Breast Cancer Classification with Ultrasound Images Based on SLIC

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Abstract. Ultrasound image diagnosis of breast tumors has been widely used in recent years. However, there are some problems of it, for instance, poor quality, intense noise and uneven echo distribution, which has created a huge obstacle to diagnosis. To overcome these problems, we propose a novel method, a breast cancer classification with ultrasound images based on SLIC (BCCUI). We first utilize the Region of Interest (ROI) extraction based on Simple Linear Iterative Clustering (SLIC) algorithm and region growing algorithm to extract the ROI at the super-pixel level. Next, the features of ROI are extracted. Furthermore, the Support Vector Machine (SVM) classifier is applied. The calculation states that the accuracy of this segment algorithm is up to 88.00% and the sensitivity of the algorithm is up to 92.05%, which proves that the classifier presents in this paper has certain research meaning and applied worthiness.

1 Introduction

Breast cancer is one of the most diagnosis tumor diseases happened to women, which affects the health and life quality seriously. There will be approximately 268,600 cancer cases diagnosed in the United States[1], which is around 30% of projected cancer cases of women. Thus, how to diagnose people with breast cancer in high efficiency is one of the most challenges in the medical field. In general, there are some equipment used to screen mammary tissue, e.g., mammography, magnetic resonance imaging and ultrasonography. In the clinical application, the ultrasound image is applied for further diagnosis to avoid missed diagnosis in mammography[2], and not only has the advantage of no-radiation and low-cost, but reflects the features of new blood vessels objectively in real time. However, the ultrasound image of a breast tumor is poor in quality, and the noise is serious because of its inherent imaging mechanism. Meanwhile the geometric features of the breast tumor itself are complex, and the internal echo distribution is uneven. All of these problems affect the judgment of radiologists.

In order to overcome the above problems, this paper addresses a novel method, a breast cancer classification with ultrasound images based on SLIC (BCCUI), to extract the ROI based on SLIC algorithm and classify benign and malignant breast tumor accurately and fast. Firstly, the super-pixel clustering block is obtained by using the SLIC algorithm to superimpose the denoised and sharpened...
breast tumor ultrasound image. Then, the region growing algorithm is used to extract the ROI. By analyzing the differences between benign and malignant features of breast tumor ultrasound images, the geometric, texture and gray features are extracted. SVM classifier is selected to classify these features in BCCUI and get a reliable result.

The main contribution of BCCUI is its capability of generating a relatively accurate diagnosis result via common ultrasound breast images. Without deep and complicated neural network, it is more convenient for most majority of hospitals to apply this method.

The rest of this paper is organized as follows: Section 2 investigates the related literature. Section 3 presents the novel method in detail. Section 4 demonstrates the experimental results. Section 5 concludes the whole paper.

2 Related Research

Computer-aided breast tumor diagnosis based on ultrasonography forms a variety of methods. In recent years, with the developing of deep learning, more and more researches try breast tumor diagnosis with neural network[3][4]. However, it needs lots of hardware resources, especially, GPU resources.

The ROI extraction problem is vital for computer-aided diagnosis and the appropriate ROI determines the performance of a method directly. The greatest difficulty in this process is image segmentation, which requires to segment tumor and normal tissue. Existing image segmentation methods are mainly based on boundary detection (such as Sobel, Canny, LoG and etc), active contour model (ACM)[5], threshold classification[6], snake model[7], watershed[8], Markov Random Field[9] and etc. They are all used to extract appropriate ROI referred to the differences of image boundaries.

One key of computer-aided diagnosis is feature extraction and there exists a large amount of methods to achieve this goal. Texture and geometry features are usually applied as the important criterion in identification of breast tumor. The present main methods are based on gray level co-occurrence matrix, Tamura texture feature, gray gradient statistics, local binary pattern, Markov random field and etc. In terms of the geometric shape of tumor, the benign tumor appears as regular shape but malignant tumor is usually irregular shape. The information commonly used is roundness, roughness, closeness and etc. Generally, these features provide the basis and reference to diagnosis.

To screening above features to figure out breast cancer, the representative features, which make classification easier, should be selected as the judgment criteria firstly. Moon et al. located the region of tumor, and then classified the benign and malignant tumor with interior echo and morphological characteristic[10]. Uniyal et al. utilized RF time sequence characteristics and machine learning method to generalize the estimated probability graph of tumor and then realized classification[11]. And Nayeem et al. proposed a method based on sparse representation to classify tumor[12]. SVM, a supervised learning method, is widely applied for classification problem, which has many advantages especially in small
size sample, non-linear and high dimension problem. In this paper, we utilize SVM as the classifier.

