Discrimination of Benign and Malignant Breast Tumors with Ultrasound Imaging

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Abstract

This work developed a computer-aided diagnosis (CAD) model for discriminating benign and malignant breast tumor with three-dimensional (3D) ultrasound (US) imaging. Compared to mammography, the patients will not be exposed to a high dose of ionizing radiation. Totally 178 3D US images of breast tumors were obtained, and the tumor masses were segmented using an active contour tool based on level set algorithm. Six texture features, six morphological features, nine ellipsoid fitting features, and the patient’s age were quantified to describe the characteristics of the tumor masses. A support vector machine (SVM) model was then developed using machine learning algorithms to classify benign and malignant breast tumors. Performance of the proposed approach was evaluated using ten-fold cross-validation. The accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and the area under ROC curve (AZ) of the SVM model are 85.39%, 86.02%, 84.71%, 86.02%, 84.71%, and 0.8981, respectively.

Keywords: Breast tumor, Three-dimensional ultrasound image, Machine learning, Image processing.

1. Introduction

Ultrasound (US) imaging, as known as sonography, is a widely applied noninvasive technique for breast cancer screening. It provides many advantages compared to other methods, e.g., mammography and biopsy (Chala et al., 2007; Crystal et al., 2003; Hieken et al., 2001; Hou et al., 2002; Stavros et al., 1995; Youk & Kim, 2010). Computer-aided diagnosis (CAD) models are built for tumor discrimination with the tumor mass information from the US imaging (Cheng et al., 2010; Huang et al., 2008). This work proposed a CAD model for breast cancer screening with three-dimensional (3D) US imaging.

The CAD models discriminate tumors based on features quantified from tumor masses. Several features have been proposed for the CAD models. In the quantification of sonographic characteristics, the texture features...
considered as characteristics to describe the difference of benign and malignant tumors (Chen et al., 2007; Moon et al., 2011). Morphological analysis of tumors was without dependence of ultrasound system (Chang et al., 2005). Practical morphological features were utilized as features for tumor classification (Sahiner et al., 2004). Moon et al. (2011) employed texture, morphological, and ellipsoid-fitting features to classify tumors with three-dimensional (3D) ultrasound images.

In this study, a CAD system was proposed for tumor discrimination with 3D US imaging. In the process, 3D US images were acquired by Voluson 730 system. Tumor segmentation was carried out with level set algorithm implemented by ITK-SNAP (Yushkevich et al., 2006). The texture, morphological, and ellipsoid-fitting features were then quantified from the tumor masses. A support vector machine (SVM) classifier was then developed to distinguish between benign and malignant tumors with the different features. It has been shown that the developed classifier can accurately classify tumors.

2. Materials and Methods

2.1 Image Acquisition

From July 2007 to January 2010, the three-dimensional (3D) ultrasound (US) images of 228 patients (age ranged from 17 to 87) were obtained in Changhua Christian hospital using Voluson 730 (GE Healthcare, Zipf, Austria) system with RSP6-16 volume transducer working from 5.6 to 18.4 MHz. The sonographic setting remained unchanged through the study. The images with tumors out of boundary were excluded. A total of 85 benign and 93 malignant solid breast masses were examined. The benignancy and malignancy of the tumors were confirmed by histopathologic diagnosis using biopsy-proved methods. The images were converted into Cartesian coordinates with 256 in gray levels by using the software 4-DView (Y. C. Chang, Huang, Huang, & Chang, 2012). The typical image size was 182 × 109 × 187 boxes with a resolution of a cubic voxel side length of 0.18 mm. Figure 1 showed a 3D US image.

2.2 Image Segmentation

Image segmentation was performed to extract the region of the tumor using the software ITK-SNAP. It archived the segmentations semi-automatically by implementing the level set algorithm (Yushkevich et al., 2006). After starting the software, the observer placed “seeds” at appropriate locations inside the tumors. Visually, the tumor was imagined as the...
combination of spherical regions of different sizes. The seeds placed inside these regions expanded until they reached the boundary of the tumors. The observer could choose appropriate parameters for optimal segmentation (Yushkevich et al., 2006). Figure 2 showed a segmentation result in 3D view. When the tumor regions were difficult to be determined by the algorithm, the segmentation was performed by experienced physicians instead.

![Figure 2. A segmentation result](image)

2.3 Feature Quantification

Features were used to describe the characteristics of tumors for classification. They could be categorized into three sets – texture, morphological and ellipsoid fitting features. The age of the patient was an important attribute and was also considered as a feature.

The textural features quantify the spatial correlation of voxel grey levels of the tumor mass. The texture features were calculated based on gray level co-occurrence matrix (GLCM) (Haralick et al., 1973), and it was extended to volumetric texture (Chen et al., 2007). Before calculating GLCM, all 3D US images were quantized to 16 grey levels. Figure 3 shows the boxed region around the tumor mass was calculated for GLCM. The $d$, $y$ and $\theta$ were respectively defined (1,1,1), 45˚ and 54˚, and they can be referred to Chen et al. (2007). Six textural feature were than calculated based on the GLCM, including the angular second moment $T_{ASM}$, contrast $T_{Con}$, inverse different moment $T_{IDM}$, entropy $T_E$, dissimilarity $T_D$, and correlation $T_{Cor}$. The details of the feature calculation can be referred to Haralick et al. (1973) and Jobanputra & Clausi (2004).

![Figure 3. The boxed region (dotted line) around the tumor mass was calculated for GLCM.](image)

The morphological features describe the superficial formation of tumor mass. There were 6 morphological features included in this study. Tumor volume $M_V$ (unit: mm$^3$) and tumor surface area $M_A$ (unit: mm$^2$) assess basic structural characteristics of the tumor mass. Classical compactness $M_{Cc}$ and discrete compactness $M_{Cd}$ quantify the connectedness of the parts within the tumor mass (Bribiesca, 2008; Moon et al., 2011). The mean radius $M_{Rm}$ and standard deviation of radius $M_{Rstd}$ were used as indices to represent the characteristics of
irregular tumor surface (Moon et al., 2011).

