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MRI Image Reconstruction using Compressive Sensing

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Abstract--- A large number of diagnostic images which also include the MRIs are generated by the imaging departments of the hospitals for medical and legal reasons. This results in the creation of a huge amount of data in the form of images which are required to be stored for a long period. The primary challenge for the picture archiving and communication systems (PACS) allowing to store the image data and the display and reconstruction of the image for recalling at various sites. Image compression and reconstruction are necessary to cope up with these tasks. Significant efforts have been made in the recent towards the application of compressive sensing techniques for acquiring the data in MRI process. The primary aim of the theory of Compressive Sensing (CS) in signal processing is reducing the quantity of data that is acquired for successfully reconstructing the signals. Decreasing the number of coefficients of the acquired images will result in reduced acquisition time i.e. nothing but the duration for which the images are exposed to the MRI apparatus. This paper aims at using optimization algorithms in designing the scanner of the MR integrated with the CS, which results in the reduction of the scan time of the MRI. From a small set of acquired samples, images of satisfactory quality can be obtained. Various Compressive Sensing based optimization algorithms for reconstructing the MRI images are assessed, and a relative comparison is done for further research in this paper.

Keywords — Compressive Sensing(CS), Magnetic Resonance Imaging (MRI), Image compression, Image reconstruction, K-space.

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is an advanced and non-intrusive medicinal imaging procedure and diagnostic device for visualising the images of the different structures and organs like lungs, cardiac, bonds of the body (Fessler et al., 2010; Finn et al., 2006). Generally, the MRI takes quite some time for collecting the information about the body conditions of the patients which has an adverse effect on their physical health. Additionally, if the number of samples considered is large it will result in complicated real-time analysis and requirement of higher storage capacities (Jelena 2015; Otazo et al., 2012).

The scanners of MRI furnish data that are spatial Fourier transform samples Magnetic resonance (additionally referred to as k-space) of the object which is being investigated. (Guerquin-Kern et al., 2011, (Majumdar et al., 2011). The samples of k-space for every time frame is compiled and hence the raw data will be in k-t space. The main issue is the reconstructing each of the time frames so that it results in an MRI video (x-t space). The physics of its hardware limits the speed of acquiring the data in the MRI scanner. Generally, if the number of samples in k-space compiled for every time then the time frames which can be obtained is small and vice versa (Majumdar et al., 2012). Accelerating the process of acquisition in all the applications of MRI is of considerable significance. The recently proposed theory of (CS) indicates that the compressible or sparse signals can be reconstructed with the help of random measurements with the sparsity basis (Wiaux et al., 2010). MRI complicates the real-time analysis by having a large number of samples and needs large storage capacities. The findings in the recent researches of signal processing show the possibility for recovering a signal utilising a small quantity of information which is collected. Depending on this the sampling rate which is considerably lower than that of Nyquist rate can be achieved without compromising on the quality. This technique can be applied for 1D as well as 2D signals (Jelena, 2015). The main aim of Compressive Sensing is reducing the amount of acquired data needed for successfully reconstructing the signals. Reducing the number of coefficients of the obtained image results in lower time for acquiring the images (Wang et al., 2014). MRI requires two essential conditions for successfully applying CS: 1) The sparse coding in the domain of right transform can be used for naturally compressing images of the medical field. and 2) The encoded samples are directly retrieved by the MRI scanners instead of the direct pixel samples (Nan et al., 2015). CS-MRI reported an acceleration factor amid 3 and 6 for acquiring the images which have resulted in the application of novel imaging techniques (Kim et al., 2009).

1.1 CS MRI reconstruction methods

The recent years have seen the development of various techniques for enhancing the quality of reconstruction CS MRI (Yang et al.; 2015, Yeh et al., 2005; Jelena, 2015). These approaches can be commonly bifurcated in three ways.

1. Structuring arbitrary k-space samplings, for example, k-space sampling of the variable density, and arbitrary sampling was an effective technique, yet artefacts are hard to recognize from genuine signals at larger factors of reduction.

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2. A second methodology was to utilize a scope of sparsity bases in spatial and temporal measurements to give adequate sparsity in order to faithfully reconstruct utilising the subset of the biggest transform coefficients.

The Walsh transform, discrete wavelet change, curvelet change, Walsh change, discrete wavelet transform, curvelet transform, were generally utilized as sparsity transforms. Nonetheless, without adequate k-space information, the sparse coefficients which were transformed from sampling signals were unable to represent the original image thus degrading the quality of the images which were reconstructed.

