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Combined Use of Local and Global Features for Classification of Breast Lesion Using DCE-MRI Images

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Abstract: Recently, the use of dynamic contrast enhanced-magnetic resonance imaging (DCE-MRI) technique is widely used to detect and diagnose breast cancer. This technique has shown to be very useful particularly in screening women with high risk for breast cancer, as well as assessing the potential effects of new therapy. Thus, the aim of the present study is to appraise the efficacy of combined employment of global and local features in discriminating malignant and benign lesions. A dataset of one hundred and twenty one (121) DCE-MRI investigations was assembled and used. Out of that number, fifty (50) were biopsy-proved malignant tumors and seventy-one (71) were benign. Firstly, the suspicious mass regions were automatically detected and segmented with 3D region growing algorithm. Meanwhile, Local and global features were used. Thereafter, sequential floating forward selection method (SFFS) and support vector machine classifier (SVM) were used for classification. The overall classification performance of different kind of features were evaluated via receiver operating characteristic (ROC) analysis in a 3-fold cross validation scheme. It was observed that global feature produced classification accuracy of 84.32 % followed by local feature with accuracy of 85.95 %. When the local and global features were combined, the classification accuracy increased to 94.36 %. Based on the obtained results, this study has demonstrated that the combined use of local and global features could effectively function as a better indicator in differentiating malignant and benign tumors.

Keywords: Breast Cancer, DCE-MRI, Local and Global Features, Benign and Malignant Tumor

1. Introduction

In recent years, breast cancer has shown to be the leading cause of death in women following the lung cancer. [1] Scientific evidences have shown that early diagnosis of breast cancer plays a vital role in minimizing the rate of death among cancer patients. [2, 3]. In spite of the fact that X-ray mammography has demonstrated to be the most powerful tool for diagnosing breast cancer even up till now, yet the performance of screening by mammography is not satisfactory enough for young women with cancer [4, 5]. Meanwhile, based on the dissatisfaction by the use of mammography, other methods have emerged. Among them is DCE-MRI which has shown to be the most powerful tool with higher sensitivity when diagnosing patients with cancer. Despite the higher sensitivity, MRI has shown to have a lower sensitivity than mammography [6].

Recently, DCE-MRI has been used to obtain an effective information during diagnosis and treatment of breast cancer [7, 8]. Thus, the use of breast DCE-MRI tool has demonstrated to be better and has shown to be the most useful tool when managing a breast cancer patients [9, 10]. Based on this, breast lesions are classified following the uptake of gadolinium contrast agent during contrast enhancement [11].

In spite of the established standardization protocols, the main demand in breast MRI suffers from high inter-observer variability [12]. Furthermore, breast MRI needs a maximum time for processing and interpreting the images. Meanwhile, when MRI screening is done, it is necessary to carefully select texture features locally and globally from DCE-MRI in order to diagnose, detect and prognoses cancer assessment effectively. In order to detect the efficacy of lesion segmentation and important texture features, many researchers have carefully selected features from local and global regions from breast DCE-MRI images to discriminate malignant and benign lesions.

For example, Aghaei et al [13] computed 22 global kinetic features from 155 patients who underwent neoadjuvant chemotherapy. This study was carried out evaluate the relationship between the 22 global kinetic features which four (4) sets were selected to foretell the response of breast cancer patients. Hence, their prediction yielded an Area under curve ROC of 0.83. Phadke and Rege [14], proposed the use of local and global features to classify abnormalities in mammogram. A novel computer aided technique was put forward to classify abnormalities in mammograms using fusion of local and global features. After their analysis, both features increased classification accuracy from 88.75% to 93.17%. Some studies [15, 16] used linear classifier to find out other feature sets. Similarly, Yuan et al [17] selected DEC-MRI features using a Bayesian network which produced an area under a receiving operating characteristics (ROC) curve (AUC of 0.78) using a dataset of 168 malignant and 45 benign breast lesions. Meanwhile, Lekosh et al [18] extracted 32 GLCM features from lesion region and achieved a classification accuracy of 92%, sensitivity of 94.73% and specificity of 83.34%.

