the points on the boundary and the points on the

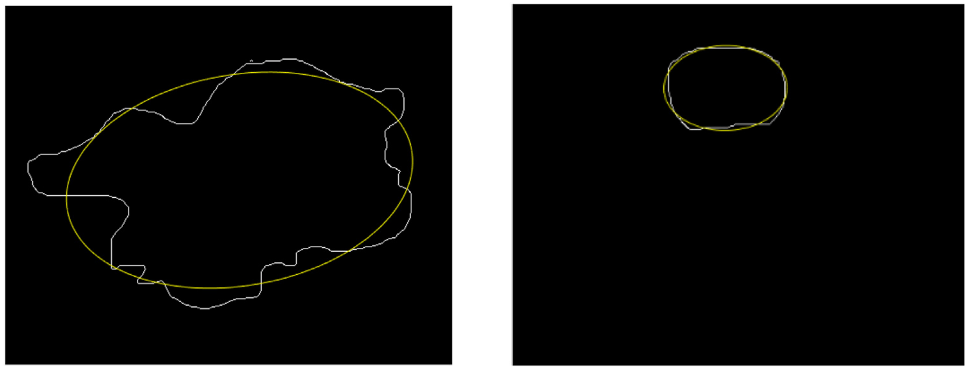

Fig. 2. Shape fitting map of breast tumors: (a) Malignant tumor, (b) Benign tumor.

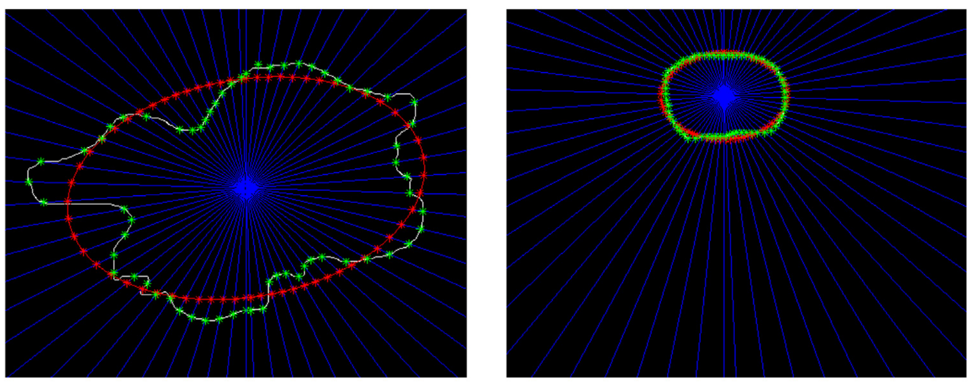

Fig. 3. Elliptic fitting in tumor ultrasound image: (a) Malignant tumor, (b) Benign tumor.

ellipse. As shown in Fig. 3, red points are the intersection of ray and elliptic curve, and green points are the intersection of ray and tumor edge.

By calculating the difference between red points and green points (Fig. 3), the shape histogram of the breast tumor was obtained. As shown in Fig. 4, the histograms had positive and negative intervals, the positive interval represented the part of the tumor edge convex out of the ellipse, and the negative interval represented the part of the tumor edge concave within the ellipse. Three edge features could be extracted from Fig. 4: Sum of maximum curvature, Sum of maximum curvature and peak, Sum of maximum curvature and standard deviation.

2.2.1.1. Sum of Maximum Curvature (SMC). The curve based on the shape histogram was shown in Fig. 5. The curve's curvature characterized the morphological changes of breast tumors.

Based on the shape histogram, the curvature of each numerical point in all intervals was calculated and defined as C_{ij}. Then maximum C_{ij} in each interval was taken out and added, which defined as SMC.

$$C_{ij} = \frac{\left|h_i''(j)\right|}{\{1+\left[h_i'(j)\right]^2\}^{3/2}} \tag{1}$$

$$SMC = \sum_i \max\left(C_{ij}\right) \tag{2}$$

where i $(i = 1, 2, \ldots, N)$ is the number of histogram intervals. $h_{i(j)}$ is the first derivative of the j^{th} point in the i^{th} interval and $h_i''(j)$ is the second derivative of the j^{th} point in the i^{th} interval. C_{ij} is the curvature of the j^{th} point in the i^{th} interval.