3. The third class involves techniques of optimisation, for example, the focal underdetermined framework arrangement, conjugate slopes for recovering the nonlinear signals. In these techniques, a basic regularization method was ordinarily used to adjust the sparsity of the entire image, with respect to the required consistency of the data. But a single threshold may not satisfy the two conditions at the same time hence influencing the accuracy of the final reconstruction, particularly for high reduction factors.

The techniques based on CS will reconstruct the images by building a nonlinear optimization problem which exploits the sparsity of the MRI in the transform domains of contour or wavelet. A novel approach for evaluating the reconstruction of MR images from k space data which is sub sampled instead of applying the techniques based on CS, the accuracy of reconstruction was accomplished by the exploitation of the rank deficiency of the image (Majumdar et al., 2011).

II. COMPRESSED SENSING

The theorem of Nyquist–Shannon sampling builds up a satisfactory criteria at which the reconstruction of the signal can be achieved without any doubt from the set of measurements. In MRI, a 2D image represents the 2D signal, while the 3D image and series of 2D dynamic images represent the 3D signals(Feng et al., 2017).

The Nyquist criterion is nothing but a data intensive, time-consuming, which poses a challenge for storing, and transmitting data in various applications. Compression of signals has been extensively utilised in JPEG2000, MPEG and JPEG. The compressed form of the data can be acquired at a lower sampling rate rather than sampling the signals at the rate of sampling which is higher and later cancelling out the unwanted coefficients. In simpler words, since the data present in any signal is lesser than the required number of coefficients for completely characterising the arbitrary signal, the compression and data acquisition processes can be integrated directly in order to sample the given signal at its information rate rather than that of Nyquist. Sparsifying transformation is used for compressing the images which are a result of the post-compression and standard sensing techniques for acquiring the data that is completely sampled. The compression of this kind does not result in reduced acquisition time. However, the techniques of CS randomly acquire a subset of measurements and eliminate undersampling artefacts in the reconstruction stage (Feng et al., 2017; Gamper et al., 2008).

CS was first proposed in a general abstract setting in the literature of Information Theory and Approximation Theory by Donoho and Cande`s et al. (2006) and was deciphered into MRI by Lustig et al., (2007). A few random linear combinations which are comparitively smaller than the number of samples of the signal values were measured and reconstructed with reasonable precision from these measurements with the help of a nonlinear process. The CS technique requires: (a) the ideal picture have a sparse portrayal in a known transformation domain (b) the associating artefacts because of k-space undersampling be indistinguishable (commotion like) in that transformation domain. (c) a reconstruction which is nonlinear may be utilized for enforcing both sparsity of the picture portrayal and consistency with the obtained information (Michael Lustig et al., 2007)

III. RESULTS & DISCUSSIONS

MRI is a technique that provides images of high-quality with an aid of intrinsic magnetic properties in matter. It is a non-invasive technique for obtaining the images of the internal parts in a body with high-resolution. This capability of the MRI has made it an indispensable clinical diagnosis tool for diagnosing of various diseases, that range from small injuries to multiple sclerosis.

At the point when an individual is put in an MRI scanner, material components react to the magnetic field as indicated by its magnetic vulnerability, that is a proportion of how polarized it is. Three essential classes of items concerning magnetic vulnerability: ferromagnetic, diamagnetic, and paramagnetic are present. The diamagnetic materials react by creating a small attractive field in the opposite direction of the magnetic field which is applied and these substances cannot be magnetised at all (for example plastic). The materials which are paramagnetic in nature are magnetisable, however just for the period for which magnetic field is present. Ferromagnetic materials are firmly attracted into an attractive field - and are magnetised permanently, for example, lodestone (Revett, 2011).

3.1 Nuclear magnetic resonance physics

NMR basically depends on the behaviour of the particular nuclei established in strong magnetic field which is static and additionally exposed to oscillating magnetic fields, the energy from this magnetic field is absorbed by the individual atoms with a condition that the energy level is the rate one for the specific atom. When the secondary magnetic field which also oscillates is turned off, then atoms present within the sample releases packets of energy, that can be identified with the help of an appropriate receiver. which is detected using an appropriately designed receiver. Along these lines, the samples are examined to decide whether the specific atom exists in the material sample, and furthermore, the amount can also be decided (Revett, 2011).

