Efficient Resolution Enhancement Algorithm for Compressive Sensing Magnetic Resonance Image Reconstruction

Osama A. Omer[1,2(✉)], M. Atef Bassiouny[3], and Ken'ichi Morooka[1]

[1] Graduate School of Information Science and Electrical Engineering, Kyushu University, 744 Motooka, Nishi-Ku, Fukuoka 819-0395, Japan
omer.osama@gmail.com
[2] Department of Electrical Engineering, Aswan University, Aswan 81542, Egypt
[3] Arab Academy for Science, Technology and Maritime Transport, Aswan, Egypt

Abstract. Magnetic resonance imaging (MRI) has been widely applied in a number of clinical and preclinical applications. However, the resolution of the reconstructed images using conventional algorithms are often insufficient to distinguish diagnostically crucial information due to limited measurements. In this paper, we consider the problem of reconstructing a high resolution (HR) MRI signal from very limited measurements. The proposed algorithm is based on compressed sensing, which combines wavelet sparsity with the sparsity of image gradients, where the magnetic resonance (MR) images are generally sparse in wavelet and gradient domain. The main goal of the proposed algorithm is to reconstruct the HR MR image directly from a few measurements. Unlike the compressed sensing (CS) MRI reconstruction algorithms, the proposed algorithm uses multi measurements to reconstruct HR image. Also, unlike the resolution enhancement algorithms, the proposed algorithm perform resolution enhancement of MR image simultaneously with the reconstruction process from few measurements. The proposed algorithm is compared with three state-of-the-art CS-MRI reconstruction algorithms in sense of signal-to-noise ratio and full-with-half-maximum values.

Keywords: MRI · Wavelet transform · Sparsity · Resolution enhancement

1 Introduction

Sparsity has been demonstrated to be a powerful tool in several problems in last years [1]. It has been recognized that it is possible to make a good reconstruction of medical images by exploring sparsity and redundancy of these images. Also, it is known that sparsity is an important structure in MR images. As a good feature of sparse signals, it is well known that sparse signals require fewer samples than required by the Shannon-Nyquist sampling theorem. Therefore, to shorten magnetic resonance imaging (MRI) scanning time, compressed sensing is widely applied in the MRI reconstruction.

On the other hand, there are several approaches for increasing the resolution of MR images. Among these approaches, the problem of super-resolution (SR) reconstruction

V. Murino and E. Puppo (Eds.): ICIAP 2015, Part I, LNCS 9279, pp. 519–527, 2015.
DOI: 10.1007/978-3-319-23231-7_46

has been studied by many researchers in recent years. The SR problem is defined as restoring a high-resolution (HR) image from a sequence of low-resolution (LR) images [6]. The SR approaches have the feature that they don't require high magnetic field's strength which affects human bodies [6]. Nowadays, most MRI scanners used for medical purposes have magnetic field value of 1.5 or 3 Tesla. Most of the super-resolution approaches are formulated as a post-acquisition image processing techniques.

Although there is doubt that SR is not achievable in MRI [7, 8, 9], since the Fourier encoding scheme excludes aliasing in frequency and phase encoding directions, simulation results show that SR techniques can achieve resolution enhancement in MRI [10-14].

Reconstruction of HR MR image from a few samples is still challenging task in MRI reconstruction. This paper proposes a new method for enhancing the resolution for MRI using resolution enhancement technique using multi-sparse measurements. Like the work done in [12], the resolution enhancement is done simultaneously with the reconstruction process rather than being done as a post-process. However, in this paper the simultaneous resolution enhancement and reconstruction is adopted with the compressed sensing which combines wavelet sparsity with the sparsity of image gradients, where the magnetic resonance images are generally sparse in wavelet and gradient domain.

2 Sparsity of MRI Reconstruction

Compressed sensing focuses on reconstructing an unknown signal from a very limited number of samples. Because information such as boundaries of organs is very sparse in most MR images, compressed sensing makes it possible to reconstruct the same MR image from a very limited set of measurements while significantly reducing the MRI scan duration. In the literature, compressed sensing MRI algorithms minimize a linear combination of total variation and wavelet sparsity constrains [3, 4, 5].