2.2.1.2. Sum of Maximum Curvature and Peak (SMCP). Curvature describes the degree of curvature of curves in each interval, but it cannot reflect the peak value of curves. Therefore, it is necessary to consider the degree of variation of the curve peak value in each interval in the shape histogram. SMCP is obtained by weighting peak curvature, which defined as:

$$SMCP = \sum_i \left|\max_j(C_{ij}) * \max_j h_i(j)\right| \tag{3}$$

where $\max_j(C_{ij})$ $(i = 1, 2, \ldots, N)$ represents maximum curvature of each interval, $\max_j h_i(j)$ $(i = 1, 2, \ldots, N)$represents maximum peak value of each interval. Multiplication of $\max_j(C_{ij})$ and $\max_j h_i(j)$ is helpful to distinguish more accurately the cases where the shape of the local contour of the tumor is identical but different from that of the ellipse.

2.2.1.3. Sum of Maximum Curvature and Standard Deviation (SMCSD). The peak fluctuation degree of each interval in the shape histogram reflected the difference between different breast tumors. The standard deviation of each interval in the shape histogram was

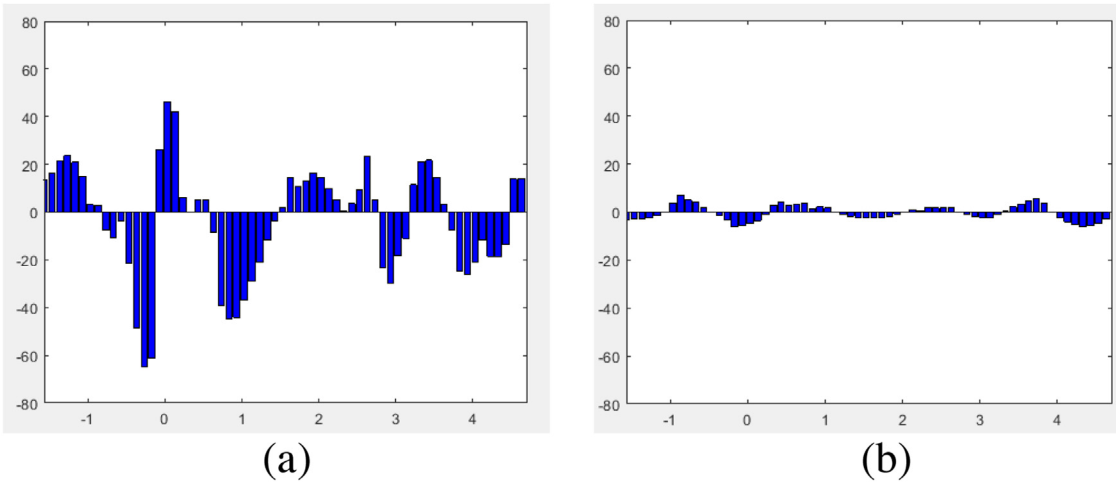

Fig. 4. Difference histogram: (a) Malignant tumor, (b) Benign tumor.

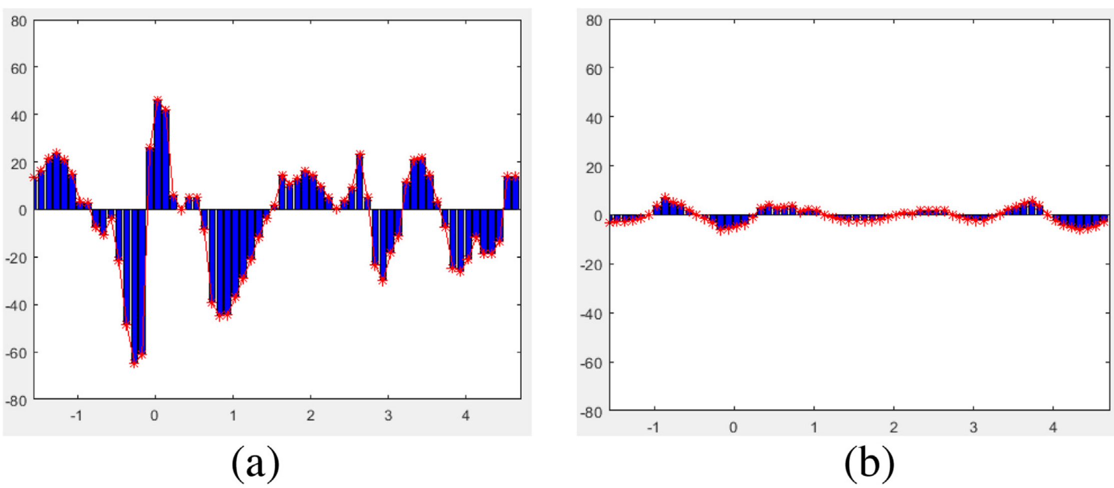

Fig. 5. The curve based on the points in the difference histogram intervals: (a) Malignant tumor, (b) Benign tumor.

