



Conference on ENTERprise Information Systems / International Conference on Project MANagement /
Conference on Health and Social Care Information Systems and Technologies, CENTERIS / ProjMAN /
HCist 2016, October 5-7, 2016

Breast Cancer Response Prediction in Neoadjuvant Chemotherapy Treatment Based on Texture Analysis

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Abstract

MRI modality is one of the most usual techniques used for diagnosis and treatment planning of breast cancer. The aim of this study is to prove that texture based feature techniques such as co-occurrence matrix features extracted from MRI images can be used to quantify response of tumor treatment. To this aim, we use a dataset composed of two breast MRI examinations for 9 patients. Three of them were responders and six non responders. The first exam was achieved before the initiation of the treatment (baseline). The later one was done after the first cycle of the chemo treatment (control). A set of selected texture parameters have been selected and calculated for each exam. These selected parameters are: Cluster Shade, dissimilarity, entropy, homogeneity. The p-values estimated for the pathologic complete responders pCR and non pathologic complete responders pNCR patients prove that homogeneity ($P\text{-value}=0.027$) and cluster shade ($P\text{-value}=0.0013$) are the more relevant parameters related to pathologic complete responders pCR.

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Peer-review under responsibility of the organizing committee of CENTERIS 2016

Keywords: Breast cancer, Response Prediction, Texture Analysis, Neoadjuvant Chemotherapy

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1. Introduction

MRI modality is the best technique used in the diagnosis and treatment planning of breast cancer. Recently, many works have been proposed in order to use quantification of texture analysis as a biomarker of response during the neoadjuvant chemotherapy (NAC). A more recent study achieved by Bhooshan et al. [1] applied to DCE-MRI breast images, used texture analysis along with other computerized methods such as shape and kinetic features in an attempt to determine their utility as prognostic markers. The authors of this study found that in terms of textural features, a common indicator of malignancy was lesion heterogeneity, which could be described by using different mathematical algorithms for texture analysis such as contrast and maximal correlation coefficient. In the work of Arfan Ahmed [2], the authors proposed a textural analysis study to assess the efficiency of dynamic contrast enhanced magnetic resonance imaging (DCE-MRI) in predicting response to chemotherapy in a cohort of breast cancer patients. They have proved that contrast, variance, difference in variance, sum average, sum variance, sum entropy, cluster shade and cluster prominence showed significant differences between responders and partial responders of chemotherapy. More recently, Michoux et al [3] proposed to assess the performance of a predictive model of non-response to neoadjuvant chemotherapy (NAC) for patients with breast cancer on the basis of texture, kinetic, and BI-RADS parameters measured from dynamic MRI. Each study used different protocol acquisition, T1 weighted MRI in [2], T2 weighted MRI and T1 W GRE, fat suppressed sequence for [3]. For this reason, each study gives different results.

In our study we have used a 3D gradient echo-based TWIST (Time-resolved angiography with Stochastic Trajectories) sequence, which employs the strategy of k-space under-sampling during acquisition and data sharing during reconstruction [4].

This paper is organized as follows. In Section 2, the proposed approach is presented. In section 3, we present our results and discuss them. Finally, conclusions are summarized in Section 4.

2. Proposed method

Texture based feature extraction techniques such as co-occurrence matrix, Fractals, Gabor Filters, variations of wavelet transform and other transform have also been widely used in recent works [5], [6]. For Gray level Co-occurrence matrix (GLCM), a set of texture features from gray scale image are extracted [7].

In this work, the visual texture of breast tissues was assessed from the grey level co-occurrence matrix (GLCM). From the GLCM, four textural features describing gray levels interdependence in the image were estimated. These features are: cluster shade, dissimilarity, entropy and homogeneity. Computation parameters of GLCM were: distance of one pixel between two neighboring pixels, average of the angular relationships on the four main directions.

For each exam a region of interest (ROI) was selected, than texture parameters were estimated, we illustrate in fig1, an example of an responder tumor fig. 1.a, and non-responder tumor, fig. 1.d (see Fig. 1).