TVCMRI: In [3], Ma et al. proposed the method jointly minimizing the L1 norm of the image, total variation (TV) of the wavelet coefficients, and the least squares of the error as a solution for CS-MRI. This algorithm is based upon an iterative operator-splitting framework. The cost function proposed in [3] is formulated as

$$J(y) = \left\|\mathbf{R}y - b\right\|_2^2 + \alpha\left\|\mathbf{\Phi}y\right\|_{TV} + \beta\left\|y\right\|_1 \tag{1}$$

where **R** is a matrix representing the partial Fourier transform, y is the MR image to be reconstructed, b is the measured data in k-space, **Φ** is a matrix representing the wavelet transformation β, α are positive weighting parameters and $\|y\|_{TV} = \sum_i \sum_j \sqrt{\left(\nabla_1 y_{ij}\right)^2 + \left(\nabla_2 y_{ij}\right)^2}$, where ∇_1, ∇_2 are the forward difference operators, of a variable *y*, on the first and second coordinates, respectively.

FCSA: In [4], Huang et al. proposed to jointly minimizes the L1 norm of the wavelet coefficients, total variation (TV) of the image, and a least squares of the error as a solution the for CS-MRI. The cost function proposed in [4] is formulated as

$$J(y) = \|\mathbf{R}y - b\|_2^2 + \alpha\|y\|_{TV} + \beta\|\mathbf{\Phi}y\|_1 \tag{2}$$

The minimization of TV(y) leads to sparsity of the gradient of y, which is the case of MR images, while minimizing $\|y\|_1$ leads to sparsity of y, which is not the case of MR images. Therefore, minimization of (2), which leads to sparsity of image gradient and sparsity of wavelet coefficients of the image, leads to better results compared to minimization in (1), which leads to sparsity of gradients of wavelet coefficients and sparsity of images values, as will be shown in simulation results.

WaTMRI: In [5], the quad-tree sparsity constraint is combined with the sparsity of wavelet coefficients and sparsity of gradient image. The cost function of this algorithm is formulated as

$$J(y) = \|\mathbf{R}y - b\|_2^2 + \alpha\|y\|_{TV} + \beta\left(\|\mathbf{\Phi}y\|_1 + \sum_{g\in G}\|\mathbf{\Phi}y_g\|_2\right)$$

where G indicates the set of all parent-child groups and y_g is the data belonging group G.

CS-MR imaging is interested in low sampling ratio. In [3,4,5], authors follow the sampling strategy that is randomly choose more Fourier coefficients from low frequency and less on high frequency.

3 Sparsity-Based HR MRI Reconstruction

Inspired by the success of the minimization of L1-norm and TV in CS-MRI reconstruction, we design the reconstruction of HR CS-MRI by fusing multi measurements in the proposed HR CS-MRI reconstruction model. In the proposed model called CS-MRISR, we propose to penalize the least square of error measure, sparsity of wavelet coefficients and sparsity of gradient image. The proposed cost function is formulated as

$$J_2(y) = \sum_{k=1}^{N}\left[\|\mathbf{RDBF}_k y - b_k\|_2^2\right] + \alpha\|y\|_{TV} + \beta\|\mathbf{\Phi}y\|_1 \tag{3}$$

where **D** is the sampling operator, **B** is the blurring operator and $\mathbf{F}_k$ is the warping operator for k-th image. It is commonly assumed that the point spread function (PSF) induced by the MRI acquisition process is space-invariant, so that we used the same operator ***B*** *for all images.*

To fasten the proposed algorithm, we utilize the composite splitting algorithm [15]; 1) Splitting variable y into two variables x and z, 2) Performing operator splitting over each of the two variables independently, and 3) Obtaining the solution y by linear combination of z and x. Therefore, the optimization problem can be divided into three sub-problems that alternatively solved;

1. Minimize least square problem:

$$\widehat{y} = \arg\min_{y} \sum_{k=1}^{N} \frac{1}{2} \left[\left\| \mathbf{RDBF}_k y - b_k \right\|_2^2 \right] \tag{4}$$

2. De-noising:

$$\widehat{x} = \arg\min_{x} \left\{ \frac{1}{2} \left\| x - \widehat{y} \right\|_2^2 + \alpha \left\| x \right\|_{TV} \right\} \tag{5}$$

