ORIGINAL ARTICLE

Value of Magnetic Resonance Imaging Texture Analysis in the Differential Diagnosis of Benign and Malignant Breast Tumors

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Key words: breast tumor; texture analysis; magnetic resonance imaging; differential diagnosis

Objective To investigate the difference in texture features on diffusion weighted imaging (DWI) images between breast benign and malignant tumors.

Methods Patients including 56 with mass-like breast cancer, 16 with breast fibroadenoma, and 4 with intraductal papilloma of breast treated in the Hainan Hospital of Chinese PLA General Hospital were retrospectively enrolled in this study, and allocated to the benign group (20 patients) and the malignant group (56 patients) according to the post-surgically pathological results. Texture analysis was performed on axial DWI images, and five characteristic parameters including Angular Second Moment (ASM), Contrast, Correlation, Inverse Difference Moment (IDM), and Entropy were calculated. Independent sample *t*-test and Mann-Whitney *U* test were performed for intergroup comparison. Regression model was established by using Binary Logistic regression analysis, and receiver operating characteristic curve (ROC) analysis was carried out to evaluate the diagnostic efficiency.

Results The texture features ASM, Contrast, Correlation and Entropy showed significant differences between the benign and malignant breast tumor groups ($P_{ASM} = 0.014$, $P_{contrast} = 0.019$, $P_{correlation} = 0.010$, $P_{entropy} = 0.007$). The area under the ROC curve was 0.685, 0.681, 0.754, and 0.683 respectively for the positive texture variables mentioned above, and that for the combined variables (ASM, Contrast, and Entropy) was 0.802 in the model of Logistic regression. Binary Logistic regression analysis demonstrated that ASM, Contrast and Entropy were considered as the

specific imaging variables for the differential diagnosis of breast benign and malignant tumors.

Conclusion The texture analysis of DWI may be a simple and effective tool in the differential diagnosis between breast benign and malignant tumors.

BREAST cancer is a common malignant tumor and the main cause of death for the females. It accounted for up to 7%-10% of the malignant tumors occurred over the whole body of women and presented an increasing tendency in China.^[1] Early diagnosis and therapy of breast cancer could improve survival of the patients. Currently imaging methods including mammography, ultrasound and magnetic resonance imaging (MRI) are frequently used to diagnose breast cancer.^[2] Although MRI examination could increase detection rate of breast cancer, it had a relatively poor specificity. In this study we expected to improve diagnostic accuracy of breast cancer by using quantitative texture analysis of MRI diffusion weighted imaging (DWI) images.

PATIENTS AND METHODS

Patients

We retrospectively reviewed the medical records of patients admitted to the Hainan Hospital of Chinese PLA General Hospital between July 2012 and July 2018, and enrolled 56 patients pathologically diagnosed with massive breast cancer, 16 with fibroadenoma of breast and 4 with intraductal papillary neoplasm of breast after surgery in this study. The exclusion criteria included: (1) The images of DWI had evident artefacts; (2) The MR data were not acquired from the same MR 1.5T scanner. All the patients were females with a mean age of 49.8 ± 9.0 years. The subjects were classified into the benign group (20 patients with a mean age of 43.7 ± 11.3 years) and the malignant group (56 patients with a mean age of 49.8 ± 9.0 years) based on pathological results. The onset age of the two groups showed comparable ($t = 2.448$, $P = 0.017$).

The Ethics Committee of Chinese PLA General Hospital gave us permission to carry out this study, and this study did not require the informed consents from the enrolled subjects because DWI scans were routinely performed in clinical practice at our institute.

MR imaging

Bilateral breast MRI was performed for all patients

in prone position with the breast hanging naturally by using a 1.5T Tesla (T) whole-body MR imaging system (Signa Hdx, GE Healthcare, Milwaukee, WI, USA). Axial DWI parameters are listed as follows: repetition time (TR) 8750 ms, time echo (TE) 86 ms, matrix 128×128 , slice thickness 4 mm, field of view $30 \text{ cm} \times 30 \text{ cm}$, and b value = 0 and 1000 s/mm^2 .

Image analysis

Axial images of breast tumor were exported as bmp format from Picture Archiving and Communication Systems (PACS), which was imported to ImagJ (1.41v, <https://imagej.nih.gov/ij/>) to calculate Angular Second Moment (ASM), Contrast, Correlation, Inverse Difference Moment (IDM) and Entropy using Gray-level Co-occurrence Matrix (GLCM) method with its plugin. Texture parameters were evaluated with the size of the step in pixels 1 and the direction of the step 0 degree.

Regions of interest (ROIs) were defined as large as possible on the solid part of tumors, avoiding the area with necrosis and cystic changes. To improve accuracy of the measurement, ROI was placed for 3 times on the same image by the same neuroradiologist, and the mean value of three replicates for the indicated texture parameter was regarded as the final value.

