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Visually weighted reconstruction of compressive sensing MRI

Heeseok Oh, Sanghoon Lee *

Department of Electrical and Electronic Engineering, Yonsei University, 134 Sinchon-dong, Seodaemun-gu, Seoul 120-749, South Korea

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ABSTRACT

Compressive sensing (CS) enables the reconstruction of a magnetic resonance (MR) image from undersampled data in k-space with relatively low-quality distortion when compared to the original image. In addition, CS allows the scan time to be significantly reduced. Along with a reduction in the computational overhead, we investigate an effective way to improve visual quality through the use of a weighted optimization algorithm for reconstruction after variable density random undersampling in the phase encoding direction over k-space. In contrast to conventional magnetic resonance imaging (MRI) reconstruction methods, the visual weight, in particular, the region of interest (ROI), is investigated here for quality improvement. In addition, we employ a wavelet transform to analyze the reconstructed image in the space domain and fully utilize data sparsity over the spatial and frequency domains. The visual weight is constructed by reflecting the perceptual characteristics of the human visual system (HVS), and then applied to ℓ_1 norm minimization, which gives priority to each coefficient during the reconstruction process. Using objective quality assessment metrics, it was found that an image reconstructed using the visual weight has higher local and global quality than those processed by conventional methods.

1. Introduction

Compressive sensing (CS) has been researched as an innovative method to reconstruct an original signal from a fewer number of measurements than the Nyquist sampling rate, which has led to the evolution of novel CS applications in several areas such as communication, machine learning, and medical imaging [1,2]. In particular, research on image reconstruction techniques for magnetic resonance imaging (MRI) by exploiting CS has been conducted by Lustig et al. [3,4]. They used incoherent undersampling schemes and reconstructed an image by minimizing the ℓ_1 norm of transformed image, subject to data fidelity constraint. Owing to the benefit of CS, it is possible to reconstruct the image with good quality as the full-sampled image, even if fewer measurements than the Nyquist sampling rate are used in k-space. Thus, it is obvious that the computational overhead can be effectively reduced when compared to full sampling.

Such methods have been extensively studied due to their excellent performance despite the use of fewer measurements with a short scan time, which overcomes the weakness of traditional algorithms with a high computational overhead [5]. Nevertheless, the use of a fewer number of measurements than the Nyquist sampling rate for CS leads to problems such as aliasing artifacts in the reconstruction, which is difficult to solve using a simple reconstruction method.

In contrast, when compared to using only the MR image over the spatial domain, it is possible to obtain a reconstructed image with higher quality via CS by utilizing the sparse signal over the transform domain (Table 1).

For this reason, several studies have been performed to investigate effective reconstruction mechanisms so as to achieve higher visual quality after taking the sparsifying transform.

In Gho et al. [6], the authors attempted to improve the quality of a tissue image acquired through double-inversion recovery (DIR) via the contourlet transform as a sparsifying transform for CS reconstruction after reflecting the directionality of the coefficients. However, this method does not deal with spatial or frequency information and thus, it can only be employed for images that have a specific direction. The authors made an effort to increase the overall improvement in quality rather than focusing on partial tissue as the region of interest (ROI) of an image. In Majumdar and Ward [7], the researchers developed an algorithm by utilizing Schatten p-norm minimization for denoising; the quality of the reconstructed images was ultimately improved. However, the applicability of the algorithm is limited for improving the quality of a certain ROI of an image. Currently, it is difficult to find works pertaining to ROI-based image reconstruction using CS, even though such methods have significant advantages in terms of diagnosis, treatment, and examination. To emphasize the superiority of the proposed concept over conventional algorithms, a block diagram of the MR image reconstruction process is depicted in Fig. 1. Through the full sampling process (dotted line), the original reference image x is shown to be reconstructed from the

* Corresponding author.
E-mail address: slee@yonsei.ac.kr (S. Lee).

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Table 1
Parameter description for compressive sensing and MRI reconstruction.

- Compressive sensing
  - y: measurements
  - Ψ_f^{-1}: Fourier transform
  - Φ: sensing matrix (undersampling matrix)
  - x: original image (full sampled)
- MRI reconstruction
  - Ψ^{-1}: sparsifying transform
  - Ψ_w^{-1}: wavelet transform as sparsifying transform
  - w_r: ROI weight
  - w_w: wavelet weight
  - $\hat{x}$: reconstructed image (undersampled)

k-space data. In the full-sampled reference image, various tissues can be seen in the texture representation.

On the other hand, conventional MR image reconstruction is performed through variable density undersampling of the CS, which allows for a significant reduction in the data scan time when compared to full sampling. In the reconstructed image $\hat{x}$ some parts include the tissue region with relatively high frequency so that an aliasing artifact can be observed due to the lack of a sampling rate. In general, since conventional methods attempt to improve the overall quality, there is a limitation to improving the quality of a specific region more locally, which leads to a diagnosis with reduced accuracy. In Fig. 1, an improvement in the quality can be observed in the image $\hat{x}$ reconstructed with the weight via the following sequential steps: variable density undersampling, ROI extraction, visual weight construction, and ROI-based MRI reconstruction with visually weighted CS. Even if a loss in visual quality occurs in the non-ROI region, clearer images of brain tissue can be obtained.