3. Sparsity constraint in the wavelet domain

$$\widehat{z} = \arg\min_{z} \left\{ \frac{1}{2} \left\| z - \widehat{y} \right\|_2^2 + \beta \left\| \mathbf{\Phi} z \right\|_1 \right\} \tag{6}$$

The reconstructed MR image is the weighted sum of the de-noised term and the constrained wavelet coefficients

$$y = \frac{\widehat{z} + \widehat{x}}{2} \tag{7}$$

Finally, at each iteration, values of y are projected in the reasonable range of MR images which is [0,255] for 8-bit MR images. The convergence of the proposed algorithm is guaranteed as the cost function is convex. Note: even if the MR imaging is dominated by Rician noise, other types of noise appear while fusing multiple LR measurements, including shifting error and blurring operator modelling error. The shifting error is modelled in the literature by Laplacian noise [16], while the blurring operator modelling error is better modelled by Gaussian noise, therefore, we implicitly modelled the overall contaminating noise by Gaussian noise.

4 Simulation

4.1 Setup

In the simulation, we used 4 low-resolution (LR) measurement data that are sensed from 128 × 128 positions. The resolution enhancement factor is used as 2 in each direction. The relative shift of the simulated object to generate LR measurements is assumed to be known. The fewer measurements we samples, the less MR scanning time is need. So MR imaging is always interested in low sampling ratio cases. The sampling ratio is fixed to be approximately 20%. We follow the sampling strategy of previous works [3, 4, 5]. All measurements are mixed with 0.01 white Gaussian noise. We conduct experiments on two images, namely, “Synthetic Image” and “Brain Image”. For fair comparison, the comparison with other algorithms is done with the same forward imaging operator.

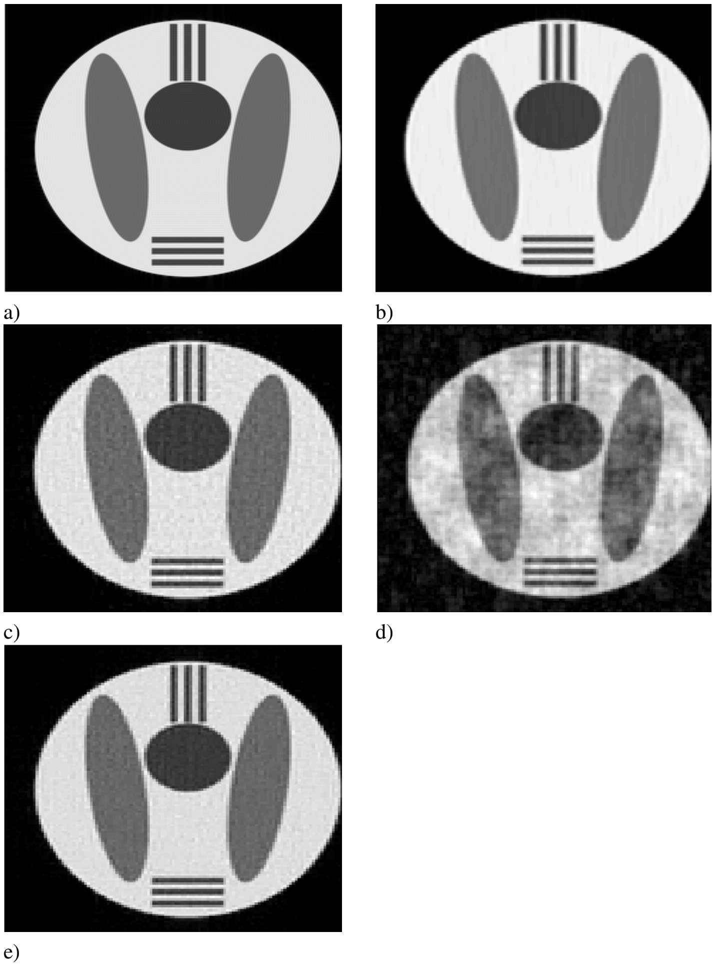

Fig. 1. Original test image #1, b) Proposed CS-MRI reconstruction c) LR FCSA-based MRI reconstruction, d) LR TVC -based MRI reconstruction, e) LR WaTMRI reconstruction

4.2 Simulation Results

The proposed CS-MRISR is compared with the following methods; 1) total variation L1 Compressed MRI (TVCMRI [3]), 2) Fast Composite Splitting Algorithm (FCSA [4]) and 3) Wavelet Tree Sparsity MRI (WaTMRI [5]). To evaluate these algorithms SNR, full-width-half-maximum (FWHM) and visual results are used.