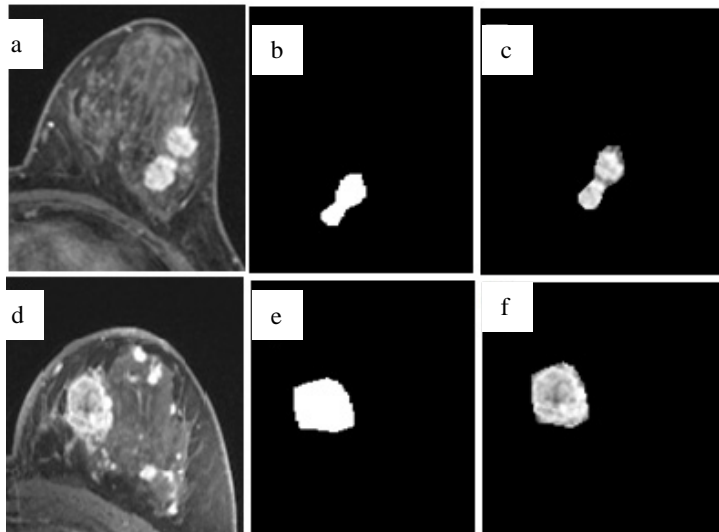


Fig. 1. (a, d) original images ; (b, e) Binary mask of ROI; (c, f) Tumors selected as ROI

3. Results and discussion

In this study, we use a collection of breast dynamic contrast-enhanced (DCE) MRI dataset containing images from a longitudinal study to assess breast cancer response to neoadjuvant chemotherapy from **the Cancer Imaging Archive (TCIA)[4]: QIN Breast DCE-MRI**. Images were acquired at four time points: prior to the start of treatment (Visit 1, V1), after the first cycle of treatment (Visit 2, V2), at midpoint of treatment course (Visit 3, V3), and after completion of treatment (prior to surgery) (Visit 4, V4). The shared datasets are from the V1 and V2 studies of 10 patients (BreastChemo 1, 5, 6, 8, 10, 12, 13, 14, 15, and 16) – 3 pathologic complete responders (pCRs) and 7 non-pCRs. Boxplot representation for the four selected texture parameters at the second exam, and a comparison at exam2 between pCR and pNCR are shown in figure 2.

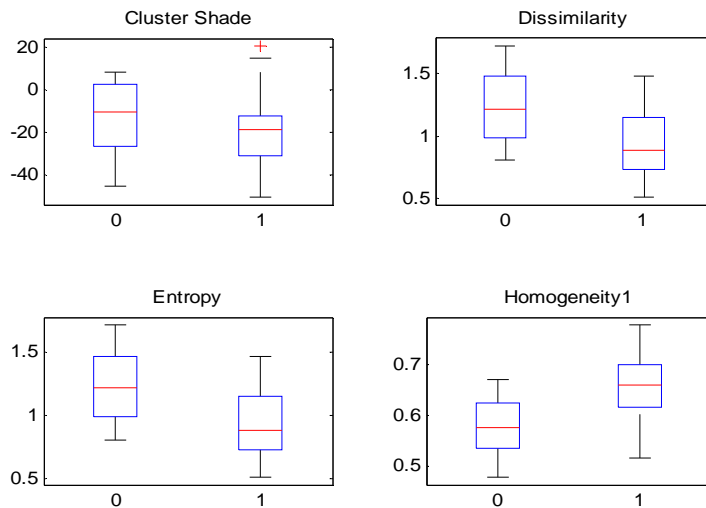


Fig.2 Boxplot representation for texture parameters at the second exam, and comparison at exam2 for pCR and pNCR patients, 0: pCR patients, 1: pNCR patients.

