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Abstract. A three-dimensional breast density estimation method is presented for high spectral and spatial resolution (HiSS) MR imaging. Twenty-two patients were recruited (under an Institutional Review Board–approved Health Insurance Portability and Accountability Act-compliant protocol) for high-risk breast cancer screening. Each patient received standard-of-care clinical digital x-ray mammograms and MR scans, as well as HiSS scans. The algorithm for breast density estimation includes breast mask generating, breast skin removal, and breast percentage density calculation. The inter- and intra-user variabilities of the HiSS-based density estimation were determined using correlation analysis and limits of agreement. Correlation analysis was also performed between the HiSS-based density estimation and radiologists' breast imaging-reporting and data system (BI-RADS) density ratings. A correlation coefficient of 0.91 ($p < 0.0001$) was obtained between left and right breast density estimations. An interclass correlation coefficient of 0.99 ($p < 0.0001$) indicated high reliability for the inter-user variability of the HiSS-based breast density estimations. A moderate correlation coefficient of 0.55 ($p = 0.0076$) was observed between HiSS-based breast density estimations and radiologists' BI-RADS. In summary, an objective density estimation method using HiSS spectral data from breast MRI was developed. The high reproducibility with low inter- and low intra-user variabilities shown in this preliminary study suggest that such a HiSS-based density metric may be potentially beneficial in programs requiring breast density such as in breast cancer risk assessment and monitoring effects of therapy. © 2016 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: [10.1117/1.JMI.3.4.044507](https://doi.org/10.1117/1.JMI.3.4.044507)]

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1 Introduction

Several factors contribute to the risk of developing breast cancer. Among the most influential to cancer risk are genetic factors such as family history and BRCA1/BRCA2 gene mutations, along with personal and environmental factors such as current age, age at menarche, age at first full pregnancy, personal history, diet, radiation exposure, and geographical location.¹ Breast density has also been shown to be an important factor for estimating breast cancer risk, and density classification methods were initially proposed to categorize cancer risk based on the spatial distribution of ductal tissue.^{2,3} An abundance of evidence exists demonstrating a positive correlation between mammographic percent density and breast cancer risk.^{4–10} In addition to density, various studies have indicated a relationship between parenchymal texture patterns and risk of cancer development^{11–21} or specific cancer risk factors such as BRCA1/BRCA2 gene mutation.^{11,21}

Percent density obtained from mammographic images refers to the ratio of the area of dense tissue present in a mammogram to the total area of the breast. The current standard clinical breast mammographic density assessment method involves assigning a score based on a coarse binning of approximate parenchymal density. The recommended method of binning densities was described by the breast imaging-reporting and data system (BI-RADS) density standard, in which density is given in four

categories, i.e., A to D, corresponding to the fatty and dense breasts. However, the interpretations of the four density scores A to D tend to correlate more with the degree of mammographic sensitivity loss than to actual quantitative percent density.²² Several studies have examined the correlation between BI-RADS density and automated or semiautomated mammographic percent density and estimated volumetric density calculations, with some reporting good correlation and some reporting large overlap between BI-RADS categories (especially BI-RADS B and C).^{23–26}

Several methods have been developed to estimate breast density from mammographic images,²⁷ including planimetry,^{28,29} gray-level thresholding,^{30–32} more complicated methods using calibration phantoms,^{33,34} and detailed x-ray physics models.^{35,36} However, since the breast is a three-dimensional (3-D) object and a mammogram is the projection of a 3-D object to a two-dimensional (2-D) image, the breast density estimated from a 2-D mammogram may not reflect the actual density value because of overlapping anatomy. Recently, studies have assessed breast density from breast tomographic images^{37–39} and magnetic resonance images. MRI-based density can be calculated as the ratio of fibroglandular content to both fibroglandular and fat content. The majority of MRI-based density calculations are performed on T_1 -weighted images, using either semiautomated segmentation,^{40–43} or automated segmentation/tissue clustering,^{44–49} although some have used two- and three-point Dixon methods to better separate the water and fat signal.^{50–53} Breast density has

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also been positively correlated with parenchymal enhancement observed in breasts imaged using dynamic contrast-enhanced MRI (DCE-MRI).^{54,55} Accurate measurements of breast density are increasingly important for the assessment of cancer risk and the evaluation of the effects of prophylactic therapy on breast density.