calculated, defined as $PSD(i)$. Then SMCSD is obtained by weighting the curvature with the peak standard deviation.

$$PSD(i) = \sqrt{\frac{1}{m}\sum_{j=1}^{m}(h_i(j) - \bar{h}_i)^2} \tag{4}$$

$$SMCSD = \sum_i \left| \max_j(C_{ij}) * PSD(i) \right| \tag{5}$$

where $\overline{h_i}$ represents average peak value in the i^{th} interval.

2.2.2. Morphologic features extraction

2.2.2.1. Roughness. Roughness is determined as the absolute value of the difference between the radial length of adjacent points on the tumor edge at a certain direction. Roughness reflects the roughness of the edge and the number of burrs. The roughness is defined as follows:

$$R = \frac{1}{N}\sum_{i=1}^{N} \left| d(i) - d(i+1) \right| \tag{6}$$

where N represents the number of edge pixels. $d(i)$ represents the distance from the i^{th} point on the edge to the center of mass。

2.2.2.2. Regularity. The least square method was used to fit the ellipse and there was overlapping area between the ellipse and the tumor, shown in Fig. 6. The more overlapping, the more regular it is. The regularity formula is as follows:

$$rr = \frac{S_1}{S_2} \tag{7}$$

where S_1 represents the overlapping area between fitting ellipse and tumor and S_2 represents the area of the tumor.

2.2.2.3. Aspect ratio. The aspect ratio refers to the ratio of height to width of the smallest rectangular box containing the tumor area, which reflects the growth pattern of tumors to some extent. As shown in Fig. 7, the green box was the outer frame of the tumor. The aspect ratio formula is as follows:

$$DWR = Depth/Width \tag{8}$$

where *Depth* represented the longitudinal length of the tumor and *Width* represented the transverse width of the tumor.

2.2.2.4. Ellipticity. Ellipticity is the ratio of fitting ellipse circumference to tumor boundary circumference, which is defined as:

$$tuoyuandu = \frac{\pi(S.A + S.B)}{L} \tag{9}$$

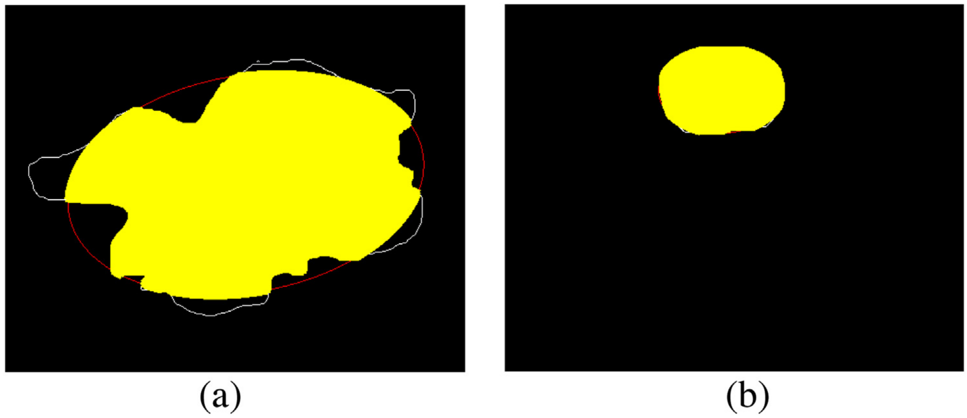

Fig. 6. The overlapping area between fitting ellipse and tumor: (a) Malignant tumor, (b) Benign tumor.

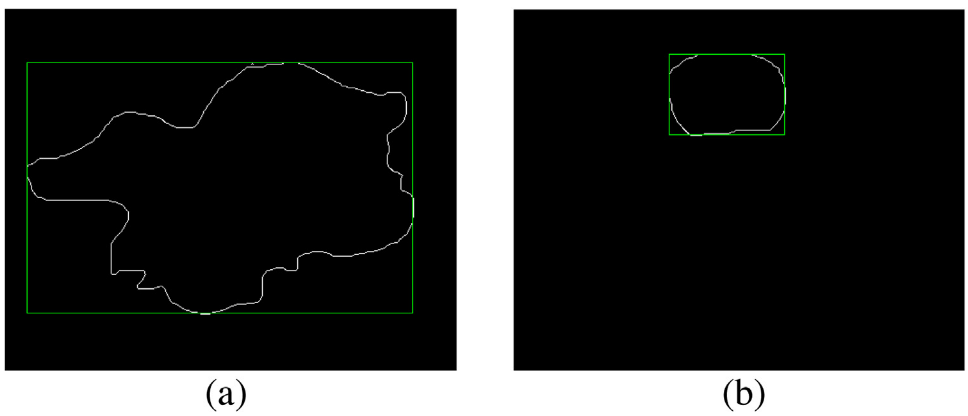

Fig. 7. Tumor contour block diagram: (a) Malignant tumor, (b) Benign tumor.