3 BCCUI

The BCCUI can be separated as the following three parts: ROI extraction, features extraction and SVM classifier. The ultrasound image is firstly pre-processed and then handled with SLIC to extract the ROI of the breast tumor ultrasound image. Next, we extract the geometric, texture and gray features in ROI and construct the image model. After that, the features are analyzed by the model that we have trained with SVM to gain the final diagnosis result. The Figure 1 illustrates whole flow diagram of the method.

![Flow Diagram of BCCUI](image)

**Fig. 1.** The whole procedure of BCCUI for ultrasound image diagnosis.

3.1 Extraction of Region of Interest

As the ultrasound breast tumor images have the characteristic of uneven distribution of intensity and unclear boundary of tumor, histogram equalization and denoise process have been applied in original image. Figure 2 shows that the contrast between tumor and background are enhanced in the processed image, which is convenient for extracting ROI.

![Image Preprocess](image)

**Fig. 2.** Image preprocess. (a) is the raw ultrasound image. (b) is formed from (a) with histogram equalization and denoise process.

SLIC is an efficient method to decompose an image in visually homogeneous regions, which is based on the gradient ascent to segment image. Based
on the color similarity and spatial distance of pixels, the super-pixel clustering block is obtained by local K-means clustering. Given the initial seed point, the step size of super-pixel is calculated as

\[ S = \sqrt{\frac{N}{K}}, \]

(1)

where \( N \) is the pixel number of the ultrasound image and \( K \) is the targeted number of super-pixel blocks. With the step size \( S \), each block, a 3x3 area, is selected and the pixel with the lowest gradient in the block is selected as the clustering center \( C_i \), which denotes the five-dimensional space as

\[ C_i = [l_i, a_i, b_i, x_i, y_i], \]

(2)

where \([l_i, a_i, b_i]\) is the color vector in CIELAB color space and \([x_i, y_i]\) is the location of the pixel. The distance \( D' \) of \( C_i \) and \( C_j \) can be obtained as

\[ d_c = \sqrt{(l_j - l_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2}, \]
\[ d_s = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}, \]
\[ D' = \sqrt{\left(\frac{d_c}{N_c}\right)^2 + \left(\frac{d_s}{N_s}\right)^2}, \]

(3)

where \( d_c \) is the color difference between the two pixels and \( d_s \) is the Euclidean distance between them. \( N_c \) and \( N_s \), which denote color character and spatial character respectively, are normalization constant. The pixels around the seed point in 2Sx2S area can be related to the seed point in the distance \( D' \). Compared with K-means clustering, the search range of SLIC is limited to 2Sx2S area as Figure 3 shows, which makes it faster and more stable.

![Fig. 3. The comparison between K-means global search and SLIC search. (a) shows that the K-means algorithm needs to search each pixel of the image, but the SLIC only traverses the pixels in the 2Sx2S area, which is faster and more effective.](image)

We combine SLIC and region-growing arithmetic to separate ROI and the fundamental step is as the following algorithm.
Algorithm 1 The extraction algorithm of ROI based on SLIC and region-growing

**Input:** Ultrasound image  
**Output:** ROI boundary and segment

1: function GETROI  
2:  Read ultrasound image  
3:  Get matrix of super-pixel block  
4:  if The tumor has been labeled then  
5:    Select the center pixel of the labeled area as seed point \((x, y)\)  
6:  else  
7:    Select the seed point \((x, y)\) manually  
8:  end if  
9:  \(i = 0\)  
10:  for Traverse every super-pixel block in the matrix do  
11:    \(g_i = \text{GrayAvg}(i)\) \(/\!/\text{Calculate the average intensity of the block}\)  
12:    \(i++\)  
13:  end for  
14:  while Find the appropriate neighbor do  
15:    for traverse the whole SLIC matrix do  
16:      if \(N_4\) (the super-pixel area, \((x, y)\)) == 1 then  
17:        Save this area into list \(T_0\)  
18:      end if  
19:    end for  
20:    \(i = 0\)  
21:    for traverse the list \(T_0\) do  
22:      if \((g_i - \text{intensity of seed point})\) \(\geq\) threshold then  
23:        Save this area into list \(T_1\)  
24:      end if  
25:      \(i++\)  
26:      for traverse the pixels in list \(T_1\) do  
27:        Record the intensity of pixels  
28:      end for  
29:    end for  
30:  end while  
31:  return Save all these pixels as a new image  
32: end function

3.2 Features Extraction

In the clinical diagnosis, doctors usually distinguish between benign and malignant breast tumor on the shape, texture, echo attenuation, edge character, calcification and etc[14][15][16]. The Figure 4 illustrates four benign breast tumor ultrasound images and the Figure 5 illustrates another four malignant tumor images. And we conclude the differences between benign and malignant breast tumor as presented in Table 1.