Here we report a 3-D breast density estimation method using high spectral and spatial resolution (HiSS) MR imaging in order to improve measurements of breast density. HiSS MRI⁵⁶ is an echo-planar spectroscopic imaging (EPSI) technique that uses a rapidly alternating readout gradient to acquire a train of gradient echoes during the proton-free induction decay (FID). Applying a 3-D Fourier transform yields two spatial dimensions and one spectral frequency dimension for each imaged slice. The spectra obtained from HiSS acquisitions display detailed water and fat peaks. The Fourier component images from HiSS data allow for isolation of signals from predominately water-based fibroglandular tissue and fatty regions, demonstrating better spectral resolution than mDixon methods^{57,58} and more complete fat signal suppression than T_1 -weighted methods.^{59,60} Earlier work showed that HiSS is a potentially useful noncontrast imaging method for breast lesion detection and characterization,^{61–65} showing similar performance levels [from a receiver operating characteristic (ROC) analysis] with DCE-MRI⁶³ in the task of distinguishing between cancer and noncancer cases. In this work, we expand the application of noncontrast HiSS breast MRI to the quantitative assessment of breast density.

The spectroscopy approach of HiSS MRI has the potential to improve automated delineation of lesions,⁶⁶ as well as that of fibroglandular tissue. To test this hypothesis, we used spectroscopic information provided by HiSS MRI, along with semiautomated breast segmentation and automatic tissue clustering to yield a HiSS-based breast density measurement. Here, we report on the performance of this new 3-D density measurement method and compare it to radiologist-assigned BI-RADS density scores from mammography. The research presented here focuses only on breast density estimation. The analysis of spatial parenchymal patterns from HiSS images will be investigated in further research.

2 Materials and Methods

2.1 Data Acquisition and Database

Collected clinical data came from 22 patients who were at high risk of breast cancer due to either personal or familial history. Data for this research were acquired with informed consent from each patient, under an Institutional Review Board approved protocol in compliance with the Health Insurance Portability and Accountability Act. Patients' ages ranged from 23 to 71 years (mean 50.9, median 51 years). Patients received standard-of-care clinical digital x-ray mammogram, as well as MRI scans on either a 1.5T Philips Achieva MR scanner or a 3T Philips TX Achieva MR scanner (both Philips Healthcare, Andover, Massachusetts), using 16-channel InVivo breast coils for all scans. Bilateral HiSS acquisitions were performed during the clinical MR scans by adding additional scan time (typically extra 15 min). The MR protocols included a bilateral T2-weighted turbo spin echo sequence, a full-coverage, bilateral HiSS scan, a single-slice, high spectral resolution HiSS scan, a two-echo modified Dixon (mDixon) sequence, a DCE-MRI sequence, and a diffusion-weighted imaging (DWI) sequence.

Table 1 Scanning and reconstruction parameters for the whole-breast bilateral HiSS scans.

Parameter	1.5T	3T
TR (ms)	4392	2820
TE (ms)	22	23
Spatial resolution (mm ³)	$0.8 \times 0.8 \times 3$	$0.8 \times 0.8 \times 3$
SENSE factor (RL)	3	3
Spectral resolution/ bandwidth (Hz)	23.9/549	23.9/549
FID sampling time (ms)	42	42
Acquisition matrix size	$320 \times 474 \times 60$	$320 \times 474 \times 60$
Acquisition field of view (mm ³)	$256 \times 384 \times 180$	$256 \times 384 \times 180$
Reconstructed matrix size	$480 \times 480 \times 60$	$480 \times 480 \times 60$
Echo train length	23	23
Acquisition time (m:ss)	~11:45	~6:30

The full bilateral HiSS data were acquired using a multislice EPSI sequence, with SENSE acceleration, implemented via a software patch.⁶⁷ The HiSS acquisition parameters are presented in Table 1. Following the spectral-spatial reconstruction of HiSS data, separate images were created with pixel values proportional to the integral of either the spectral water or the fat peak (Fig. 1); these images are referred to as water-peak integral (WPI) or fat-peak integral (FPI) images, respectively.

2.2 HiSS-Based Breast Density Estimation

An automatic segmentation algorithm that uses the anatomical information provided by the HiSS WPI and FPI images is developed in this study. The examples of a WPI image and an FPI image calculated from a single slice of an HiSS image set are shown in Fig. 1. The value in each voxel of an integral image represents the area under the respective spectral peak. As evidenced by the images, voxels with high water content tend to contain low fat content, and vice versa. Peak-integral images are often highly correlated with peak-height images, but they represent all of the underlying Fourier components associated with either the water or fat resonance present in a local volume, as opposed to just the peak. The segmentation algorithm is applied slice-by-slice to yield the density component within an entire breast volume. The presented algorithm for breast density estimation on the HiSS data includes breast mask generating, breast skin removal, and breast percentage density calculation.

