Impact of the Number of Iterations in Compressed Sensing Reconstruction on Ultrafast Dynamic Contrast-enhanced Breast MR Imaging

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Purpose: To assess the impact of the number of iterations of compressed sensing (CS) reconstruction on the kinetic parameters and image quality in dynamic contrast-enhanced (DCE)-MRI of the breast, with prospectively undersampled CS-accelerated scans.

Materials and Methods: Breast examinations including ultrafast DCE-MRI using CS were conducted for 21 patients. Images were reconstructed with different numbers of iterations. The peak enhancement ratio of the aorta and wash-in slope, initial area under the curve, and $K_{\text{trans}}$ of the breast lesions were measured. The root mean square error and structural similarity between the images using 50 iterations and images with a lower number of iterations were evaluated as criterion for quantitative image evaluation.

Results: Using an insufficient number of iterations, the contrast-enhanced effect was highly underestimated. In all semi-quantitative parameters, the number of iterations that stabilized the parameters in malignant lesions was higher than that in benign lesions. At least 15 iterations were needed for semi-quantitative parameters. For $K_{\text{trans}}$, there were no significant differences between 10 and 50 iterations in both malignant and benign lesions.

Conclusion: The kinetic parameters using ultrafast DCE-MRI with CS are affected by the number of iterations, especially in malignant lesions. However, if the images are reconstructed with an adequate number of iterations, ultrafast DCE-MRI with CS can be a powerful technique having high temporal and spatial resolution.

Keywords: breast, compressed sensing, iteration, magnetic resonance imaging, ultrafast dynamic contrast-enhanced-MRI

Introduction

Dynamic contrast-enhanced (DCE)-MRI is widely used as a powerful imaging tool to evaluate breast lesions. For DCE-MRI, a contrast agent is injected into the blood stream before or during the acquisition of a series of $T_1$-weighted images using fast imaging techniques. By analyzing the changes of the MR signal intensity over time, semi-quantitative analyses based on the time-intensity curve (TIC) can be performed, and quantitative parameters can be estimated by fitting pharmacokinetic models. Several studies have shown the benefit of qualitative and quantitative kinetic parameters for distinguishing malignant from benign lesions¹–⁴ and assessing the response of breast cancer to neoadjuvant chemotherapy⁵ and radiation therapy.⁶ Detailed kinetic information, particularly for quantitative kinetic parameters, requires high temporal resolutions. On the other hand, morphological assessment of the lesion, another important feature of lesion characterization, requires high spatial resolution. Recently, compressed sensing (CS) has become available for the acceleration of dynamic MRI acquisitions, which is achieved by enabling the reconstruction of subsampled data.⁷ Along with the promising results from ultrafast DCE-MRI with much shorter acquisition time,⁸–¹² CS is regarded as one of the accelerated methods to

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use in the clinical setting. Utilization of CS algorithms can improve the temporal/spatial resolution of DCE-MRI, and several works describing retrospective simulations have demonstrated the feasibility of such improvements.\textsuperscript{9,13,14–16} Many of the reports on DCE-MRI using CS are retrospective studies in which fully sampled raw data sets are downsampled after data collection. Khalasa and Fessler\textsuperscript{17} showed how the regularization parameters used in CS reconstruction affected the TIC. In many studies for optimizing the parameters used in the CS reconstruction, the calculation of image reconstruction was continued until iterative reconstruction converges to get images that satisfy the L1 minimization problem. However, because many CS reconstruction techniques are computationally intensive, the generation of images using these techniques can take a significant amount of time, this not ideal in a clinical settings. With the number of iterations in the numerical CS optimization typically fixed to avoid prolonged reconstruction times, a careful analysis of its effect on the final results is highly desirable, in particular to minimize the estimation error in lesion-enhancement characteristics. The aim of this study was to assess the impact of the number of iterations used in CS reconstruction on kinetic parameters and the image quality in ultrafast DCE-MRI of the breast, with prospectively undersampled CS-accelerated scans.

