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Quantitative breast mass classification based on the integration of B-mode features and strain features in elastography

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ABSTRACT

Background: Elastography is a new sonographic imaging technique to acquire the strain information of tissues and transform the information into images. Radiologists have to observe the gray-scale distribution of tissues on the elastographic image interpreted as the reciprocal of Young's modulus to evaluate the pathological changes such as scirrhous carcinoma. In this study, a computer-aided diagnosis (CAD) system was developed to extract quantitative strain features from elastographic images to reduce operator-dependence and provide an automatic procedure for breast mass classification.
Method: The collected image database was composed of 45 malignant and 45 benign breast masses. For each case, tumor segmentation was performed on the B-mode image to obtain tumor contour which was then mapped to the elastographic images to define the corresponding tumor area. The gray-scale pixels around tumor area were classified into white, gray, and black by fuzzy c-means clustering to highlight stiff tissues with darker values. Quantitative strain features were then extracted from the black cluster and compared with the B-mode features in the classification of breast masses.
Results: The performance of the proposed strain features achieved an accuracy of 80% (72/90), a sensitivity of 80% (36/45), a specificity of 80% (36/45), and a normalized area under the receiver operating characteristic curve, Az = 0.84. Combining the strain features with the B-mode features obtained a significantly better Az = 0.93, *p*-value < 0.05.
Conclusions: Summarily, the quantified strain features can be combined with the B-mode features to provide a promising suggestion in distinguishing malignant from benign tumors.
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1. Introduction

As an adjunct to mammography, ultrasound (US) is widely used in distinguishing between benign and malignant breast lesions [1]. The Breast Imaging Reporting and Data System (BI-RADS) lexicon for US was defined by American College of Radiology [2] to standardize the descriptive terminology. The sonographic descriptors defined in BI-RADS lexicon such as shape, orientation, margin, lesion boundary, echo pattern, and posterior acoustic features were evaluated to be important in classify breast lesions in the prior studies [3–5]. With the standardized BI-RADS descriptors, the radiologists improved their agreement and performance in US interpretation across all experience variables in the literature [5].

After quantification, the sonographic descriptors were used in various computer-aided diagnosis (CAD) systems to estimate the likelihood being a carcinoma [6–8]. The quantitative characteristics extracted from B-mode images such as shape features were used in describing the physical properties of breast tumors [9,10]. The mechanical property of tumors is also investigated for histological and pathological relevance. For example, the pathological changes of the scirrhous carcinoma correlate with tissue stiffness [11]. As a newly developed sonographic imaging modality [12–14], elastography estimates the tissue stiffness by calculating the tissue displacement under a certain force. In quasi-static elastography, the tissue displacement is induced by manual pressing on the transducer such as the respiratory movement of patients utilized in this study. As another form of elastography,

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shear wave elastography [15], automatically radiates shear waves inside tissues and reconstructs the elasticity properties of tissues from the propagated shear wave. However, the simplicity of quasi-static elastography makes it can be implemented using conventional US hardware.

The gradient of the displacement or strain is converted to the pixel value for imaging. Clinically, the size ratio between the strain area in elastographic images and tumor area in B-mode images was evaluated to interpret breast tumor malignancy [16–20]. The definition is the maximum horizontal length of the tumor measured in the elastographic image divided by the corresponding length measured in the B-mode. A tumor with an elastographic images/B-mode size ratio greater than 1.0 had high likelihood being malignant. The stiffness contrast and normalized shear strain area were also used to diagnose breast tumors [14,19,21–24]. The stiffness contrast is the ratio between the mean strains estimated in the background to that estimated within the breast tumor. The area obtained from the strain area can be normalized via the tumor size measured from the B-mode image. The performances of Az, area under the receiver operating characteristic (ROC) curve achieved 0.84–0.99 in the results of the literature.

However, by observing the elastographic images, the shape and boundary of tumor area are not as clear as those in B-mode images. Radiologists have to manually compare elastographic images and B-mode images to estimate the stiffness of tumor area which is operator-dependent. Burnside et al. indicated that inter-observer variability was an influence factor to the diagnostic performance [17]. Prior CAD approach which extracted quantitative elasticity features from acoustic radiation force impulse imaging achieved an accuracy of 80% in classifying breast tumors [25]. In this study, we proposed an automatic procedure to extract strain features from quasi-static elastography in a CAD system for tumor classification. Tumor segmentation was first applied to the B-mode images and the resulting tumor contour was mapped to the elastographic image. The fuzzy c-means clustering (FCM) [26] was then used to automatically extract stiff tissues with darker values for feature extraction. Compared to other CAD systems [6–10], the current study explored the performance difference between the quantitative strain features and B-mode features. The complementary advantage of combining both feature sets was also evaluated in the experiment. The flowchart of the diagnostic procedure is shown in Fig. 1.