NMR is an anomaly dependent on the quantum mechanics, and magnetic properties of the nucleus of the atom. Angular momentum and magnetic moment which consist of neutrons and protons in odd numbers are present in all the nuclei.

The equation of Larmor precession frequency indicates that for a specific substance the resonant frequency of the NMR is directly related to the intensity of the magnetic field which is applied.

The NMR will examine the nuclei by their alignment along with the constant magnetic field that is applied (Govil et al., 2008).

The protons, are those where the molecules of water aid in the generation of MRI signals. A robust static field parallel to the static field polarizes the protons, resulting in the net magnetic moment orientation. The Excitation field produces a component of magnetization m transverse to the static field by applying a radio frequency (RF). This magnetization angle varies cyclically at the frequency which is proportional to the static field strength. Transverse component m(r) of the processing magnetization will emit the radio frequency signal that can be identified by the receiver coil. The reconstruction of the MR image makes an effort in visualising the transverse magnetization m(r), describing the spatial distribution of the transverse magnetization (Lustig et al., 2008) Image acquisition.

The framework of an MRI has various components with an assortment of RF transmitters/ receivers, super paramagnetic magnets, pulse sequence and a control centre based on computers. The sequences of pulses is based on the software system which allows the creation of specific kinds of scanned images depending on the parameters which control the working of the hardware parts by the radiologists. Around 10-20 minutes is usually required for a scan based on the diseases or conditions under investigation (Revett, 2011).

Construction of one single MR image primarily involves the grouping of the series of frames. Exciting the RF signals will result in the production of transverse magnetisation in each acquisition, that is later sampled along the specified trajectory in k-space. The techniques of MRI imaging generally use the sequence of acquired images which sample the k-space mainly because of the different physiological and physical constraints. The information from this sequence of acquired images is utilised for reconstructing the image. The 'slice' represents in the region of the body which is scanned. In MRI, a selectively thin slice can be excited through the 3-D volume which helps in the reduction of collected data to 2D in k-space for every slice.

3.2 Rapid imaging

Conventional spin-warp MRI is a relatively slow technique due to the collection of N x N image that needs to be repeated in the sequence N times to fill up every line of k-space. The total scan time would be N x TR where TR is the sequence repetition time. In order to bring down scan time either N or TR (or both) have to be reduced. N was reduced by collecting more than a single line of k-space per repetition. Sequence repetition time can be reduced by using a low flip angle or by either dephasing or recycling transverse magnetisation after each repetition. The acquisition of MR is a procedure of navigating curves in multidimensional k-space in which the physical imperatives restrict the k-space traversal speed (Lustig et al., 2008)

3.3 Spatial encoding

When the receiver coil is placed next to the object then current in the coil is induced by transverse magnetization. If the coil of the receiver is put next to the object then current is induced in the coil by transverse magnetization. The spatial encoding will vary the phase and frequency with respect to the volume for each measurement such that the initial distribution of magnetization can be retrieved from integrals. This is the integral of the magnetization over the entire volume. (Polina, 2010). In the MR signals, the spatial information can be encoded by the superimposition of the extra magnetic fields on the static fields which are strong (Lustig et al., 2008).

IV. APPLICATIONS OF COMPRESSED SENSING TO MRI

4.1 Rapid 3-D Angiography

In MR angiography, short scan times obtained due to breath-holding or contrast passage which make difficult to acquire adequate spatial resolution. In conventional FT acquisitions, increasing key resolution proportionally increases scan time. Imaging time is decreased for a fixed pixel size if the FOV is reduced (Peters et al., 2000)

Angiography is a significant technique for diagnosing vascular disease. In angiography, the dynamics of contrast agent bolus consists of the critical diagnostic data. In order to capture the dynamics of high temporal and spatial resolution in a large field of view is required. Angiograms are characteristically sparse in representing the pixels. The requirement for high temporal and spatial resolution firmly supports under sampling. CS enhances the existing techniques by considerably reducing the facts that come about because of under sampling. MR angiography is quickened by CS, empowering superior temporal resolution and furthermore enhancing the goals of existing symbolism without a compromise on the time required for scanning. Majority of the artefacts which emerge during the linear reconstruction from under sampled data is avoided by the nonlinear reconstruction in CS (Lustig et al., 2008).