Materials and Methods

Patients

The study was approved by the Institutional Review Board with waiver of informed consent, because of the retrospective collection of the clinical breast MRI data. High-temporal CS-accelerated examination was part of the hybrid protocol with conventional DCE-MRI with the same total image acquisition time as our standard clinical breast DCE-MRI protocol. The dataset includes 21 DCE-MRI examinations acquired from 20 female and one male (mean 53.9 years; range 33–82 years) who underwent clinical breast DCE-MRI with a high-temporal CS-accelerated examination for either the evaluation of suspicious lesions on mammography/ultrasonography or preoperative evaluation, from December 2015 to March 2016. The raw data of each CS-accelerated examination were saved and available for prospectively testing various CS reconstruction parameters. The diagnosis was pathologically confirmed based on the histopathology of surgically excised specimens and/or needle core biopsies. There were 18 breast cancers: nine invasive carcinomas of no special type, two invasive lobular carcinomas, one mucinous adenocarcinoma, and six ductal carcinomas in situ (DCISs). There were three benign lesions pathologically confirmed as papilloma \((n = 1)\), fibroadenoma \((n = 1)\), and fibroepithelial neoplasm \((n = 1)\). The remaining five lesions were diagnosed as benign on MRI and followed-up for at least 12 months without showing any sign of malignancy. The study population of the current analysis was partially overlapped with the previous study\textsuperscript{18} which aimed to visualize breast vessels associated with ipsilateral breast lesions.

MRI acquisition

Bilateral breasts were scanned using a 3T system (MAGNETOM Skyra, Siemens Healthcare, Erlangen, Germany) and an 18-channel dedicated breast coil, with patients in the prone position. The DCE-MRI consisted of ultrafast MRI using the prototype sequence (from 13 s before to 60 s after contrast injection), followed by standard DCE-MRI sequence of initial phase (60–120 s), delayed phase (300–360 s) and high spatial resolution post-contrast images between these two phases (120–300 s). The ultrafast DCE-MRI data used for the current analysis were acquired using a prototypical non-fat-suppressed 3D volumetric interpolated breath-hold examination (VIBE) sequence using a variable-density sampling in the phase-encoding plane obeying a Gaussian distribution with the following imaging parameters: TR = 5.04 ms, TE = 2.46 ms, flip angle (FA) = 15°, slice thickness = 2.5 mm, 60 partitions, matrix size = \(384 \times 269\), FOV = 360 \(\times 360\) mm\(^2\), CS acceleration = 16.5, and temporal resolution = 3.65 s. DCE-MRI was sequentially acquired at 20 consecutive time points (preceded by 2 s preparing time) with a total acquisition time of 75 s. Thirty seconds after scan commencement, 0.1 mL/kg gadoteridol was injected at 2 mL/s, followed by 20 mL of saline flush injected at 2 mL/s. For the analysis of the quantitative parameters, pre-contrast \(T_1\) maps with \(B_1\) field inhomogeneity correction using the dual-FA method (2° and 15°) were acquired.

Compressed sensing image reconstruction

Compressed sensing reconstruction was conducted with the following minimization problem:

\[
\Phi(x) = \|Ax - y\|^2_2 + \lambda \|Wx\|_1
\]

(1)

where \(A\) represents the system matrix including undersampled Fourier transform and coil profiles, \(x\) is the reconstructed image, \(y\) is the measured \(k\)-space data, \(W\) is a linear operator that first performs a Haar wavelet decomposition in both spatial and temporal dimension with a regularization parameter, \(\lambda\). The regularization in this CS reconstruction is done for low- and high-frequency components in wavelet space. In this study, these regularization parameters were chosen for each frequency, 0.002 and 5.000, respectively. The number of iterations for a fast iterative shrinkage-thresholding algorithm\textsuperscript{19} optimization using a time-averaged starting point = 1, 2, 3, 5, 10, 15, 20, 25, 30, 40, and 50.

The reconstruction was implemented in C++ and integrated into the scanner reconstruction pipeline. Reconstructions with a varying number of iterations were performed retrospectively within the scanner environment on CPU system. Reconstruction time per each number of iterations was recorded and compared.
Data analysis

DCE-MRI parameters

Semi-quantitative parameters were derived voxel by voxel from the TIC and analyzed using a custom-made Matlab (The MathWorks, Inc., Natick, MA, USA) program. The semi-quantitative parameters were as follows: wash-in slope (WIS) between arrival and peak enhancement time, peak enhancement ratio (PER) along the kinetic curve, and initial area under the curve (IAUC), which was defined as the area from contrast arrival to after 5th phase.

From the DCE-MRI data sets, the quantitative parameter $K_{trans}$ (the transfer constant of contrast from the plasma to the tissue extracellular extravascular space [EES]) was calculated based on the Tofts model using the DCE Tool plug-in for Osirix (http://kyungs.bol.ucla.edu/software/DCE_tool/DCE_tool.html). The pharmacokinetic analysis was performed using the population-based arterial input function reported by Walker, et al., modified by Frits-Hansen. Semi-quantitative and quantitative parameters were obtained for the selected set of number of iterations.