Statistical analysis

The texture feature data following normal distribution were presented as mean $\pm$ SD and analyzed with independent t test for intergroup comparison. Data with non-normal distribution were expressed as median (quantile range) and intergroup comparison was performed with Mann-Whitney U test. If the texture parameters showing significant differences between the malignant group and the benign group, Logistic regression analysis was applied to establish Regression model using backwards method. The variables that would be enrolled in the logistic regression equation were determined by *Wald* χ^2 value, and diagnostic point was computed based on false positive rate obtained according to the preoperative MRI diagnosis and pathological diagnosis.^[3-4] Receiver operating characteristic (ROC)

curve was drawn with 1-specificity as horizontal coordinate and sensitivity as vertical coordinate, and the point with maximal sum of specificity plus sensitivity was regarded as the optimal diagnostic point. The area under ROC curve (AUC) was calculated to evaluate the diagnostic efficiency.

Statistically significant difference was set at a P value less than 0.05. Statistical analyses were performed using the SPSS Statistics Software Version 22.0 (SPSS Inc., Chicago, IL, USA).

RESULTS

Comparisons of texture features between the benign and malignant groups

As illustrated in **Table 1**, the texture parameters ASM ($P=0.014$, $U=352.500$), Contrast ($P=0.019$, $t=2.405$), Correlation ($P=0.010$, $U=275.000$) and Entropy ($P=0.007$, $t=2.761$) between the benign and malignant groups showed significant differences, however IDM showed no significant difference between the two groups ($P=0.305$, $U=473.000$). ROC analysis demonstrated that the AUC was 0.685, 0.681, 0.754 and 0.683, and the optimal diagnostic point was 0.0075, 908.7935, 0.0004 and 4.9345 for ASM, Contrast, Correlation and Entropy, respectively (**Table 2**).

Results of Logistic regression analysis of texture features

Binary Logistic regression analysis was performed with texture parameters ASM, Contrast, Correlation and Entropy which were regarded as independent variables, and then a regression equation was obtained as following: $P=1/1+e^{-(-12.137+58.453 \times \text{ASM}+0.003 \times \text{Contrast}+1.980 \times \text{Entropy})}$. The diagnostic point was 0.819 according to the false positive rate (21.4%) based on the current clinical data with sensitivity 0.607 and specificity 0.800, which could be explained as follows: (1) If $P>0.819$, the case should be diagnosed with malignant breast tumor; (2) If $P<0.819$, the case should be diagnosed with benign breast tumor. The equation was applied to the present group data, and the predictive accuracy for differentiation of benign and malignant breast tumors was 79.5%. Further ROC analysis demonstrated that AUC was 0.802 for the combined variables enrolled in the regression equation (**Table 3**, **Figure 1**).

DISCUSSION

DWI has been a commonly used MR sequence to differentiate benign from malignant breast tumors based on visual assessment and post-processed apparent diffusion coefficient (ADC) value. Compared with DWI, texture analysis is time-saving, because ADCs

Table 1. Comparisons of texture parameters of DWI between the two groups

Group	n	ASM [median (QR)] ^a	Contrast [§]	Correlation [median (QR)] ^a	IDM [median (QR)] ^a	Entropy [§]
Malignant group	56	0.006 (0.010)	1070.423±511.094	0.0003 (0.0000)	0.034 (0.020)	5.421±0.912
Benign group	20	0.008 (0.020)	782.637±424.783	0.0004 (0.0000)	0.046 (0.050)	4.715±1.028
t/U value		352.500	2.405	275.0000	473.000	2.761
P value		0.014	0.019	0.001	0.305	0.007
95%CI		-0.002-0.017	54.132-577.751	0.0001-0.0004	-0.006-0.026	0.191-1.179

§: Plus-minus values are means $\pm$ SD. ^a The data were expressed as median (quantile range, QR), and intergroup comparison was analyzed with Mann-Whitney U text.

DWI: diffusion weighted imaging; ASM: Angular Second Moment; IDM: Inverse Difference Moment.

Table 2. Receiver operating characteristic curve analysis for the positive texture variables in the Logistic regression model between the breast benign and malignant tumor groups

Parameter	AUC	Critical value	95%CI	Sensitivity	Specificity	Above critical value	Below critical value
ASM	0.685	0.0075	0.550-0.820	0.550	0.750	Benign	Malignant
Contrast	0.681	908.7935	0.543-0.820	0.700	0.625	Malignant	Benign
Correlation	0.754	0.0004	0.628-0.881	0.600	0.821	Benign	Malignant
Entropy	0.683	4.9345	0.547-0.818	0.550	0.732	Malignant	Benign

AUC: area under ROC curve.