**Geometric Features Extraction** In BCCUI, four geometric features are extracted. They are aspect ratio, roundness, compactness and roughness.
Fig. 4. Benign tumors. Ellipse, smooth boundary, even distribution of internal echo, posterior enhancement, smooth envelope.

Fig. 5. Malignant tumor. Irregular shape, uneven boundary, posterior echo attenuation, no envelope.

Table 1. Differences between benign and malignant breast tumor ultrasound images.

| character type       | benign                      | malignant                   |
|----------------------|-----------------------------|-----------------------------|
| shape                | regular (round/ellipse)     | irregular                   |
| direction            | parallel with epidermal     | perpendicular to epidermal  |
| edge                 | smooth                      | uneven                      |
| boundary             | sharp with clear echo       | unclear                     |
| internal echo        | even, low echo              | uneven, low echo            |
| posterior echo       | increased                   | attenuation                 |
| aspect ratio         | $\leq 1$                    | $> 1$                       |
| micro calcification  | no                          | yes                         |
| skin infiltration    | no                          | yes                         |

1. Aspect Ratio

The aspect ratio can be calculated as

$$AR = \frac{h}{w} = \frac{\max(i) - \min(i)}{\max(j) - \min(j)},$$

where $h$ is the height of minimum enclosing rectangle of tumor and $w$ is the width of minimum enclosing rectangle of tumor. $i$ and $j$ denote the horizontal and vertical ordinate of the rectangle's sides as the Figure 6.

Fig. 6. Aspect ratio. (a) shows the height and width of malignant breast tumor and (b) shows the height and width of benign breast tumor.
2. **Roundness**
   The roundness can be calculated as
   \[ RD = \frac{4\pi S}{L^2}, \]
   where \( S \) is the area of the breast tumor and \( L \) is perimeter. If the tumor is closer to round, the \( RD \) is closer to 1.

3. **Compactness**
   The compactness can be calculated as
   \[ CP = \frac{S}{4\pi L^2}. \]

4. **Roughness**
   The Roughness can be calculated as
   \[ RG = \frac{1}{N} \sum_{i=1}^{N} |d(i) - d(i + 1)|, \]
   where \( N \) is pixels number of the tumor image and \( d_i \) is the normalized radial length.

**Texture Features Extraction** In BCCUI, four texture features are extracted based on Gray-level Co-occurrence Matrix \( GLCM(i, j|d, \theta) \). They are contrast ratio, energy, homogeneity and correlation.

1. **Contrast Ratio**
   Contrast ratio is the ratio of the luminance of the brightest pixel to that of the darkest pixel in the image, which expresses the image definition and the fluctuation of tumor groove.

2. **Energy**
   The energy can be calculated as
   \[ E = \sum_{i} \sum_{j} \{i, j|d, \theta\}^2. \]

3. **Homogeneity**
   The homogeneity can be calculated as
   \[ H = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} L - 1 \frac{p(i, j|d, \theta)}{1 + (i - j)^2}. \]

4. **Correlation**
   The correlation can be calculated as
   \[ COR = \sum_{i} \sum_{j} \frac{(i - \mu_x)(j - \mu_y)P(i, j|d, \theta)}{\sigma_x \sigma_y}, \]
where $\mu_x$, $\mu_y$, $\sigma_x$ and $\sigma_y$ are the mean values and standard deviations of the normalized GLCM respectively as

$$
\mu_x = \sum_i \sum_j P(i, j|d, \theta) \mu_y = \sum_j \sum_i P(i, j|d, \theta),
\sigma_x = \sum_i (i - \mu_x)^2 \sum_j P(i, j|d, \theta), \sigma_y = \sum_j (j - \mu_y)^2 \sum_i P(i, j|d, \theta).
$$

\[ (11) \]

**Gray Feature Extraction** The posterior echo attenuation of the tumor is also an important basis for diagnosis. Thus we take the gray mean of the area at the back of tumor as a feature. As the Figure 7 illustrates, if there’s echo attenuation behind the tumor, the probability of malignant breast tumor is higher. If there’s no clear echo attenuation, the probability of malignant breast tumor is lower.

![Fig. 7. Posterior echo. The first rectangle in image marks the location of tumor and the second rectangle marks the posterior echo. (a) is the image of malignant tumor and (b) is the image of benign tumor.](image)

In BCCUI, the attenuation coefficient represents the gray feature as

$$
AC = \frac{\text{AvgROI}}{\text{Avgback}}
$$

where $\text{AvgROI}$ is the mean intensity value of the tumor area and $\text{Avgback}$ is the mean intensity value of the rectangle.