where *S.A* represents the length of the half-long axis of the fitting ellipse. *S.B* represents the length of the semi-short axis of fitting ellipse. *L* represents the circumference of tumor boundary.

2.2.2.5. Roundness. The roundness formula is as follows:

$$yuanxingdu = \frac{4\pi S}{L^2} \tag{10}$$

where S represents the area of the tumor area, which can be obtained by counting the pixels number in the tumor area. L refers to the perimeter of the boundary, which can be obtained by counting the pixels number on the tumor edge.

2.2.3. Statistical analysis

Statistical analysis was performed by the Student t-test. A 95 % confidence level was chosen to determine the significance of differences between groups, with a P value of less than 0.05 indicating a significant difference.

2.2.4. Tumor classification based on SVM

After the eigenvectors were computed and normalized, SVM was used to distinguish different types of tumors. It originates from statistical learning theory and aims to learn patterns from a small sample set, which has been widely using in pattern recognition, regression and classification [24,25]. Then, the SVM algorithm for classification will be briefly described. To build a hyperplane, SVM uses maximal margin to separate the two known labeled data with. In this case, Support Vectors (SV) are defined as those data points that closest to the hyper-plane.

$(x_{i,}\ y_i)$, $(i = 1, 2, \ldots, N)$, denotes a labeled training sample set, in which x is the i^{th} input vector and y denotes the corresponding class. $w \cdot x + b = 0$ is the equation of the hyperplane. Only one of the possible hyperplanes refers to the maximum margin between the nearest data points belonging to each class. The hyperplane that maximizes the margin is as follows:

$$\Phi(w) = \frac{1}{2}||w||^2 = \frac{1}{2}(w \cdot w), s.t. \quad y_i\left[(w \cdot x_i) + b\right] - 1 \geq 0 \tag{11}$$

In order to solve the optimization problem, the following Lagrange function is defined:

$$L(w, b, \alpha) = \frac{1}{2}(w \cdot w) - \sum_{i=1}^{n} \alpha_i \left\{ y_i[(w \cdot x_i) + b] - 1 \right\} \tag{12}$$

Where $\alpha_i \geq 0$ denotes the positive Lagrange multiplier, L can be transformed as follows:

$$\max Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j), s.t. \quad \sum_{i=1}^{n} \alpha_i y_i = 0, \alpha_i \geq 0 \tag{13}$$

Let α_i^* denotes the optimization value, the $w^* = \sum_{i=1}^{n} \alpha_i^* y_i x_i$. According to the Kuhn-Tucker optimality conditions, the following conditions should be satisfied:

$$\alpha_i(y_i(w \cdot x_i + b) - 1) = 0 \tag{14}$$

In most cases, α_i^* is zero, while those nonzero α_i^* correspond to SV that satisfy:

$$y_i[(w \cdot x_i) + b] - 1) = 0 \tag{15}$$

The hyperplane is expressed as follows:

$$f(x) = sgn\{w^* \cdot x) + b\} = sgn\{\sum_{i=1}^{n} \alpha_i^* y_i (x_i \cdot x) + b^*\} \tag{16}$$

Table 1
Recognition rate based on different features.

Methods	Recognition rate/%
Morphologic features	67.31
Edge-based features (SMC↘SMCP↘SMCSD)	82.69
Morphologic features + SMC	78.85
Morphologic features + SMCP	75.00
Morphologic features + SMCSD	78.85
Morphologic features + Edge-based features	82.71

As a classification threshold, b^* is determined by α_i^*.

The kernel function is very important in this algorithm to implicit mapping. Different kernel functions were analyzed in SVM learning to classify the edge-based features. The results showed that the classification based on the linear kernel function used in this research was better than using others kernel functions (shown in the result part).