2.2.1 Generation of breast mask

In the first step, binary masks of both WPI and FPI images (Fig. 2) are created using a two-class fuzzy c-means clustering algorithm applied to each component image separately. Using the WPI mask, the user manually selects two points: one indicating the top level of the chest wall muscle and another indicating the lower extent of the breast, for which in this work, the

Fig. 1 (a) WPI image and (b) FPI image calculated from a single slice of an HiSS image set. The value in each voxel of an integral image represents the area under the respective spectral peak. As evidenced by the images, voxels with high water content tend to contain low fat content, and vice versa. Peak-integral images are often highly correlated with peak-height images, but they represent all of the underlying Fourier components associated with either the water or fat resonance present in a local volume, as opposed to just the peak. Also, integrating removes $T2^*$ weighting. The arrow on the top indicates the user's input of top level of the chest wall muscle and the arrow on the bottom indicates the user's input of the lower extent of the breast.

Fig. 2 Binary masks created by clustering the (a) WPI and (b) FPI images using two-class FCM segmentation. The lower portion of the WPI image is discarded because it contains primarily muscle and other nonbreast tissue, while the upper portion contains the relevant parenchyma/ductal tissue. The FPI image contains most of the breast shape information, which is used to obtain the full breast mask. The arrow on the top indicates the user's input of top level of the chest wall muscle and the arrow on the bottom indicates the user's input of the lower extent of the breast.

most anterior point of the latissimus dorsi muscle was chosen as it is a reproducible, unambiguous landmark (Figs. 1 and 2).

The portion of the FPI mask above the lowest extent of the breast is added to the portion of the WPI mask above the chest wall location to form an initial breast mask. An erosion/dilation filter with a two-pixel disk kernel⁶⁸ is applied to the mask to exclude areas of the FPI image that are inside the chest cavity. The breast mask (Fig. 3) is then filled in by applying a conventional morphological hole-filling routine.⁶⁸

2.2.2 Skin removal

Skin surrounding breast tissue contains a substantial amount of water that would typically bias a density calculation as skin is

not part of the parenchymal tissue. Therefore, a boundary-labeling algorithm⁶⁹ is applied to the masked-WPI image to indicate the locations of skin in the image, enabling skin removal. Since the air signal is dark and the breast fatty tissue is dark, the skin appears bright in the WPI image. In short, a marching gradient-search routine is applied at each point along the indicated boundary of the image (Fig. 4). At each boundary point, the algorithm searches a line of pixels toward the center of the breast for a large negative pixel-value gradient. The gradient threshold in this work was a between-pixel gray-level difference of 10 (around 4% of maximum signal intensity). A large negative gradient indicates that the inner boundary of the skin is crossed and thus the interior of the breast has been reached. The pixels

Fig. 3 (a) The binary breast mask before skin-removal. This mask will dictate the extent to which tissue in the WPI and FPI images will be included in the breast density calculation. (b) The WPI image after applying the breast mask. All of the thoracic anatomy (chest wall, heart, and muscles) has been removed, leaving only breast water content and the skin.

before the large gradient are then removed. The corresponding pixels from the full-breast mask are also removed.

The lack of a negative gradient indicates the presence of breast tissue that has developed against the skin. While in general there is little parenchyma touching the sides of the breast, around the nipple there is often ductal tissue, which both touches the skin and extends deep into the breast. Therefore, it is crucial to set an upper limit on the length of the line of pixels searched. If no upper limit is set, the skin-removing algorithm will remove very large regions of the breast while searching for a large gradient. Our upper limit was determined by implementing the skin-removal algorithm using a limit of six pixels as the maximum length of pixels to search prior to the algorithm having completely removed the skin while preserving ductal tissue next to the skin. We assume a maximum skin thickness is 5 mm.⁷⁰

2.2.3 Calculation of HiSS-based breast density

The finalized breast-tissue masks are applied to their respective image slices (see Fig. 5 for examples of final segmentations), and breast parenchymal density is calculated from HiSS data for both left and right breasts. The central point of the chest wall between the breasts is manually identified to designate