The ellipsoid fitting features proposed by Moon et al. (2011) describe the similarity of a tumor mass to its best-fitted ellipsoid. This is motivated by the fact that malignant tumors are often in irregular shapes. Nine ellipsoid fitting features were applied in this study. Three of them were related to the properties with the ellipsoid and the tumor, including axis ratio \( M_{E_{ar}} \), surface ratio \( M_{E_{sr}} \), and volume covering ratio \( M_{E_{vr}} \). The outside region \( M_{E_{or}} \) and inside region \( M_{E_{ir}} \) quantified the numbers of regions of a tumor outside and inside, respectively, its best-fitted ellipsoid. The sum of regions \( M_{E_{r}} \) is the sum of outside and inside regions \( M_{E_{or}} \) and \( M_{E_{ir}} \). The angularity is used to evaluate the protruding level in the outside region and indenting level in inside region. The feature \( M_{E_{or,t}} \) is the number of regions whose angularity is larger than a threshold for outside region. Similarly, the feature \( M_{E_{ir,t}} \) is the number of regions whose angularity is smaller than a threshold for inside region. The settings of threshold are referred to Moon et al. (2011). The feature \( M_{E_{r,t}} \) is the sum of \( M_{E_{or,t}} \) and \( M_{E_{ir,t}} \).

2.4 Tumor Classification

Support vector machine (SVM) classifiers were developed to differentiate benign tumors from malignant ones. The inputs to the classifiers were the features quantified from the US tumor images. In this study, soft margin SVM classifiers with radial basis function (RBF) kernel were trained using the LIBSVM package developed by Chang & Lin (2011). The margin parameter \( C \) and kernel parameter \( \gamma \) were determined using greedy search. The details of model parameter selection can be referred to LIBSVM (Chang & Lin, 2011).

2.5 Performance Evaluation

Receiver operating characteristic (ROC) curves were calculated to measure the performance of the developed classifiers in terms of six indices, including area under the curve (\( A_{Z} \)), accuracy, specificity, sensitivity, negative predictive value (NPV), and positive predictive value (PPV). The ROC indices were calculated using ten-fold cross-validation (CV).

3. Results and Discussion

A SVM model was trained to classify breast tumors with the features in each set, respectively, as the inputs. Note that the patient’s age was always included as an input to the models. Table 3 listed the performance of the models. It is shown that the accuracy difference among the classifiers built with the different feature sets are within 2%. The averaged accuracy of the SVM models is 84.8%.

Table 1. Performance of the proposed CAD system with different feature set

<table>
<thead>
<tr>
<th>Feature Set</th>
<th>Texture</th>
<th>Morphological</th>
<th>Ellipsoid fitting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>83.71%</td>
<td>85.39%</td>
<td>82.58%</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>83.87%</td>
<td>86.02%</td>
<td>81.72%</td>
</tr>
<tr>
<td>Specificity</td>
<td>83.53%</td>
<td>84.71%</td>
<td>83.53%</td>
</tr>
<tr>
<td>PPV</td>
<td>84.78%</td>
<td>86.02%</td>
<td>84.44%</td>
</tr>
<tr>
<td>NPV</td>
<td>82.56%</td>
<td>84.71%</td>
<td>80.68%</td>
</tr>
<tr>
<td>( A_{Z} )</td>
<td>0.8931</td>
<td>0.8981</td>
<td>0.8946</td>
</tr>
</tbody>
</table>

TP: true positive (the number of malignant tumor classified correctly); FN: false negative (the number of malignant tumors classified incorrectly); FP: false positive (the number of benign tumor classified incorrectly); TN: true negative (the number of benign tumor classified correctly). Accuracy=
Sensitivity and NPV are critical indices to evaluate the performance of a CAD system. This is because the consequence of misclassifying a benign tumor which in fact is a malignant one is more severe compared to misclassifying a malignant tumor. Hence a CAD model with a lower false negative (FN) is preferred. Table 1 shows that the model developed with the morphological features is of the highest sensitivity and NPV (respectively 86.02% and 84.71%) values, compared to the models developed with texture or ellipsoid fitting features. The morphological features should be chosen for the CAD system if only one set of features can be applied. In fact, both the morphological and ellipsoid fitting features characterize the shape of the tumor masses. They might provide similar information in terms of the tumor mass properties.

Table 2 shows the ROC indices of a classifier developed with all the features. Compared to Table 1, the CAD model trained with morphological features achieved the best performance. The model trained with all features was not better than morphological features.

### Table 2. Performance of the proposed CAD system with all the features

<table>
<thead>
<tr>
<th></th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>84.83%</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>82.80%</td>
</tr>
<tr>
<td>Specificity</td>
<td>87.06%</td>
</tr>
<tr>
<td>PPV</td>
<td>87.50%</td>
</tr>
<tr>
<td>NPV</td>
<td>82.22%</td>
</tr>
</tbody>
</table>

### 4. Conclusion

This study proposed CAD systems for breast tumor classification with 3D US imaging. The systems were composed of SVM models that used three types of features – including texture, morphological, and ellipsoid-fitting – respectively, as inputs. The model with the morphological features outperformed the models with the other features in terms of accuracy. An SVM model with morphological features as inputs was also developed. The accuracy is 85.39%.

### 5. References

179-185.
18. Yushkevich, P. A., Piven, J., Hazlett, H. C., Smith, R. G., Ho, S., Gee, J. C., & Gerig, G.