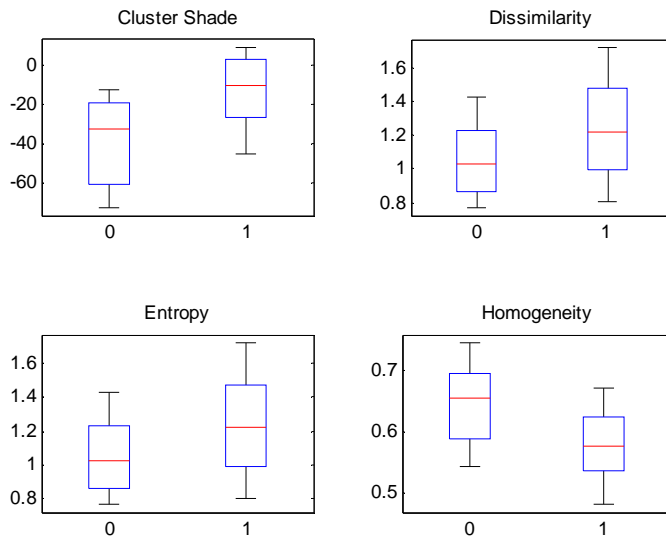


Fig.3 Boxplot representation for Cluster Shade, Entropy, Dissimilarity and Homogeneity texture parameters of pCR patients at first and second exam, 0: first exam, 1: second exam.

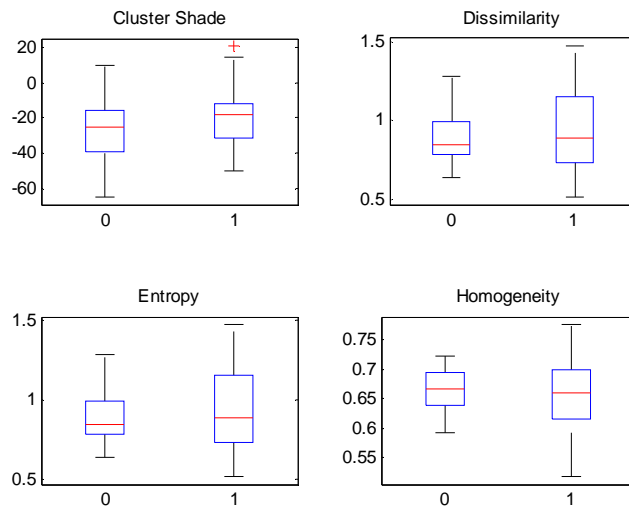


Fig.4 Boxplot representation for Cluster Shade, Entropy, Dissimilarity and Homogeneity parameters of pNCR patients at first and second exam

We observe from these representations, that in case of responders patients visit1 (1), Cluster Shade and dissimilarity increase (fig.3) in comparison with the first visit0 (0). On the other hand, homogeneity value decreases at the exam 2,

(1). In case of non responders patients. So, we see clearly, that they have not a significant variation between the first and the second exam for the four parameters (fig.4).

Table 1 shows, the mean and standard deviation and P-values for Cluster Shade, Entropy, Dissimilarity and Homogeneity texture parameters.

Table 1: mean and the standard deviation of the texture parameters selected in this study at the first and the second exam for both responders and non responders patients.

Parameter	Mean \pm STD			Mean \pm STD		
	Responder First Exam	Responder Second Exam	P- value	Non Responder First Exam	Non Responder Second Exam	P- value
Cluster Shade	-39,58 \pm 22,03	-12,51 \pm 17,30	0.0013	-27,41 \pm 20,18	-20,61 \pm 17,31	0.19
Entropy	1,05 \pm 0,21	1,22 \pm 0,28	0.065	0,88 \pm 0,17	0,93 \pm 0,26	0.28
Dissimilarity	1,05 \pm 0,21	1,22 \pm 0,28	0.065	0,88 \pm 0,17	0,93 \pm 0,26	0.28
Homogeneity	0.64 \pm 0.06	0.58 \pm 0.05	0.0027	0,66 \pm 0,03	0,65 \pm 0,06	0.43

We observe from table1 that in case of responder patients, cluster shade and homogeneity present a p-value less than 0.005. From that, we can conclude that these parameters are related to the complete response.

4. Conclusion

The goal of the study conducted in this paper was to prove that texture based feature techniques such as co-occurrence matrix features can be used to quantify and assess the quality response of tumor treatment. We used for that a dataset composed of two breast MRI examinations for 9 patients. Three of them were responders and six non responders. Four texture parameters have been selected and calculated for each exam. These parameters are: cluster shade, dissimilarity, entropy, homogeneity. We have proved in this study that cluster shade, dissimilarity, entropy and homogeneity parameters measured from breast MRI can help to assess the quality response to neoadjuvant chemotherapy. We can affirm that homogeneity and cluster shade are the more relevant parameters, because they have a p-value less than 0.005. As future works, we propose to apply other texture descriptors such as gabor filter, fractal dimension and wavelet analysis.

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