4.2 Whole-Heart Coronary Imaging

The high-resolution imaging becomes challenging due to the fact that the coronary arteries are always moving. The impact of the heart can be reduced by the synchronisation of the acquisitions in the cardiac cycles. The impact of inhalation and exhalation can be limited by following and adjusting the respiratory movement or by just imaging amid a short breath-hold interim. Nonetheless, breath-held cardiovascular activated methodologies face severe constraints with respect to timing and extremely short imaging windows. In the period of breath hold the acquisition is restricted to the cardiac cycle number. CS can enhance the process of acquiring the data, enabling the imaging of the whole heart in a solitary held breath. Reconstruction using CS suppresses the interference induced without compromising on the quality of the image (Lustig et al., 2008).

Coronary magnetic resonance angiography (MRA) is now performed mostly as a whole heart, free breathing, three-dimensional study.

Several factors influence the quality and speed of the scan like the use of the appropriate pulse sequence, cardiac and respiratory gating, preparation pulses, multi-channel cardiac coils, parallel imaging, and contrast material injection. (Kawaji et al., 2015)

4.3 Brain Imaging

The classic applications of MRI are the brain scans. 2-D Cartesian multi slice acquisitions are used in most brain scans. “The Compressibility/Sparsity of MRI” exhibit that images of the brain in the wavelet domain transform sparsity.. The idea of CS is promising in reducing the time required for collecting data while enhancing the resolution of the images. The CS considerably improves the resolution along with the time required for scanning and also suppresses the aliasing artefacts when compared to the linear reconstruction (Lustig et al., 2008)

4.4 K-T Sparse: Application to Dynamic Heart Imaging

The temporal and spatial necessities of the Nyquist criterion complicates the dynamic imaging for the objects which move. Two experiments using motion phantom, synthetic data, periodically varying in a cartoon of heart motion and acquiring the dynamic real-time motion of the heart results in temporal blurring and artefacts in the convention image that is reconstructed. The dynamic sequence of a larger rate of 25 frames per second with a considerable reduction in the image artefact was achieved with the help of CS reconstruction and random ordering (Lustig et al., 2008).

V. COMPRESSED SENSING MRI RECONSTRUCTION-RELATED WORK

The reconstruction of MRI based on CS have been carried out in many works (Majumdar et al., 2012; Wiaux et al., 2010; Yang et al., 2015; Lustig et al., 2007; Feng et al., 2017; Ma et al., 2008; Zhang et al., 2015; Otazo et al., 2012; Wang et al., 2014; Gamper et al., 2008). In which Jelena, 2015 has also given an overview of the most used 3 algorithms of optimisation for reconstructing the MRI images such as RecpF, SALSA and TwIST; and have given results of these three with a comparison to each other. Feng et al., 2017 presented a study on the various methods of compressed sensing techniques that were applied in MRI and evaluated the importance of MRI reconstruction in terms of sparse structure and relatedness. They have explained the basic CS MRI concept and provided an overview of future challenges and opportunities of CS in body MRI.

Optimization based CS MRI reconstruction works

Bioucas-Dias et al., 2007 have proposed a new class of iterative technique referred to as TwIST, which has the form of two-step iterative shrinkage/thresholding (TwIST) algorithm. It Restored MRI utilising an algorithm (with two steps) wherein all the estimates rely on the two prior estimates rather than just the prior one and converges much faster than the original IST. The drawback is that it could not solve the issue with both the TV and regularization terms and sensitive concerning iteration numbers and CPU time consumed. Ma et al., (2008) developed an algorithm based on Operator Splitting (OS), which minimizes the norm of L1, the least squares measure and total variation for the recovery of MR images from measurements that are small in number. ReconstructionMR images from a subset which is a representation of a mere 20% of the whole set of measurements is carried out and it takes more CPU time to attain relative error.

Yang et al., 2010 developed a Reconstruction from Partial Fourier algorithm, in which for every iteration RecPF adds shrinking and FFT. It achieved much higher performance with respect to reconstruction speed and quality than TwIST and OS but has algorithmic complexity. Afonso et al., 2011 presented an algorithm which depended on the method of variable splitting in order to obtain an augmented Lagrangian technique. The algorithm is suitable for all types of convex regularizers and is therefore used for more general purpose than some of the available methods which are available only for TV regularization. But, in case of image deconvolution issues along with orthogonal wavelets, a longer time is taken in order to obtain the solution. Guerquin-Kern et al., 2011 and Kowalski et al., 2014 proposed an Iterative shrinkage-thresholding algorithm (ISTA) for minimizing functionals which are not smooth with constraints of sparsity effectively and this algorithm have no parameter other than the relaxation parameter. But it estimated the large coefficients in a biased manner with convergent rate that is slow. Zhang et al., 2015 presented a fast iterative shrinkage-thresholding algorithm (FISTA), which optimizes by the addition of the Haar wavelet transform to the MRI images and the algorithm was found to be stable but it can slow down significantly and the performance regarding oscillatory behaviour is not good.