Quantitative image evaluation

The reconstructed images were evaluated by the root mean square error (RMSE) and structural similarity (SSIM). The RMSE was calculated as follows:

$$\text{MSE}(X,Y) = \frac{1}{nm} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [X(i,j) - Y(i,j)]^2$$

$$\text{RMSE}(X,Y) = \sqrt{\text{MSE}(X,Y)}$$

where $X$ and $Y$ are the reference images, which were reconstructed with the maximum number of iterations (in the present study, 50), and $Y$ are the images reconstructed with the other selected number of iterations.

The SSIM index compares local patterns of pixel intensities that have been normalized for luminance and contrast. It is based on the idea that the human visual system is good at extracting information based on structure:

$$\text{SSIM}(X,Y) = \frac{(2\mu_X \mu_Y + c_1)(2\sigma_{X,Y} + c_2)}{\mu_X^2 + \mu_Y^2 + c_1(\sigma_X^2 + \sigma_Y^2 + c_2)}$$

where $X$ and $Y$ are the local windows for the reference and reconstructed images, respectively, $\mu_X$ and $\mu_Y$ are the averages of $X$ and $Y$, respectively, $\sigma_X$ and $\sigma_Y$ are the variances of $X$ and $Y$, respectively, and $\sigma_{X,Y}$ is the covariance of $x$ and $y$. $c_1 = (K_1L)^2$ and $c_2 = (K_2L)^2$ are the two variables to stabilize the division with a weak denominator, where $L$ is the dynamic range of the pixel-values, $K_1 = 0.01$ and $K_2 = 0.03$. The SSIM index was measured between the images using 50 iterations and the remaining selected iterations by the formula above using a custom-made Matlab program.

Statistical evaluation

All $P$-values were two-sided and $P \leq 0.05$ were considered statistically significant. All statistical analyses were performed with EZR software (Saitama Medical Center, Jichi Medical University, Saitama, Japan), which is a graphical user interface for R (The R Foundation for Statistical Computing, Vienna, Austria). More precisely, it is a modified version of R commander designed to add statistical functions frequently used in biostatistics. The Dunnett’s test was performed to compare DCE-MRI parameters (WIS, PER, IAUC, and $K_{trans}$) and the image evaluation values (RMSE and SSIM) between images using 50 iterations and the remaining selected iterations.

Results

Reconstruction time

The reconstruction time was prolonged as the number of iterations increases. DCE-MRI images reconstructed using 50 iterations required approximately 35 min (Fig. 1).

Effects of the numbers of iterations on signal intensity

The images of example lesions reconstructed with different numbers of iterations at the different time points are shown in Fig. 2. The signal of the aorta (dashed arrow) using one iteration pre-contrast (Phase 1) was higher than that using 50 iterations. Conversely, the signal of the aorta using one iteration post-contrast (Phases 10 and 20) was lower than that using a higher number of iterations. This tendency was similar in the malignant lesion (arrow).

Exemplary results of the TIC for the aorta (a) and malignant lesion (b) for different numbers of iterations are shown in Fig. 3. The signal intensity pre-contrast increased as the number of iterations increased. In comparison, the signal intensity post-contrast increased as the number of iterations

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Fig. 1 The reconstruction time with different numbers of iterations. In total, 1200 images (60 slices × 20 phases) were reconstructed with each number of iterations.
increased. Therefore, the signal difference between the pre- and post-contrast images was higher for the larger numbers of iterations. This effect was greater for the aorta than for the lesion, and the required minimum number of iterations stabilizing the TIC was larger for the aorta.

**DCE-MRI parameters**

The boxplot of PER for the descending aorta using different numbers of iterations (Fig. 4) demonstrated that the PER values with < 25 iterations were lower than the values using 30 iterations. The PER values were not significantly different among those using 30 iterations or above.

The boxplots show the values if the semi-quantitative parameters (WIS, PER, and IAUC) obtained using different number of iterations in malignant and benign lesions (Fig. 5a–5f). In all semi-quantitative parameters, the number of iterations, which stabilized the parameters in malignant lesions, was higher than that in benign lesions. For malignant lesions, more than 10, 15, and 15 iterations were required for WIS, PER, and IAUC, respectively. Conversely, in benign
lesions, more than 3, 5, and 10 iterations for WIS, PER, and IAUC were required, respectively.

Figure 5g and 5h shows the boxplots of the quantitative parameter $K_{trans}$ in malignant and benign lesions with different iterations. There were no significant differences between 10 and 50 iterations in both malignant and benign lesions.

**Quantitative image evaluation**
The RMSE and SSIM between the images reconstructed using 50 iterations and images reconstructed using fewer iterations are shown in Fig. 6. The SSIM values between 50 and 40 iterations were above 0.998, and the images were considered approximately equal. There were no significant differences in the RMSE between 30 and 40 iterations, and in the SSIM between 25 and 40 iterations.