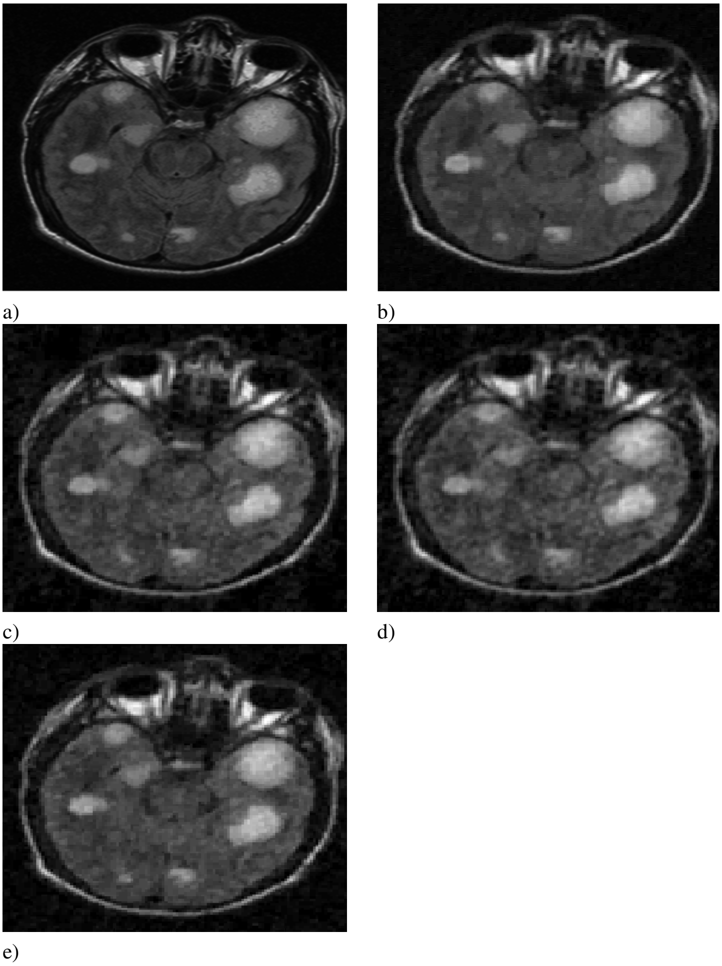

Fig. 2. a) original test image #2, b) Proposed CS-MRI reconstruction c) LR FCSA-based MRI reconstruction, d) LR TVC -based MRI reconstruction, e) LR WaTMRI reconstruction

4.3 Visual Comparisons

Figure 1a shows the original phantom image. The reconstructed MR image using the proposed algorithm is shown in Fig. 1b. The reconstructed MR images using algorithms FCSA, TVCMRI and WaTMRI are shown in Figs. 1c, 1d and 1e, respectively.

From these figures we can see that the proposed resolution enhancement algorithm improves the quality of the CS- MR image (see Fig. 1b) compared to the conventional CS-MRI algorithms (see Figs. 1d and 1e).

The results of the other experiment are shown in Fig. 2. This example confirm the results in the first example, that is the proposed algorithm can enhance the quality of the CS-MRI compared to the reconstructed LR MR images using algorithms FCSA, TVCMRI and WaTMRI.

4.4 Objective Results

The FWHM values for the PSF function of the reconstructed MR images is shown in Fig. 3. From this figure it can be shown that the proposed algorithm results in low FWHM value which indicate higher resolution compared CS-MRI reconstruction algorithms proposed in [3,4,5].