Based on this research, a new predictive model was proposed which combine the use of local and global features computed from both local and global regions of DCE-MRI breast. Thus, the purpose of this study is to evaluate the efficacy of combined use of global and local features in discriminating malignant and benign lesions using image dataset of 121 patients.

2. Materials and Methods

2.1. Data Collection

The dataset of breast DCE-MRI images used in this study was collected retrospectively from Federal Medical Centre Owerri. These datasets involved 121 examinations each with a set of DCE-MRI sequences, acquired from 121 patients using a 3 Tesla MR scanner (GE, Signa HDxt, and America). Each patient has two sets of breast DCE-MRI images taken before and after contrast media (Gadopentetate dimeglumine, Bayer, Germany) administration. In this thesis 50 cases were verified malignant and 71 as benign biopsy proved. In DCE-MRI images, there are many sequence in which feature could be extracted from but we choose the peak sequence (anterior) in this study. Figure 1 shows the corresponding pre-contrast and post- contrast images of the same slice.

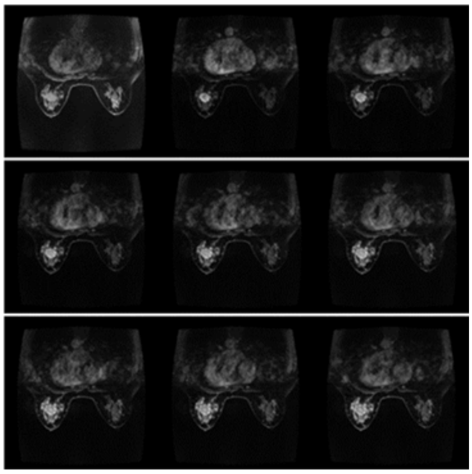

Figure 1. *Same slice of each sequence of DCE-MRI images.*

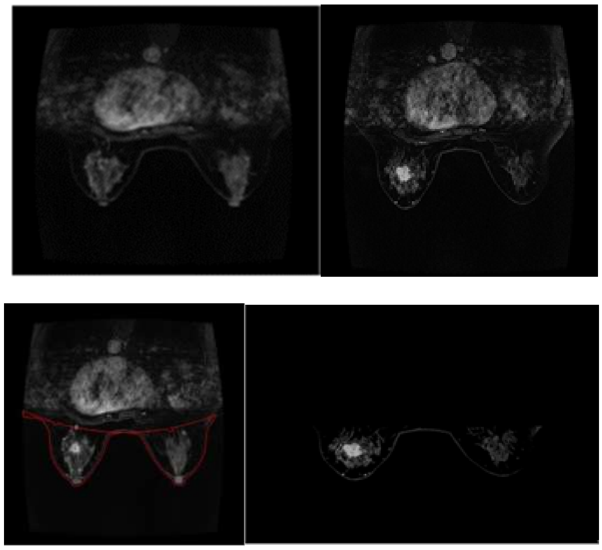

Figure 2. *Image processing steps to segment the region of interest from the background (a) showing the raw image slice, (b) showing the image slice after filtering, (c) fitting a parabolic curve as a segmentation boundary curve and (d) final segmented MR image slice.*

The methods used in the research paper is partitioned into three parts breast region segmentation, local and global feature extraction and classification.

For an effective classification result, the best features were selected from breast DCE-MRI.

Firstly, we carefully segment breast areas automatically in order not to touch the chest wall. For this purpose, an image processing technique was designed to segment the region of interest from the background and they are as followed:

1) Median filter was applied to enhance the boundaries of the pixel between the breast areas and the background.
2) Following the morphological operations which was applied to remove artificial noise and generate an enhanced curvature that will segment the interested areas from the background.
3) Then a parabolic model based curve fitting method was

also useful to generate a complete segmentation curve to separate between breast region of interest and the chest wall region.

4) Obtained a segmented region of interest which contains the local and global regions for feature extraction. Figure 3 shows the region segmentation results.