**Discussion**
The current analysis demonstrated that DCE-MRI images were strongly affected by the number of iterations. CS reconstruction used in this study was L1 minimization problem in both spatial and temporal direction. In small number of iterations, the reconstructed images were strongly affected by the regularization in time domain. As a result, the error in pre-contrast phase and the reduction of contrast-enhanced effects occurred (Fig. 2). In the quantitative image evaluation, the number of iterations needed was 30 for RMSE and 25 for SSIM. Conversely, the number of iterations that stabilized the kinetic parameters was higher for malignant lesions, likely due to hypervascularity, even though 15 iterations sufficed.
suffer from artifacts related to the point-spread-function of method and CS. However, view sharing methods sometimes investigated reconstruction methods for solving CS. Levine et al. using prospective data retrospectively collected data. Sung et al. sampling was conducted by Wang et al. breast DCE-MRI. The optimization of undersampling acquisition resulted in higher acceleration (CAIPIRINHA) which is the combination of parallel imaging, view sharing, and Dixon water–fat separation, provided higher temporal resolution (5 s/time point) while preserving diagnostic image quality, in DCE-MRI of the prostate.

Unlike PI, however, in the CS used in our study, no complementary information is collected. Using a variety of algorithms, medical images can be successfully compressed while preserving diagnostic efficacy, even at compression ratios from 9:1 to 25:1.

Several reports have demonstrated the usability of CS in breast DCE-MRI. The optimization of undersampling acquisition with 2D Gaussian distribution and radial undersampling was conducted by Wang et al. and Chan et al. using retrospectively collected data. Sung et al. and Raja et al. investigated reconstruction methods for solving CS problems. In recent years, studies using prospective data acquisition in clinical settings have begun to be published. Levine et al. proposed the combination of a view sharing method and CS. However, view sharing methods sometimes suffer from artifacts related to the point-spread-function of the undersampling scheme, such as ringing for time-resolved imaging of contrast kinetics. Kim et al. demonstrated the relationship between reconstruction parameters and $K^{\text{trans}}$ using the iterative golden-angle radial sparse parallel (iGRASP) MRI technique. The GRASP technique is a unique method, in which data are continuously acquired for a period of time, and image reconstruction is performed with flexible temporal information, such that multiple user-defined temporal resolutions with distinct numbers and positions of temporal frames can be obtained from the same dataset. In addition to breast imaging, studies using GRASP DCE-MRI have reported positive results for head/neck, cardiac, liver, and prostate imaging.

Nevertheless, CS still has several limitations. First, CS reconstruction as an optimization problem is computationally more demanding than conventional reconstructions and, therefore, needs significant computation time. Most of the reports regarding CS referred to undersampling strategy, the sparsifying transform, and reconstruction parameters (especially the regularization parameter), and there are few reports referring to numerical optimization parameters such as the number of iterations. Needless to say, the reconstruction time is prolonged as the number of iterations increases, so the optimization of the number of iterations is of great importance in clinical practice. In this study, DCE-MRI images reconstructed using 50 iterations required approximately 35 min, which is still too long for a clinical routine. Second, images obtained with a CS reconstruction are strongly dependent on the regularization parameters used in the reconstruction, and furthermore, optimal values can be substantially different between situations, i.e., the target organ and purpose of the imaging (MR angiogram, quantitative imaging, and morphological evaluation of the lesion). The specific values apply only for the specific application in which they have been used and optimized. The challenge most often noted by researchers is the difficulty of selecting parameters to optimize the performance of CS. In the cases where this challenge has been addressed, pilot studies or multiple iterations of image reconstruction were necessary to select parameters such as the sampling pattern, regularization parameter, and sparsifying transform to optimize results.
This study had several limitations. First, few benign lesions were included in this study since the MRI examination was conducted on patients with high suspicion of malignancy based on prior physical examination, mammography, and ultrasound. Second, the optimal reconstruction parameters can be dependent on the purpose of the imaging study and the target organs; therefore, values reported in this study might not be appropriate for different applications. Third, DCE-MRI scans commenced only 1 min after injection of the contrast agent, and total EES volume ($V_t$) was not calculated or evaluated in this study. Fourth, we have no ground-truth DCE-MR images for comparison because the patients underwent a single examination using CS DCE-MRI only.

In conclusion, kinetic parameters using ultrafast DCE-MRI with CS are affected by the number of iterations, especially in malignant regions. However, if the images are reconstructed with an adequate number of iterations, ultrafast DCE-MRI with CS can be a powerful technique having high temporal and spatial resolution.

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Conflicts of Interest

Marcel Dominik Nickel is employed by Siemens Healthcare GmbH, which offered the prototype sequence. The remaining authors declare that they have no conflicts of interest.

References