3. Results

3.1. Results based on edge-based feature extraction

There were 192 images of breast tumors, including 71 malignant images, 121 benign images (50 malignant images as training samples and 21 images as testing samples, 90 benign images regarded as training samples and 31 images regarded as testing samples). An SVM classifier was used to distinguish benign tumors from malignant ones after extracting different features groups from actual collected ultrasound breast tumor images ($P < 0.05$). Table 1 showed that the recognition rate could reach 82.69 % based on the three morphological quantization features (SMC, SMCP and SMCSD), which was 15.38 % higher than that of other five traditional morphological features. When the traditional features were combined with the three quantization features proposed by the present invention, the recognition rate reached 82.71 %.

3.2. Comparison of different characteristics between benign tumors and malignant breast tumors

To validate the effectiveness, the maximums, minimums and mean values of benign and malignant breast tumors under various characteristic operators were calculated, respectively, Table 2 showed the numerical comparison of different characteristics.

There were differences among several texture feature parameters, but it is not easy to be found directly. In order to observe the ability of each parameter to distinguish samples more intuitively, distance D was introduced as an index to measure the ability of a feature to distinguish two types of samples. The formulas are as follows:

$$D = \frac{\left|Max_{beni} - Max_{mali}\right| + \left|Min_{beni} - Min_{mali}\right|}{\left|\mu_{beni} + \mu_{mali}\right|} \tag{17}$$

Where Max_{beni} is maximum value (benign breast tumors). Max_{mali} is maximum value for malignant breast tumors. Min_{beni} is minimum value (benign breast tumors). Min_{mali} is minimum value for malignant breast tumors. μ_{beni} is mean value (benign breast tumors). μ_{mali} is mean value for malignant breast tumors.

D represented the ability to classify of this feature. The larger the value of D, the greater the difference in the value of the characteristic parameter between benign tumors and malignant tumors. As shown in Table 3, the three morphological features presented in this paper described the benign and malignant differences of breast tumors more accurately.

3.3. Classification performance based different features

To further illustrate the effectiveness of the edge-based feature extraction, five indicators were used to evaluate the performance of the classifier, including Accuracy, Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV).The recognition results by SVM were shown in Table 4. In group 2, the PPV was 87.5 % and the NPV was 80.56 %, which meant that our method has excellent accuracy in detecting positive and negative results.

4. Discussion

The morbidity and mortality of breast cancer are increasing in these years. To get a successful treatment, the key issue is the tumor early-stage and accurate detection [26–28]. In feature extraction part, the research mostly focused on the extraction of morphological quantitative features. However, traditional morphological quantitative features described the difference between benign and malignant breast tumors from a global point of view [29,30]. For example, roundness was used to evaluate the approximation of the shape of the tumor to that of the circle. It can be found that they did not take into account the local morphological changes of breast tumors, and the extracted benign and malignant features of breast tumors could be not accurate. To overcome this shortcoming, we designed quantitative features based on shape histogram and interval as a unit, and described the morphological changes of breast tumors from a local point of view, so as to more accurately characterize the difference between benign and malignant breast tumors.

To discriminate benign breast mass from malignant breast tumor, an edge-based feature extraction method for ultrasound images is proposed. First, curvature histogram must be detected from the breast ultrasound images. Based on this research, to recognize the tumors different features are chosen as the feature input of SVM. Attention that the output value of SVM could only be -1 or 1. While the output of the ultrasound breast image is greater than 0, it is benign, otherwise it is malignant. The satisfactory experimental results of the proposed method are presented in Table 1. The results are indicative of that the properties of breast tumor in ultrasound images can be well characterized by the proposed method. In addition, based on the same features, the classification accuracy using different classifiers should be compared. Three other classifiers (KNN, Random Forest, Discriminant Analysis Classifier) were

Table 2
Numerical comparison of different characteristics.

	Features	Benign(Max)	Malignant(Max)	Benign(Min)	Malignant(Min)	Benign(Mean)	Malignant(Mean)
1	Roughness	22.4507	35.0230	1.1732	3.3234	7.5806	14.5969
	Regularity	0.9808	0.9739	0.8721	0.7359	0.9475	0.9199
	Aspect ratio	1.1132	1.2500	0.1725	0.2768	0.5683	0.6358
	Ellipticity	1.0863	1.0513	0.8585	0.7232	0.9888	0.9420
	Roundness	1.1352	1.0447	0.3545	0.3698	0.8582	0.8020
2	SMC	50.9482	161.631	5.796	12.328	22.3121	31.5533
	SMCP	1161.8	10555	17.116	72.310	154.211	654.780
	SMCSD	419.1466	830.1394	4.5764	19.9456	45.0753	146.7479

Note: 1: Morphologic features and 2: Edge-based features.