The range of Sparsity-based:

Gamper et al., 2008 presented a dynamic nonlinear CS MRI reconstruction method for reducing the duration of scan by opting less K-space data; the concept is used in further works by Wang et al., 2014 and Majumdar et al., 2012. Majumdar et al., 2012 proposed a fast temporal differencing scheme for dynamic MRI reconstruction of real-time applications using the online scheme. A difference image is reconstructed from the time frame between the present and past frame. Then reconstructing the total image, whereas Wang et al., 2014 studied CS dynamic MRI reconstruction depended on the patch-based 3-D spatiotemporal dictionary for representing sparse data of the dynamic sequences of the image in the structure of the CS representations of the dynamic image sequence.

K-space sampling based

Yeh et al., 2005 presented a Parallel MRI scheme with k-space adaptive radius (PARS) for reconstructing MRI , in which an encoding matrix was generated locally and inverted to reconstruct the data which has been omitted for all missing k-space till complete reconstruction of data set was done. It offered both numerical stability as well as efficient inversion of encoding matrix.

VI. CONCLUSION

Over recent years, the MRI reconstruction techniques based on CS have successfully reconstructed the images from subsample K-space measurements. The researcher's goal is to obtain the most reliable and quickest CS technique from the smallest possible number of samples. The eventual aim is designing an MR scanner integrated with CS, which results in reduced scan time. In this paper, Compressed sensing based MRI reconstruction for biomedical applications were reviewed and CS techniques such as TwIST, ISTA, FISTA etc., were compared for further research development.