### 3.3 Classification

Support-vector machines [17], a supervised learning models with associated learning algorithms that analyze data, is widely used for classification and regression analysis. SVM can efficiently perform a non-linear classification using kernel trick which maps the input data into high dimensional space. We recommend using RBF as the kernel which is

$$
K(x, x_i) = \exp\left(-\frac{||x - x_i||^2}{\delta^2}\right),
$$

\[ (13) \]

And we find that using Sigmoid function also obtains the satisfied result of classification.
4 Experimental Results

The breast ultrasounds image dataset of our experiment came from imaging department of local hospital, which contains the breast tumor ultrasound images of 150 patients. All cases were confirmed by operation and pathology. There are 88 malignant breast tumor cases and 62 benign tumor cases. The size of all images is 580x775 and the format is PNG. We compile our code by using MATLAB R2017a and run it with a 2.8GHz Intel Core i5-8400 CPU.

**ROI Extraction** In Figure 10 we exhibit some ROI extraction results. The former four groups are benign and the later four groups are malignant. Observed Figure 10 BCCUI divides the tumors from image clearly with the number of super-pixel blocks as 50.

**Parameter Optimization** We take LIBSVM toolkit to find the best parameter of the classifier. In SVM, the penalty parameter $c$ and the radius of RBF $g$ affect the classification result directly, thus, we utilize SVMcgForClass function to search the best parameter $c$ and $g$ in grid. As the Figure 8 illustrates, the best condition is when $c = 6.9644$ and $g = 0.43528$.

![Diagram](image)

Fig. 8. Result of parameter optimization. Best $c = 6.9644$, $g = 0.43528$ and $CV\text{Accuracy} = 91.6667\%$. (a) is the two-dimensional diagram of result. (b) is the three-dimensional diagram of result.

**Classification** Using the above optimized parameters to training the model with our dataset, the result is obtained as Table 2 where TP, TN, FP and FN denote true positives, true negatives, false negatives and false positives respectively. Note that we have used 5-fold cross validation in our experiment.

| Index | TP | TN | FP | FN |
|-------|----|----|----|----|
| 1     | 20 | 9  | 1  | 0  |
| 2     | 16 | 12 | 0  | 2  |
| 3     | 14 | 11 | 4  | 1  |
| 4     | 18 | 9  | 3  | 0  |
| 5     | 13 | 10 | 3  | 4  |
| total | 81 | 51 | 11 | 7  |

Given TP, TN, FP and FN, some evaluation index is calculated as Table 3.
Table 3. Evaluation of the classification.

| Evaluation index       | Formula                                      | Value  |
|------------------------|----------------------------------------------|--------|
| Accuracy               | $\frac{TP + TN}{TP + TN + FP + FN}$          | 88.00% |
| Sensibility            | $\frac{TP}{TP + FN}$                         | 92.05% |
| Specificity            | $\frac{TN}{TN + FP}$                         | 82.26% |
| Positive Accuracy      | $\frac{TP}{TP + FP}$                         | 88.04% |
| Negative Accuracy      | $\frac{TN}{TN + FN}$                         | 87.93% |

**Receiver Operating Characteristic Curve** Figure 9 shows the ROC curve of the experiment. At the red dot, the sensibility and specificity are higher simultaneously in Figure 9. And we calculate the AUC is 0.91, which proves the classifier and BCCUI is effective and have a good result.

5 Conclusion

This paper introduced a novel method to classify benign and malignant breast tumor with raw ultrasound images. It has advantages of fast, accurate, friendly to embedded device and etc. From a series of experiment, it is proven that BCCUI will have a widely applied prospect.

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| Raw image | ROI contour | Extraction result (binary image) | Extraction result (gray image) |
|-----------|------------|----------------------------------|-------------------------------|
| ![Raw image](image1.png) | ![ROI contour](image2.png) | ![Binary extraction result](image3.png) | ![Gray extraction result](image4.png) |
| ![Raw image](image5.png) | ![ROI contour](image6.png) | ![Binary extraction result](image7.png) | ![Gray extraction result](image8.png) |
| ![Raw image](image9.png) | ![ROI contour](image10.png) | ![Binary extraction result](image11.png) | ![Gray extraction result](image12.png) |
| ![Raw image](image13.png) | ![ROI contour](image14.png) | ![Binary extraction result](image15.png) | ![Gray extraction result](image16.png) |
| ![Raw image](image17.png) | ![ROI contour](image18.png) | ![Binary extraction result](image19.png) | ![Gray extraction result](image20.png) |

Fig. 10. Some ROI extraction results.