Table 3
Distance between benign and malignant morphological quantitative characteristics.

	Features	Distance DOf Max values	Distance DOf Min values	Distance D betweenbenign and malignant
1	Roughness	12.5723	2.1502	0.6638
	Regularity	0.0069	0.1362	0.0766
	Aspect ratio	0.1368	0.1043	0.2002
	Ellipticity	0.0350	0.1353	0.0882
	Roundness	0.0905	0.0153	0.0637
2	SMC	110.6831	6.5324	2.1761
	SMCP	9393.2	55.1947	11.6792
	SMCSD	410.9928	15.3692	2.2227

Note: 1: Morphologic features and 2: Edge-based features.

Table 4
Recognition results by SVM.

	Accuracy($\frac{TN+TP}{TN+FN+TP+FP}$)	Sensitivity($\frac{TP}{TP+FN}$)	Specificity($\frac{TN}{TN+FP}$)	PPV($\frac{TP}{TP+FP}$)	NPV($\frac{TN}{TN+FN}$)
1	67.31 %	47.62 %	80.65 %	62.50 %	69.44 %
2	82.69 %	66.67 %	93.55 %	87.50 %	80.56 %

Note: 1: Morphologic features and 2: Edge-based features.

Table 5
Recognition results by different classifiers.

Classifiers	Accuracy	Sensitivity	Specificity	PPV	NPV
KNN	63.46	71.43	58.06	53.57	75.00
Random Forest	65.38	57.14	70.97	57.14	70.97
SVM	82.69	66.67	93.55	87.50	80.56
Discriminant Analysis	78.85	47.62	90	100	73.81

chosen and the classification accuracy were calculated, shown in Table 5. It was found that SVM could be a better classifier.

Whereas, there are still several limitations [31–33]. Only 191 ultrasound images were used in the study and the results about accuracy would be limited by the number. With the increase of the database, this will collect more and more cases and improve the accuracy of tumor recognition. The goal of the ultrasound image CAD system applied in breast cancer is to realize the automatic recognition of benign tumors and malignant tumors. It will be possible to realize the automatic identification of benign tumors and malignant tumors in the future with the development of in-depth learning technology.

In the ultrasound image CAD system of breast tumors, feature extraction is the basis of image analysis and the key link of ultrasound image diagnosis. The purpose of feature extraction is to extract features that can represent the attributes of regions of interest from the original image data [34–36]. Extracting effective features from original medical images that can accurately reflect the benign and malignant features of tumors has become one of the hot topics in medical image processing [37,38]. The more features are extracted to represent image attributes, the higher the accuracy of automatic discrimination is, and the more complex the algorithm is correspondingly. However, we just evaluated eight features and examined the potential efficiency of these three new edge-based features. To improve the accuracy of diagnosis, more additional features are needed, such as echo ratio, rear echo attenuation coefficient, echo gray standard deviation, lobular index, gray level co-occurrence matrix, tumor edge ambiguity. There will be continuous improvement in the follow-up research process. Since the morphological feature descriptors are more focus on local characteristics of the tumor while the texture feature descriptors are the global characterization of the regions of interest, the combination of the morphological feature and texture feature can further improve the accuracy of breast tumor classification [39,40]. The focus of our future work will be this combination study. In the following research, different feature selection techniques and classifiers will be considered to further improve the classification accuracy.

5. Conclusions

Breast cancer has a high morbidity and mortality, so that is the early detection of breast cancer ultrasound images is of great significance. In this paper, a new ultrasonic image feature extraction algorithm combining edge-based features and morphologic feature information is proposed. SVM with edge-based features (SMC, SMCP and SMCSD) achieved impressive performances. This study proposed an efficient and feasible approach that used the proposed classification system based on edge-based features to classify the benign and malignant tumors. It will remarkably perform adding morphologic features into the classification system. Application of the algorithm proposed in this paper has potential capability to improve the accuracy of early detection and reduce the number of misdiagnoses.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

CRediT authorship contribution statement

Yangyang Liu: Methodology, Writing - review & editing. **Li Ren:** Methodology, Software, Data curation. **Xuehong Cao:** Investigation, Supervision. **Ying Tong:** Conceptualization, Software, Writing - original draft.

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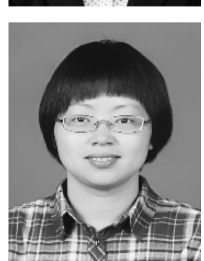

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