Texture analysis of MR images to predict breast tumor response to neoadjuvant chemotherapy

Poster No.: C-0596
Congress: ECR 2013
Type: Scientific Exhibit
Authors: N. Michoux, L. Fellah, I. Leconte; Brussels/BE
Keywords: Breast, MR, Computer Applications-Detection, diagnosis, Neoplasia
DOI: 10.1594/ecr2013/C-0596

Any information contained in this pdf file is automatically generated from digital material submitted to EPOS by third parties in the form of scientific presentations. References to any names, marks, products, or services of third parties or hypertext links to third-party sites or information are provided solely as a convenience to you and do not in any way constitute or imply ECR's endorsement, sponsorship or recommendation of the third party, information, product or service. ECR is not responsible for the content of these pages and does not make any representations regarding the content or accuracy of material in this file.

As per copyright regulations, any unauthorised use of the material or parts thereof as well as commercial reproduction or multiple distribution by any traditional or electronically based reproduction/publication method is strictly prohibited.

You agree to defend, indemnify, and hold ECR harmless from and against any and all claims, damages, costs, and expenses, including attorneys' fees, arising from or related to your use of these pages.

Please note: Links to movies, ppt slideshows and any other multimedia files are not available in the pdf version of presentations.

www.myESR.org
Purpose

MRI plays a prominent role in the diagnosis and treatment planning of breast cancer [1]. It is the best imaging modality to evaluate residual disease after neoadjuvant chemotherapy (NAC) and before surgery [2]. In particular, dynamic contrast-enhanced MRI (DCE-MRI) has demonstrated interesting results via the analysis of kinetic parameters changes after few cycles of NAC [3-5]. However, studies exploring baseline (i.e. prior to any cycle of NAC) DCE-MRI parameters are few [6-8]. Alternative post-processing approaches such as visual texture analysis has also been used to investigate breast MR images [9, 10]. Texture analysis relies on the quantification of statistical descriptors of the visual aspect (more or less coarse, fine, uniform, granular, regular or irregular) of the tissues [11]. This study aims identifying parameters (BI-RADS morphologic, kinetic and textural) potentially useful in the prediction of patients whose breast cancer will not respond to NAC.

Methods and Materials

Patients

All patients had an invasive ductal carcinoma (IDC) diagnosed on core-biopsy specimen. After multidisciplinary breast cancer management staff decision, all patients underwent NAC, consisting of 4 cycles of cyclophosphamides/anthracyclines followed by 4 cycles of taxane [12, 13] and trastuzumab in case of HER2+ tumor. Patients with incomplete pathological and radiological data (n = 6) and severe artifacts on MRI images (e.g. respiratory motion and body movement) (n = 3) were excluded. Overall, this retrospective study included 69 patients with IDC (median age 54 years, range 22-72 years). Pathologic complete response (CR) was defined as the absence of invasive cancer in breast and nodes. Partial response was defined as a decrease of invasive cancer exceeding 30%. Non-response was defined as a decrease of invasive cancer lower than 30%.

MRI

Baseline MRI examinations were performed using a 1.5T whole body imaging system (Gyroscan Intera, Philips Medical System, Nederlands). Patients were imaged in the prone position with a 3D gradient echo axial T1-weighted sequence with fat suppression. Scan parameters were TR/TE = 4.8/2.4 ms, flip angle = 10°, FOV = 355x355 mm, in-plane voxel size 0.65x0.65x1.25 mm after reconstruction. The anatomic study was followed by a dynamic study. Patients received 0.2 mmol/kg of gadobenate dimeglumine (Multihance, Bracco Imaging, Deutschland) followed by 30 mL saline flush injected at a rate of 2 mL/s with an automated injector. One pre- and five post-injection images were
acquired with a temporal resolution of approximately 60 seconds. The total acquisition time for the protocol was about 6 minutes. Analyses were performed on subtracted images (the residual difference image obtained after the third post-contrast image has been subtracted from the pre-contrast image).

**Images analysis**

MR images in 69 patients were reviewed consensually by three radiologists without knowledge of the pathological findings or mammographic and sonographic data, by using the American College of Radiology BI-RADS MR lexicon [14]. For each pathologic breast, the most representative MRI slice of the lesion was selected on the third dynamic. Three ROIs, one including healthy tissues defined as unenhancing area on subtracted images, one circumscribing the whole lesion and one corresponding to the brightest part of the lesion (from which DCE parameters maximal amplitude, up-slope and wash-out slope were assessed) were drawn manually. An automated segmentation of the lesion was also implemented.

Texture was assessed from the grey level co-occurrence matrix (GLCM) and the run length matrix (RLM) [15, 16]. Nine GLCM features (energy, entropy, contrast, homogeneity, correlation, inverse difference moment, sum average, sum variance, difference variance) describing the grey levels interdependence and eleven RLM features (SRE, LRE, GLN, RLN, RP, LGRE, HGRE, SRLGE, SRHGE, LRLGE, LRHGE) describing the distribution of runs of grey levels were estimated. A 21-components vector (including the up-slope) characterizing the lesion was thus derived for each patient.

A $k$-means clustering algorithm was used as **multi-parametric classifier for predicting the pathological response** [17]. To estimate how accurately the predictive model would perform in practice, a leave-one-out cross validation was applied to the clustering result [18].

**Results**

Significant differences between healthy tissues and tumoral lesion were found for all texture parameters. **Significant statistical differences between NR and PR+CR were found for 1 kinetic parameter, four GLCM texture parameters** and almost significant for another one GLCM parameter and 3 RLM parameters. Mass/non-mass pattern was not predictable of pathological response to NAC. The best multi-parametric predictive model was based on parameters (inverse difference moment, GLN, LRHGE, up-slope) derived from the automated segmentation. NR were classified correctly in 16/19 (Sensitivity = 84%) while PR+CR were classified correctly in 31/50 (Specificity = 62%).
Fig. 1: Example of axial subtracted images. According to the BI-RADS MR lexicon, the tumor is described as, top) ovalar mass with spiculated margins and a homogenous
enhancement in the upper external quadrant, or bottom) retro-areolar non mass-like lesion, showing a cobblestone-like pattern with a nipple invasion and a skin thickening.

**Fig. 2:** Segmentation of the tumoral lesion. An overall good agreement between both methods of delineation was observed. The main area of the lesion was retrieved. Peripheral areas were removed following contour reduction. As two functional criteria were conjointly used to identify the lesion automatically (clustering based on amplitude + up-slope parameters followed by morphological opening to erode the contour), some differences appeared. Note that gain in reproducibility was also observed.
Fig. 3: Example of pixelwise analysis of visual texture of breast MR image in a CR patient with a mass pattern. GLCM texture parameters maps revealed the multiple characteristics of the grey levels distribution. In most cases, maps were characterized either by a local or a regional component; this last one often coinciding with the lesional or perilesional tissues. Note that even in visually similar regions, heterogeneity may appear.
Conclusion

Combining kinetic and textural parameters measured from high spatial resolution breast MR images improves significantly the differentiation between NR and PR+CR, and helps predicting the pathological response to preoperative chemotherapy. Further developments (3D texture analysis, different machine learning classifiers, larger set of data) are needed to raise the overall performance of the processing to a level that is suitable for a clinical use. The rationale behind these investigations is the development of a texture-based computer assisted diagnosis (CAD) system dedicated to breast MRI. Such system would be cost-effective in comparison to genetic/molecular assessments and may contribute to an appropriate treatment outcome for patients with breast cancer initially eligible for NAC.

References


**Personal Information**