Another measure for the quality that can demonstrate the efficiency of the proposed algorithm is shown in Table 1. This table can show the higher SNR for the proposed algorithm compared to CS-MRI algorithms. For fair comparison, the reconstructed MR images by using algorithms in [3], [4] and [5] are interpolated to be compared with the original HR images. The plot of cost function versus iteration number is shown in Fig. 4 which can show the convergence of the proposed algorithm. In this figure, the maximum number of iteration is used as the stopping criteria.

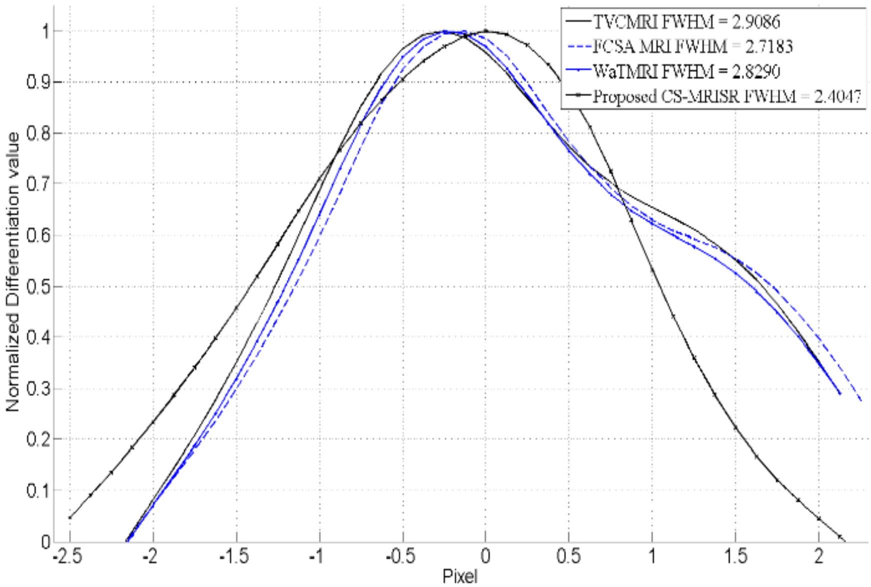

Fig. 3. FWHM comparison for the CS-MRI algorithms

Table 1. SNR comparison for different CS-based MRI reconstruction algorithms

	TVCMRI [3]	FCSA [4]	WaTMRI [5]	**Proposed**
IMAGE#1	12.0783	15.7975	15.9910	**16.3744**
IMAGE#2	10.3166	11.4029	11.9797	**12.4043**