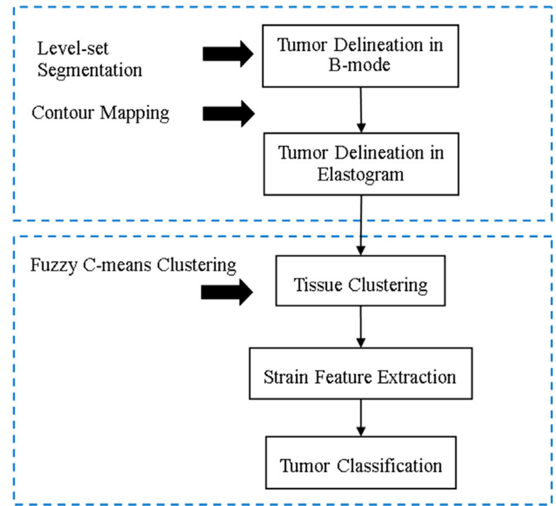

Fig. 1. The flowchart of the diagnostic procedure for elastography.

2. Materials and methods

2.1. Patients and data acquisition

This study obtained the approval from our institution review board and the patients' informed consent. A total of 90 patients underwent ultrasound examination with an ACUSON S2000 ultrasound system (Siemens Medical Solutions, Mountain View, CA) from November 2011 to June 2012. The equipped linear-array transducer was a 9L4 for the B-mode sonographic examination followed by elastography imaging. The target lesion was displayed in the B-mode sonogram with the corresponding strain image displayed side by side in the acquisition. The stiffness information is generated from the analysis of the gradient of the tissue displacement under a compression force and is converted to be a gray-scale image. The technique behind ACUSON S2000 is eSie Touch elasticity imaging which uses the respiratory movement of a patient to be the compress/decompress force source. In the acquisition, users only need to hold the transducer without placing any additional force on it. The imaging technique developed to reduce operator dependency would be sufficiently robust to establish a standard procedure. The acquired B-mode and elastographic images are 8-bit gray-scale which ranges from 0 to 255.

The pathology was proved by core needle biopsy to be the gold standard used in a classifier. Benign lesions (45/90, 50%) were composed of 23 fibroadenomas, 14 fibrocystic changes, and 8 intraductal papillomas with lesion size 1.21 ± 0.73 cm. The patient ages ranged from 18 to 80 years, mean 44 ± 12 years. For malignant lesions (45/90, 50%), 37 invasive ductal carcinomas (IDC), 2 invasive lobular carcinoma (ILC), and 6 ductal carcinoma in situ (DCIS) with lesion size 1.37 ± 0.39 cm were included. The patient ages ranged from 39 to 83 years, mean 54 ± 12 years.

2.2. Tumor segmentation

A semi-automated segmentation method was used to extract tumor area from background tissues in the B-mode image. The implementation of tumor segmentation used in this study is the same as the procedure in the previous study based on level-set segmentation and preprocessing filters [26]. For the success of tumor segmentation, image preprocessing was first applied to the B-mode image. The image contrast was enhanced by the sigmoid filter [27] as shown in Fig. 2(b). The gradient magnitude filter [28] was then applied on the contrast-enhanced image to obtain the gradient image (Fig. 2(c)). The intensity variations in the horizontal and vertical directions were calculated and combined by the filter. The previous sigmoid filter was applied again to enlarge the magnitude of the gradient image (Fig. 2(d)) for the enhancement of tumor boundary. After applying the sigmoid filter, the original gray-scale distribution with various values was reduced to extremely small (black) or large (white) values for the contrast enhancement as shown in Fig. 2(b) and (d). The contrast between black and white is the largest. The enlarged contrast also suppressed small variations such as speckle noises and only substantial edges with strong intensity gap were kept such as tumor contour.

With the seeds defined in the tumor area, the level-set segmentation automatically delineated the contour as shown in Fig. 2(e). The segmentation method developed the propagation from the seeds to tumor boundary for the modeling of complex tumor contour. The initial seeds have to be defined by user. For homogeneous tumors, any seed location would generate the same segmented contour while the results may not be consistent for heterogeneous tumors with various seed locations. It provides

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