Fig. 4 Illustration of the marching gradient search algorithm used for removing the skin from HiSS images. (a) A simulated section of a WPI image showing a bright skin line and a region of ductal tissue touching the skin. The blue arrows indicate the direction of the gradient search at each boundary voxel. (b) The same image region after the skin line is removed. The tissue region against the skin is maintained, as no negative pixel-value gradient was found within the search limit.

the divide between the left and right sides, and the WPI images and FPI images are separated into left and right images according to this divide. The HiSS-based breast density is calculated according to Eq. (1), where W_i is the value of the water integral at pixel i of the segmented WPI images, and F_i is the value of the fat integrals at voxel i , and N is the total number of voxels in the breast (without skin). Left breast, right breast, and overall bilateral densities are calculated.

$$\text{Breast density} = \frac{\sum_{i=1}^N W_i}{\sum_{i=1}^N (W_i + F_i)}. \quad (1)$$

Because of finite repetition time (TR) values, fat and water peaks are subject to T_1 weighting, following the gradient echo signal equation:

$$S/M_0 = \sin(\text{FA})(1 - e^{-\frac{\text{TR}}{T_1}})e^{-\frac{\text{TE}}{T_2^*}} / \left[1 - \cos(\text{FA})e^{-\frac{\text{TR}}{T_1}} \right], \quad (2)$$

where FA is a flip angle, TE is an echo time. Since $\sin(\text{FA})$ has the same value for both fat and water peaks, and the broadening due to finite T_2^* is accounted for by calculating peak integral values, rather than peak values, they do not contribute to the calculation of the T_1 -weighting correction coefficient ($T_1\text{wCC}$)

$$T_1\text{wCC} = \frac{1 - \cos(\text{FA})e^{-\frac{\text{TR}}{T_1}}}{1 - e^{-\frac{\text{TR}}{T_1}}} - 1. \quad (3)$$

Due to the shorter T_1 values of the fat signal, $T_1\text{wCC}$ for fat is equal to or less than 0.01% and is not taken into consideration

Fig. 5 Example slices from an HiSS WPI dataset at each BI-RADS density category after applying the final breast mask. An outline has been included to show the extent of the breast. (a) BI-RADS 1, total breast density = 10.3%. (b) BI-RADS 2, total breast density = 15.9%. (c) BI-RADS 3, total breast density = 23.3%. (d) BI-RADS 4, total breast density = 16.2%.

for $T1$ -weighting correction. Thus the final density calculation is given by

$$\text{Breast density} = \frac{\sum_{i=1}^N W_i * [1 + T1wCC(\text{water})]}{\sum_{i=1}^N \{W_i * [1 + T1wCC(\text{water})] + F_i\}}. \quad (4)$$

The $T1$ values for fat and parenchymal tissue at $1.5T$ and $3T$ had been calculated as the weighted averages of $T1$ values measured in two studies.^{71,72} $T1wCC$ was found to be 0.9% and 3.6% for water peaks at $1.5T$ and $3.0T$, respectively.

2.3 Radiologists-Determined BI-RADS Density Score

The BI-RADS densities established by a radiologist were acquired retrospectively from radiology reports. The BI-RADS categorical scores of A-D were recorded as density ratings.⁷³

2.4 Evaluation of the Breast Density Estimations

2.4.1 Correlation between left and right breast density estimates

Correlation analysis was performed to evaluate the symmetry between the left breast and right breast percentage densities. The noninferiority test,⁷⁴ a two one-sided test with an equivalence margin of $\delta = 10\%$ dense and a significance level of 0.05, was performed between left and right breast densities.

2.4.2 Inter-user variability of density estimation

To assess the inter-user variability of the HiSS-based density measurement technique, density was estimated for all 22 patients by two different users (a medical physicist and an expert breast radiologist with 12 years of breast imaging experience). The breast density estimates were computed 3 months apart, on the same workstation under similar lighting conditions. Both users viewed HiSS images using the default MATLAB[®] image display with identical contrast settings, where they chose locations for both the chest wall and latissimus dorsi positions for use in calculating the HiSS-based breast density as previously described. The second user interpreted the images without knowledge of the inputs given by the first user. Note that after each user input the top level of the chest wall muscle and the lower extent of the breast, the algorithm proceeded automatically (as described earlier) to yield the percent density.