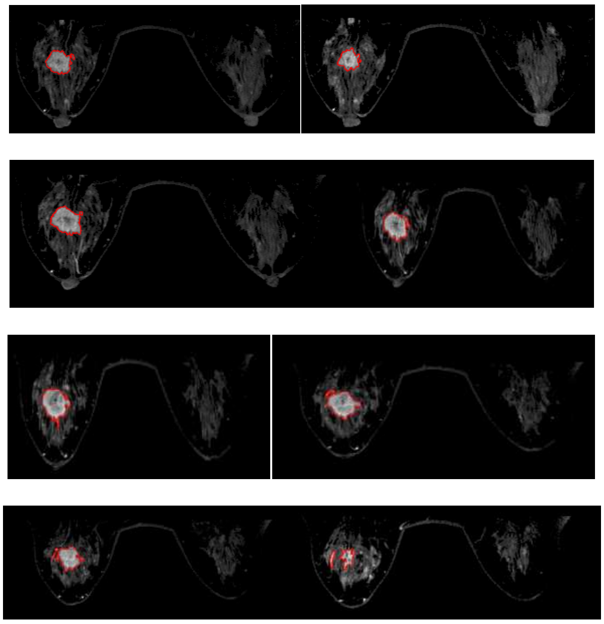

Figure 3. *The region segmentation results.*

2.2. Lesion Segmentation

In order to get the best features from local region, an algorithm was proposed to segment lesions from region of interest. According to the diagnostic report given by the doctor, the pixels within the lesion area were selected. It was of interest to segment lesions automatically. Considering the higher brightness in lesions, the region with the largest mean gray value was extracted and was considered as the suspicious region. The region center was taken to be the initial seed point to start the 3D growing process. The lesion segmentation result is presented in Figure4 below.

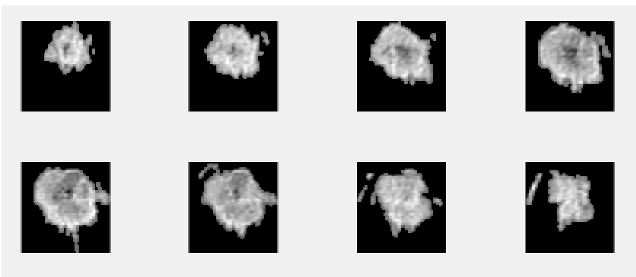

Figure 4. *Lesion segmentation results.*

2.3. Feature Extraction

Meanwhile, after the segmentation of region of interest, texture features were computed from local and global region. Local features extracted 7 histogram features and 22 GLCM features while global features extracted 13 GLRLM features and 13 GLZSM features. Local features were computed from the lesion area while global features were computed from whole part of the breast image. Thereafter, features were then used for classification to ascertain their effectiveness in discriminating malignant and benign. Thereafter, features were calculated based on the segmented region of interest from the left and right side breast tumor. Thus, 29 features were computed from the local region while 26 features were computed from the global and they are (GRLRM, GLCM, GLSZM and histogram features) which were computed to quantify the spatial pattern of the images. Nevertheless, Features were obtained on the entire segmented 3D region of interest and the number of these features were then selected by a feature selection procedure to remove uninformative and unimportant features. Meanwhile, sequential floating forward selection method was used to minimize the loss of information.

Table 1. *List of selected feature.*

	Selected features	Description
1	Local GLCM	STD of local difference
2	Local GLCM	initial enhancement parameter
3	Local GLCM	initial enhancement rate
4	Local GLCM	Cluster shade
5	Local GLCM	cluster Prominence
6	Local GLCM	compactness
7	Local GLCM	complexity
8	Local GLCM	Homogeneity contrast
9	Global GLRLM	high gray levels run emphasis
10	Global GLRLM	high gray levels run emphasis
11	Global GLSZM	zone size variance
12	Global GLSZM	large zone emphasis
13	Global GLSZM	gray level non-uniformity
14	Global GLSZM	small zone emphasis
15	Local Histogram	Uniformity
16	Local Histogram	Energy
17	Local Histogram	kurtosis
18	Local Histogram	Skewness

2.4. Classification

Local and global features (26 and 29 respectively) were combined to form a feature vector for each region of interest. Using 3 cross-validation methods, 2 sets were used for training SVM classifier to distinguish malignant and benign lesions.