To get a high-quality image on ROI with reduction in imaging time, the inner volume method is introduced in Feinberg et al. [8]. Using the irradiated planes with different flip angles, a spatially limited signal region is selectively constructed from image. This would make possible to obtain a high-quality ROI image without sacrificing image resolution, while achieving reduction of scan time. However, ROI should be decided to reconstruct an image before the scanning by using the inner volume method. Moreover, this ROI in an image cannot be changed when the radiologists need to examine the other tissue. On the other hand, the proposed method in this paper enables to select the ROI from the zero-filling image with undersampling and to improve the quality of image for a certain tissue any time even if an MR image have been scanned.

The main motivation for this work is a reduction in the scan time of an MR image while improving the visual quality of the ROI for medical diagnosis, treatment, and examination. The CS technique is utilized for the undersampling process, and a reconstruction algorithm with the visual weight is derived from the CS measurements. Due to an undersampling that is less than the Nyquist sampling rate, an aliasing effect can be observed in the reconstructed image. Thus, the visual quality of both the ROI (i.e., a particular tissue) and the entire image can be improved by applying the visual weight on the wavelet and spatial domains through optimization. The wavelet transform should be a good tool to analyze the MRI image over the two domains. This advantage can give particular information over the sparse expression of the signal to assess and improve the quality of a reconstructed image [9]. Here, we apply the visual weight to the wavelet domain for reflecting the spatial and frequency characteristics of the human visual system (HVS). We construct an algorithm that applies the visual weight on the wavelet domain to solve the optimization problem for image reconstruction. Furthermore, in the spatial domain, the total variation is taken into account by including the ROI weight to improve the quality of a certain region in an MR image.

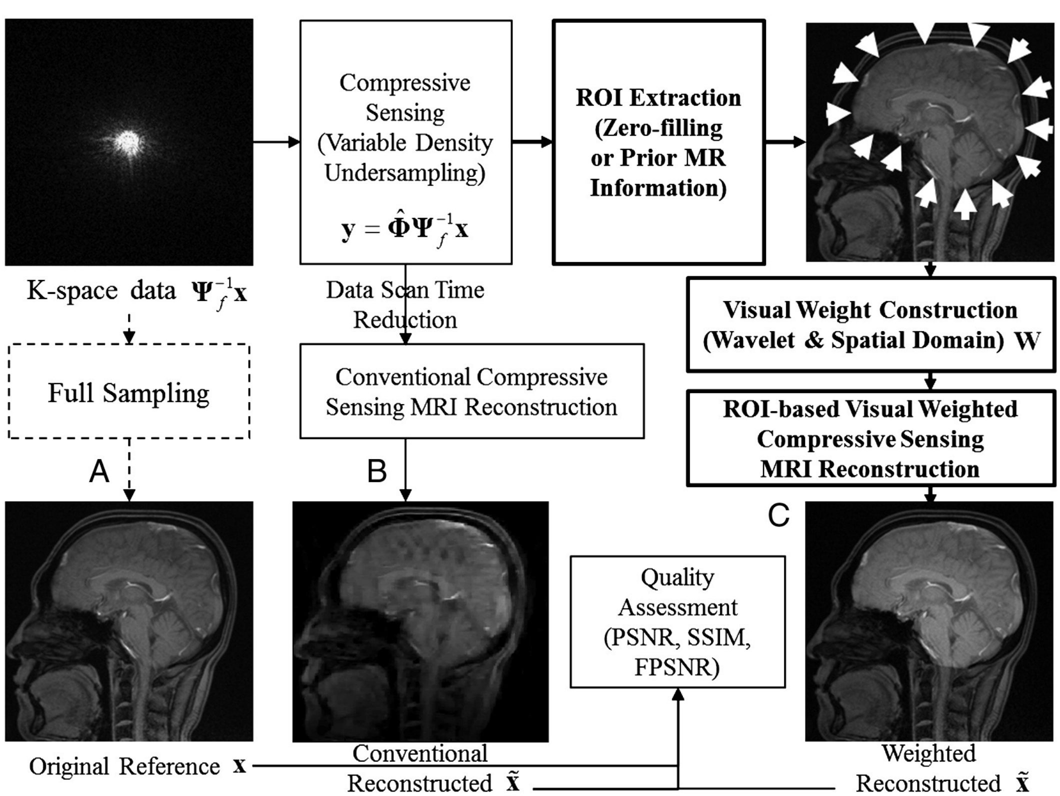

Fig. 1. Outline of the CS MRI. The dashed line denotes general MRI, the solid line represents conventional CS MRI, and the bold line denotes the proposed method of visual weighted CS MRI reconstruction based on the ROI.