The correlation of density measurements between users was assessed using the Pearson correlation coefficient with a significance level of 0.05. Limits of agreement were calculated to assess the inter-user reproducibility for HiSS-based density as the 95% confidence interval of the mean discrepancy between user density estimates.⁷⁵ Inter-user agreement for density estimation based on HiSS data was also evaluated using the intra-class correlation coefficient (ICC).^{76,77}

2.4.3 Intra-user variability of density estimation

The intra-user reproducibility of the breast density calculation method was also assessed. Two estimates of HiSS-based density were computed by the same user, 3 months apart, on the same workstation under similar lighting conditions. The user's second interpretation was conducted without knowledge of the inputs chosen during their first reading.

The correlation of density measurements by the same user was assessed using the Pearson correlation coefficient with a significance level of 0.05. Limits of agreement were calculated to assess the intra-user reproducibility for the HiSS-based density as the 95% confidence interval of the mean discrepancy between intra-user density estimates.

2.4.4 Inter-modality density comparison

As noted earlier, breast density measurements were acquired in this study using two different methods: (1) a volumetric estimate of the ratio of parenchymal fibroglandular tissue to total breast tissue using the water and fat contents from HiSS data as a surrogate, and (2) the standard clinical BI-RADS density rating assigned by a radiologist. To assess the relationship between these two density metrics, Spearman correlation coefficients were calculated using a significance level of 0.05 to indicate statistical significance. To investigate the difference in image-measured density between BI-RADS B and C, a Wilcoxon ranked-sum test was applied with a significance level of 0.05.

3 Results

3.1 Left Versus Right Breast Density Comparison Based on HiSS Data

The bilateral breast density comparison based on HiSS data is shown in Fig. 6. Based on the medical physicist's assessment, a correlation coefficient of 0.91 ($p < 0.0001$) was obtained between the percent density values from the left and right breast HiSS images. This high correlation is expected within our population given the high symmetry between breasts within a patient.

The 90% confidence interval of the difference between left and right breast densities for the HiSS-based technique falls within $[-10, 10]$ percentage points (Fig. 6) based on the noninferiority test, indicating that the left and right breast density estimates are not statistically different.

3.2 Inter-user Variability of HiSS-Based Density Estimation

Figure 7 shows the inter-user variability on a Bland–Altman plot of the HiSS density discrepancy versus the average density estimate with the limits of agreement indicated. The Pearson correlation coefficient for the HiSS-based density measurements from two different users was 0.99 ($p < 0.0001$). The limits of agreement for HiSS-based density were $[-0.8, 1.4]$ percent density. A high inter-user agreement for breast density estimation was observed with an ICC value of 0.99.

3.3 Intra-user Variability of HiSS-Based Density Estimation

Figure 8 shows the intra-user variability on a Bland–Altman plot of the HiSS density discrepancy versus the average density estimate with the limits of agreement indicated. The Pearson correlation coefficient for the HiSS-based density measurements from the same user was 0.99 ($p < 0.0001$). The limits of agreement for HiSS-based density were $[-0.2, 0.4]$ percent density. These results indicate that there is very low intra-user variability in the calculation of the HiSS-based density.

Fig. 6 Contralateral breast density comparison for computed HiSS-based density estimates. The noninferiority of left versus right density was computed using a two one-sided test.

Fig. 7 Bland-Altman plot showing the inter-user variability for breast density estimates from the HiSS data. The solid line indicates the average difference between density estimates based on initial inputs from two different users. The dashed lines represent the 95% confidence interval for the mean discrepancy.

3.4 Inter-modality Density Comparison

Figure 9 shows HiSS-based breast percent density estimates versus BI-RADS density ratings. The Spearman correlation coefficient for HiSS-based density versus BI-RADS density score was 0.55 ($p = 0.0076$). The distributions of HiSS-based density estimates for breasts assigned BI-RADS B and C were found to be statistically different ($p < 0.05$), with HiSS-based density estimates of BI-RADS C group higher than those of BI-RADS B group.

Fig. 8 Bland-Altman plot showing the intra-user variability for breast density from HiSS data. The solid line indicates the average difference between density estimates based on initial inputs from the same user. The dashed lines represent the 95% confidence interval for the mean discrepancy.

Fig. 9 Comparison of total breast density (including left and right breasts) as calculated from HiSS data and the density measurement with the corresponding BI-RADS score assigned by a radiologist.

4 Discussion and Conclusion

We have developed a breast segmentation algorithm that uses the anatomical information provided by the WPI and FPI of HiSS images. The breast percentage density was estimated based on these HiSS images with low inter- and low intra-user variabilities.