Table 3. Binary Logistic regression coefficients, standard error and *P* value of texture parameters

Independent variable	Regression coefficient	Standard error	Wald χ^2	<i>P</i> value
ASM	58.453	31.984	3.340	0.068
Contrast	0.003	0.001	10.181	0.001
Entropy	1.980	0.664	8.882	0.003
Constant	-12.137	4.071	8.870	0.003

Figure 1. ROC curve of texture parameters of logistic regression model for breast benign and malignant tumors.

are calculated based on signal intensity of pixels using 2 *b*-value images (*b*=0 s/mm² and 1000 s/mm²), however texture parameters of DWI are measured on the images acquired with a *b* value of 1000 s/mm². Up to now, reports on texture analysis of DWI that enables differential diagnosis of breast tumors were rare. In this study we performed GLCM texture analysis on raw DWI images, aiming to verify whether texture analysis could differentiate benign from malignant breast tumors.

In this study, we extracted 5 frequently used texture features to differentiate benign from malignant breast tumors. When extracting GLCM texture features, we used the default settings (size=1 pixel and direction=0 degree) because texture values measured with GLCM method are insensitive to moving window size and direction.^[5]

The results revealed that texture parameters ASM, Contrast, Correlation and Entropy of DWI images presented significant differences between the benign and malignant breast tumors. ASM and Correlation showed significant decrease of the malignant breast tumors

compared with the benign breast tumors. ASM reflects homogeneity, the value of which is quite high when the image has perfect homogeneity or when pixel intensity is very similar.^[6] In the present study, the malignant group presented a lower ASM value compared with the benign group, which indicated that malignant breast tumors might have heterogeneous tumor parenchyma.^[7]

Texture Correlation reflects linear dependency of grey levels of neighboring pixels,^[6] and higher values can be obtained for similar gray-level regions.^[8] Texture Correlation have been used to differentiate benign from malignant breast tumors for ultrasound images. In the present study^[8-11] texture Correlation of DWI image was used to distinguish benign from malignant breast tumors. The result indicated that malignant breast tumor lacked similar gray-level regions, which might be consistent with lower ASM value. Therefore, the decreased texture ASM and Correlation showed optimal performance in distinguishing malignant breast tumors from benign breast ones.

The texture Contrast reflects amount of gray-level variation of an image, and a high Contrast value indicates the presence of noise or wrinkled texture in an image.^[12] The increased texture Contrast of malignant breast tumors suggested that the higher noises or wrinkled textures were identified in the malignant breast tumor lesions, which may be associated with the local heterogeneous intensity.

The texture Entropy represents amount of information needed for image compression. The higher texture Entropy represents the more loss of image information or message.^[13] In this study, the malignant breast tumors had higher texture Entropy value compared with the benign breast ones, which suggested that the malignant breast tumors lost more image information or message, thereby indicating increased complexity presented in the malignant breast tumors.

Although texture ASM, Contrast, Correlation and Entropy had a relative classifying efficacy for the breast tumors, single texture parameter showed the lower diagnostic sensitivity and specificity. Therefore, we wondered if multiple texture parameters analysis would improve diagnostic accuracy and obtain the best differential efficacy. Binary logistic regression analysis revealed that ASM combined with Contrast and Entropy which were enrolled in the regression equation attained the better diagnostic sensitivity and specificity (0.607 and 0.800 respectively) at the diagnostic point.

Furthermore, ROC analysis was used to evaluate

diagnostic efficacy of single texture parameter and the combined texture parameters enrolled in the regression equation in differentiating the benign from malignant breast tumors. AUC of the combined texture parameters was 0.802, which was larger than that of signal texture parameter (0.681-0.754). Therefore, logistic regression model achieved the best diagnostic efficacy in classifying the benign and malignant tumors than signal texture parameter analysis did.

The regression equation was applied to differentiate the benign from malignant breast tumors, and the results showed the final predictive accuracy rate was 79.5% for 76 cases, which demonstrated the relatively higher accuracy of the logistic regression equation. Although the texture analysis had a relatively lower accuracy rate for diagnosis, its AUC of the three combined texture features was relative larger (0.802) and reached the good level of diagnostic efficiency,^[14] therefore which could be used to differentiate the benign from malignant breast tumors.

The limitations of this study are: (1) The study only included three types of massive breast tumors; (2) The sample size was relatively small for benign breast tumors; (3) Only DWI images were used for texture analysis and other MR images should be enrolled in the future.

In summary, this study demonstrated that texture ASM, Contrast and Entropy derived from DWI images enrolled in the logistic regression equation could differ benign from malignant breast tumors.

Conflict of interest statement

The authors have no conflict of interest to disclose.

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