In this research work SVM with a polynomial kernel function produces the best classification result compared to other functions from the previous study. However, a total of 55 features were calculated in this paper 29 from local region and 26 from global region. These features sets were separately used on our dataset to compare the efficiency of each category in discriminating malignant and benign DCE-MRI. However, to reduce the redundant features, sequential forward floating selection (SFFS) method was employed. In this research paper, 3-fold cross validation procedure was used. The sample was partitioned into 3 subsamples, out of these subsamples; a single subsample was retained as the validation data to testing the model and the remaining 2 were used to training. The 3 cross validation process was then repeated 3 times with each of the 3 subsample used once as the validation data. The experimental were then averaged to obtain the final estimation.

3. Results

Based on the SFFS method, 18 features were selected out of 55 extracted features from local and global regions. Table 1 indicates the selected features. It can be seen that combined use of local and global features plays an important role in classification. From the above selected features, the classification performance (Accuracy, sensitivity and specificity) with local, global and combined local and global was evaluated. Results show that combined local and global features increased classification accuracy and achieved acceptable results 94.36% accuracy, 97.70% sensitivity and 88.32% specificity. When local features were used it achieved 85.95%accuracy, 95.26% sensitivity and 79.00% specificity. With global features 84.32% accuracy, 94.32% sensitivity and 79.85%specificity as seen in table 2.

Notwithstanding, classification ability of each of these features were also evaluated by area under receiver characteristic curve (ROC) as shown in figure 5. The computed AUCs are 0.8496, 0.8583 and 0.8842 when classifying the two groups, 50 malignant and 71 benign cases using local features, global feature and combined local and global features.

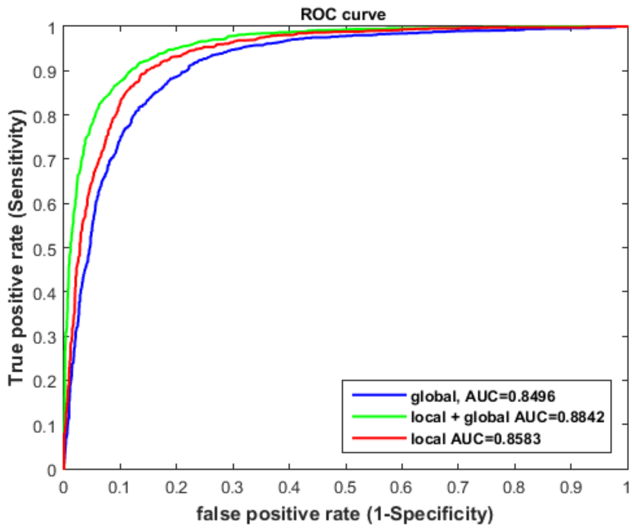

Figure 5. *ROC curve comparing the three features.*

Table 2. *Classification performance analysis.*

Classification performance analysis			
Features	Accuracy	sensitivity	specificity
Global features (26)	84.32%	94.32%	79.85%
Local features (29)	85.95%	95.26%	79.00%
Global+ local features (55)	94.36%	97.70%	88.32%

Table 3. *Comparing this work with previous works.*

Study	**Year**	**Method**	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
Fusco et al [22]	2017	Dynamic features	87.50%	92.30%	81.80%	
Chen et al [23]	2017	Textural features	88.75%	82.93%	88.75%	0.8360
Dalmis et al [24]	2016	Morphological and dynamic features				0.8543
Li et al [25]	2019	Bilateral TIC+ conventional features	91.96%	88.89%	94.03%	0.9058
Our method		global +local features	94.36%	97.70%	88.32%	0.8842

4. Discussion

(DCE-) MRI is a relatively new method in clinical applications, with high sensitivity and relatively lower specificity in detecting breast lesions that appear with suspicious features on mammography, solography and clinical examinations [19]. In the previous study, attempts have been made to classify breast DCE-MRI images as either malignant or benign using features from global or local region. Nonetheless, no attempt has been made to combine global and local region in discriminating malignant and benign lesions.