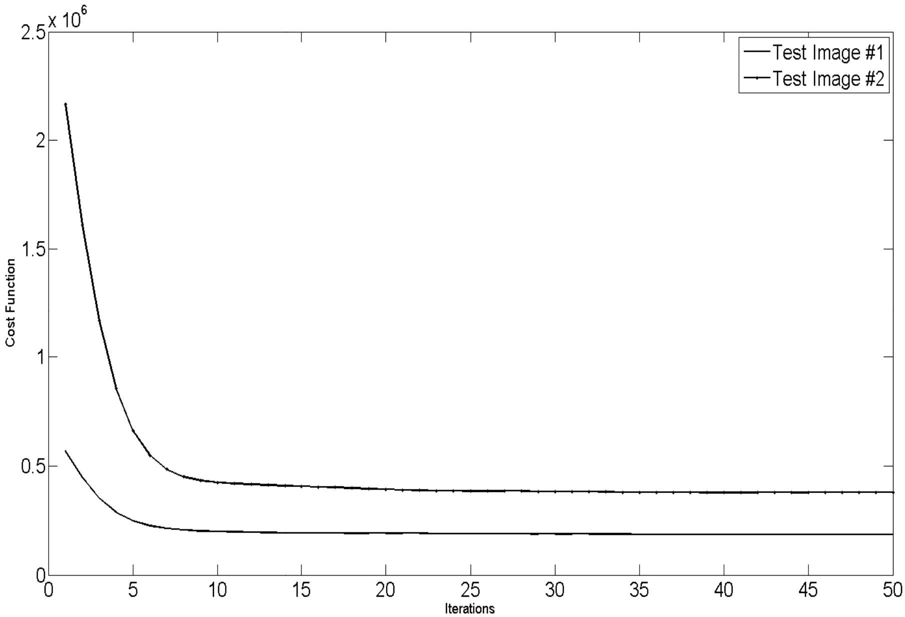

Fig. 4. Convergence of the proposed algorithm

5 Conclusion

We proposed a CS-MRI reconstruction algorithm that reconstructs a HR MR image from multi LR measurements. The proposed algorithm adopts the idea of compressed sensing with the resolution enhancement algorithm. The proposed algorithm reconstructs the HR MRI directly from the LR measurements. Based on the simulation results, the proposed algorithm can efficiently reconstruct MR images from very low samples, with sampling ratio about 20%. The proposed algorithm outperforms three state-of-the-art CS-MRI reconstruction algorithms in sense of SNR, FWHM and visual results. The proposed algorithm outperforms the state-of-the art algorithms because of the fusion of multiple LR measurements.

References

1. Donoho, D.: Compressed sensing. IEEE Trans. on Information Theory **52**(4), 1289–1306 (2006)
2. Lustig, M., Donoho, D., Pauly, J.: Sparse MRI: The application of compressed sensing for rapid MR imaging. Magnetic Resonance in Medicine **58**(6), 1182–1195 (2007)
3. Ma, S., Yin, W., Zhang, Y., Chakraborty, A.: An efficient algorithm for compressed MR imaging using total variation and wavelets. In: Proc. of the IEEE Computer Society Conf. on Computer Vision and Pattern Recognition (2008)
4. Huang, J., Zhang, S., Metaxas, D.: Efficient MR Image Reconstruction for Compressed MR Imaging. Medical Image Analysis **15**(5), 670–679 (2011)
5. Chen, C., Huang, J.: Compressive sensing MRI with wavelet tree sparsity. In: Proc. of the 26th Annual Conference on Neural Information Processing Systems (NIPS), Nevada, USA, December 2012
6. Van Reeth, E., Tham, I.W.K., Tan, C.H., Poh, C.L.: Super-resolution in magnetic resonance imaging: A review. Concepts in Magnetic Resonance Part A **40A**(6), 306–325 (2012)
7. Scheffler, K.: Superresolution in MRI? Magnetic Resonance in Medicine **48**, 408 (2002)
8. Peled, S., Yeshurun, Y.: Superresolution in MRI – Perhaps sometimes. Magnetic Resonance in Medicine **48**, 409 (2002)
9. Uecker, M., Sumpf, T.J., Frahm, J.: Reply to: MRI resolution enhancement: how useful are shifted images obtained by changing the demodulation frequency? Magnetic Resonance in Medicine **66**, 1511–1512 (2011)
10. Tieng, Q.M., Cowin, G.J., Reutens, D.C., Galloway, G.J., Vegh, V.: MRI resolution enhancement: how useful are shifted images obtained by changing the demodulation frequency? Mag. Res. in Medicine **65**, 664–672 (2011)
11. Peled, S., Yeshurun, Y.: Superresolution in MRI: Application to human white matter fiber tract visualization by diffusion tensor imaging. Magnetic Resonance in Medicine **45**, 29–35 (2001)
12. Omer, O.A.: High Resolution Magnetic Resonance Image Reconstruction in K-Space. ICIC Express Letters, Part B: Applications **5**(6), 1659–1666 (2014)
13. Plenge, E., Poot, D.H.J., Bernsen, M., Kotek, G., Houston, G., Wielopolski, P., et al.: Super-resolution reconstruction in MRI: better images faster?. In: Haynor, D.R., Ourselin, S., (eds.) SPIE Medical Imaging, vol. 8314. SPIE Press, Bellingham, P83143V (2012)
14. Scherrer, B., Gholipour, A., Warfield, S.K.: Superresolution reconstruction to increase the spatial resolution of diffusion weighted images from orthogonal anisotropic acquisitions. Medical Image Analysis **16**, 1465–1476 (2012)
15. Beck, A., Teboulle, M.: A fast iterative shrinkage-thresholding algorithm for linear inverse problems. SIAM Journal on Imaging Sciences **2**(1), 183–202 (2009)
16. Farsiu, S., Robinson, M.D., Elad, M., Milanfar, P.: Fast and Robust Multiframe Super-resolution. IEEE Trans. on Image Processing **13**(10), 1327–1344 (2004)