After comparing density estimates obtained by one user with no experience in reading breast MR images and by one who is very experienced, we observed very low inter-reader variability. Thus the results from this preliminary study demonstrate that HiSS images can be used for calculating breast density with high reproducibility, and that accurate evaluation of breast density may not require an experienced radiologist.

When comparing mammographic percent density to an MRI-calculated density, one is comparing an inherently 2-D estimate (with no 3-D detail) to a volumetric measurement, and this distinction can impact the comparison between the two. MRI divides the breast tissue into tomographic “slices” that preserve much more of the fibroglandular depth information. Volumetric measurements calculated using the more detailed local breast composition information available from HiSS-MRI images may therefore be a more accurate method of assessing breast density.

Inter- and intra-user variabilities of a density estimation technique play important roles in assessing the utility of a given method. While there is no ground truth to which to compare the output of a breast density measurement method, if appropriate standards are established, the decisions made from the results of a method with low variability will be more deterministic. In the clinical setting, high variability in breast density could mean the difference between receiving additional screening or forgoing additional, potentially unnecessary tests. It is promising that HiSS-based breast density estimates exhibited both low inter-user and low intra-user variabilities.

Several studies have presented a large overlap of quantitative breast percent densities with BI-RADS density score, especially prevalent at BI-RADS B and C.^{23,24} Thus HiSS may be used for estimating the breast density during screening. Although, further studies are required to establish appropriate clinical action at different HiSS-based density levels since the quantitative density values may not coincide with the suggested BI-RADS density score bins, which were developed for a 2-D density estimate. We believe that this HiSS imaging-based breast density calculation method can be standardized and can be substituted for other MRI methods when fat and water signals are available.

Although our HiSS-based volumetric density measurements correlate moderately with BI-RADS density scores, it can be easily argued that BI-RADS density scores are more subjective and more interchangeable, especially for BI-RADS B and C scores, which are poorly differentiated by human readers.^{23,24} In this preliminary study, our HiSS-based breast density estimation method is showed to be objective, quantitative, and reproducible, and thus warrants further study in estimating the breast percentage density. For example, when precontrast DCE-MRI images are used to perform breast density estimation, the MRI intensity within a single voxel includes contributions from multiple tissues (e.g., both adipose and fibroglandular tissues), and such partial volume effects make it difficult to accurately classify these voxels into a specific tissue group. The advantage of HiSS is having separated WPI and FPI images, thus enabling subvoxel contributions and the potential to accurately estimate breast density.

There are some limitations in our study, such as the small sample size, including that there is only one case each from each of the BI-RADS A and D groups based on radiologists' estimates. The majority of cases are BI-RADS B and C. Based on this preliminary study, we do not believe that we can reliably map percentage density estimated from HiSS images

to BI-RADS density A to D. A larger HiSS dataset that includes a balanced BI-RADS A to D dataset is needed in order for us to establish the percentage range breast density as the cutoffs for categorizing women's breast density into A, B, C, and D categories. It will allow us to better understand the relationship between breast percent density estimated from HiSS images and the reference standard, i.e., the BI-RADS density category from a radiology report. A larger dataset is needed to also validate the results from our preliminary study, and to relate the percentage density to other clinical outcomes, such as parenchyma enhancements from DCE-MRI and breast cancer risk. In addition, a larger number of experienced human readers is needed to further evaluate the reproducibility of the HiSS-based breast density estimation method developed in this study. We will perform the comparative analysis of density measures from HiSS, mammography, and precontrast DCE-MRI on a large dataset in the future.

In summary, we developed a computerized objective breast density estimation method using HiSS spectral data and compared it to clinical BI-RADS density scores. We were able to show that our new method is highly reproducible with low inter- and intra-user variability. Our results suggest that such a HiSS-based density metric may be potentially beneficial in programs requiring breast density such as in breast cancer risk assessment and monitoring effects of therapy.

Disclosures

MLG is a stockholder in R2 technology/Hologic and receives royalties from Hologic, GE Medical Systems, MEDIAN Technologies, Riverain Medical, Mitsubishi, and Toshiba. She is a cofounder of and stockholder in Quantitative Insights. HL receives royalties from Hologic. It is the University of Chicago Conflict of Interest Policy that investigators disclose publicly actual or potential significant financial interest that would reasonably appear to be directly and significantly affected by the research activities.

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