In this study, we presented a classification scheme based on support vector machine (SVM) using combination of features extracted from global and local region to classify breast DCE-MRI images as either malignant or benign lesions. The results indicated that combination of local and global features exhibit a significant strong risk indicator than using only local and global features which were commonly used in previous studies. The database is divided into three subsets, two sets were used to train the SVM classifier and the other is used to test the SVM classifier. The combination of local and global features produced the best result compared when only local or global feature is used. Meanwhile, SVM was evaluated as the most powerful tool for the design of a classifier responsible for describing malignant and benign breast lesions from DCE-MRI dataset.

A lot of works have been carried out on SVM as a classification tool. SVMs have been shown to perform well in medical diagnosis application [20], and have also been shown to perform well when dealing with relatively small training sets [21]. The segmented region of interest were subjected to features extraction in which three feature sets namely local feature, global feature and combined local and global features were used. It is of interest to note, that machine used in training the classifiers can lead to classifier over fitting when subjected with a large number of features. Thereafter, SFFS feature selection method was used to select the best features from all the extracted features which were then used for classification.

Furthermore, the performance of this work is to test sensitivity, specificity and accuracy. Sensitivity indicates percentage of correctly classified positive samples; specificity gives percentage of correctly classified negative samples whereas accuracy indicates percentage of correctly classified samples (positive as well as negative) out of total samples. Sensitivity is the probability for a diagnostic test. It is also termed as true positive fraction. The percentage of sensitivity is given by:

$$Sensitivity = \frac{Tp}{Tn+Fn} X\ 100\ \% \tag{1}$$

Specificity is the probability of negative for a diagnostic test. It is also termed as true negative fraction. The percentage of specificity is given by.

$$Specificiyt = \frac{Tn}{Tn+Fp} X\ 100\ \% \tag{2}$$

Accuracy is the probability that a diagnostic test is correctly performed. It is calculated by:

$$Accuracy = \frac{Tp+Tn}{Tp+Fn+Tn+Fp} X\ 100\ \% \tag{3}$$

Where TN is true negative, TP is true positive, FN is false negative and FP false positive.

Performance of the classification is tested for the three cases. SVM classifier is trained using only global features, local features and the combination of local and global features. The three cases are given in table 2. From the results it is obvious that when classification is done using only global features, specificity is 79.85%. Using only local features, the specificity is 79.00% which indicates large number of false positives. Hence, combination of local and global features has improved specificity to 88.32% and also improved the accuracy of classification from 85.95 to 94.36%.

5. Conclusion

In this research work, a method was proposed to classify malignant and benign lesions of segmented ROI breast tissues from DCE-MRI images using local feature, global features and combination of the two features (local and global). The local features used are 7 histogram features and 22 GLCM features whereas global features used are 13 GLRLM and 13 GLSZM features. The proposed system obtained acceptable results in classifying malignant and benign lesions by using SVM classifiers with polynomial kernel function. From the results, the combination of these two features (local and global) improved classification accuracy, sensitivity and specificity.

Combined use of morphological features with features used in the proposed method can also be tested for classification of sample into malignant and benign lesions. New features can also be added in order to ascertain the effective performance of this system.

6. Recommendations

The future work of this research is to analyze the best sequence for texture feature extraction using the combination of T1, T2, X-ray and DCE-MRI images to ascertain their efficacy in discriminating malignant and benign lesions. Although, a high accuracy was achieved in this work but it does not guarantee replication on datasets, especially those datasets that were not tested in this work. Therefore, it is suggested that in future, research be extended to improve the performance system and result validation by testing with larger sets. Meanwhile, it is strongly believed that breast cancer classification studied and presented in this work will contribute significantly to improve the interpretation of breast DCE-MRI cancer.

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