REFERENCES

1. Bi, D. J., Le Xie, Y., Ma, L., Xie, X., & Niu, P. (2015, November). A comparative study of compressed sensing approaches with splitting Bregman framework for radial UTE MRI. In Applied Superconductivity and Electromagnetic Devices (ASEMD), 2015 IEEE International Conference on(pp. 39-41). IEEE.
2. Jelena, B. (2015, June). Comparison of algorithms for compressed sensing of magnetic resonance images. In Embedded Computing (MECO), 2015 4th Mediterranean Conference on (pp. 303-306). IEEE.
3. Guerquin-Kern, M., Haberlin, M., Pruessmann, K. P., & Unser, M. (2011). A fast wavelet-based reconstruction method for magnetic resonance imaging. IEEE transactions on medical imaging, 30(9), 1649-1660.
4. Majumdar, A., Ward, R. K., & Aboulnasr, T. (2012). Compressed sensing based real-time dynamic MRI reconstruction. IEEE Transactions on Medical Imaging, 31(12), 2253-2266.
5. Wiaux, Y., Puy, G., Gruetter, R., Thiran, J. P., Van De Ville, D., & Vandergheynst, P. (2010, April). Spread spectrum for compressed sensing techniques in magnetic resonance imaging. In Biomedical Imaging: From Nano to Macro, 2010 IEEE International Symposium on (pp. 756-759). IEEE.
6. Yang, Y., Liu, F., Xu, W., & Crozier, S. (2015). Compressed sensing MRI via two-stage reconstruction. IEEE Transactions on biomedical engineering, 62(1), 110-118.
7. Lustig, M., Donoho, D., & Pauly, J. M. (2007). Sparse MRI: The application of compressed sensing for rapid MR imaging. Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine, 58(6), 1182-1195.
8. Lustig, M., Santos, J. M., Lee, J. H., Donoho, D. L., & Pauly, J. M. (2005). Application of compressed sensing for rapid MR imaging. SPARS,(Rennes, France).
9. Donoho, D. L. (2006). Compressed sensing. IEEE Transactions on information theory, 52(4), 1289-1306.
10. Feng, L., Benkert, T., Block, K. T., Sodickson, D. K., Otazo, R., & Chandarana, H. (2017). Compressed sensing for body MRI. Journal of Magnetic Resonance Imaging, 45(4), 966-987.
11. Govil, J., Govil, J., & Nandra, A. (2008, April). Advances in quantum computing: Nuclear magnetic resonance (non reviewed). In Southeastcon, 2008. IEEE (pp. 48-48). IEEE.
12. Lustig, M., Donoho, D. L., Santos, J. M., & Pauly, J. M. (2008). Compressed sensing MRI. IEEE signal processing magazine, 25(2), 72-82.
13. Golland, P. (2000). Spatial Encoding In MRI And How To Make It Faster. Massachusetts Institute of Technology, Boston.
14. Revett, K. (2011). An Introduction to Magnetic Resonance Imaging: From Image Acquisition to Clinical Diagnosis. In Innovations in Intelligent Image Analysis (pp. 127-161). Springer, Berlin, Heidelberg.
15. Peters, D. C., Korosec, F. R., Grist, T. M., Block, W. F., Holden, J. E., Vigen, K. K., & Mistretta, C. A. (2000). Undersampled projection reconstruction applied to MR angiography. Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine, 43(1), 91-101.
16. Kawaji, K., Foppa, M., Roujol, S., Akçakaya, M., & Nezafat, R. (2015). Whole heart coronary imaging with flexible acquisition window and trigger delay. PloS one, 10(2), e0112020.
17. Bioucas-Dias, J. M., & Figueiredo, M. A. (2007). A new TwIST: two-step iterative shrinkage/thresholding algorithms for image restoration. IEEE Transactions on Image processing, 16(12), 2992-3004.
18. Ma, S., Yin, W., Zhang, Y., & Chakraborty, A. (2008, June). An efficient algorithm for compressed MR imaging using total variation and wavelets. In Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on (pp. 1-8). IEEE.
19. Yang, J., Zhang, Y., & Yin, W. (2008). A fast TVL1-L2 minimization algorithm for signal reconstruction from partial Fourier data.
20. Kowalski, M. (2014, October). Thresholding rules and iterative shrinkage/thresholding algorithm: A convergence study. In Image Processing (ICIP), 2014 IEEE International Conference on (pp. 4151-4155). IEEE.
21. Afonso, M. V., Bioucas-Dias, J. M., & Figueiredo, M. A. (2011). An augmented Lagrangian approach to the constrained optimization formulation of imaging inverse problems. IEEE Transactions on Image Processing, 20(3), 681-695.
22. Zhang, G., Deng, H., Chen, Y., Shen, Z., & Wu, R. (2015, August). Investigating the stability of fast iterative shrinkage thresholding algorithm for MR imaging reconstruction using compressed sensing. In Fuzzy Systems and Knowledge Discovery (FSKD), 2015 12th International Conference on (pp. 1296-1300). IEEE.
23. Fessler, J. A., & Noll, D. C. (2004, April). Iterative image reconstruction in MRI with separate magnitude and phase regularization. In Biomedical Imaging: Nano to Macro, 2004. IEEE International Symposium on (pp. 209-212). IEEE.
24. He, L., Chang, T. C., Osher, S., Fang, T., & Speier, P. (2006). MR image reconstruction by using the iterative refinement method and nonlinear inverse scale space methods. UCLA CAM Report, 6, 35.
25. Van Geuns, R. J. M., Wielopolski, P. A., de Bruin, H. G., Rensing, B. J., van Ooijen, P. M., Hulshoff, M., ... & de Feyter, P. J. (1999). Basic principles of magnetic resonance imaging. Progress in cardiovascular diseases, 42(2), 149-156.
26. Finn, J. P., Nael, K., Deshpande, V., Ratib, O., & Laub, G. (2006). Cardiac MR imaging: state of the technology. Radiology, 241(2), 338-354.
27. Otazo, R., Feng, L., Chandarana, H., Block, T., Axel, L., & Sodickson, D. K. (2012, May). Combination of compressed sensing and parallel imaging for highly-accelerated dynamic MRI. In Biomedical Imaging (ISBI), 2012 9th IEEE International Symposium on (pp. 980-983). IEEE.
28. Wang, Y., & Ying, L. (2014). Compressed sensing dynamic cardiac cine MRI using learned spatiotemporal dictionary. IEEE Trans. Biomed. Engineering, 61(4), 1109-1120.
29. Gamper, U., Boesiger, P., & Kozerke, S. (2008). Compressed sensing in dynamic MRI. Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine, 59(2), 365-373.
30. Yeh, E. N., McKenzie, C. A., Ohliger, M. A., & Sodickson, D. K. (2005). 3Parallel magnetic resonance imaging with adaptive radius in k-space (PARS): Constrained image reconstruction using k-space locality in radiofrequency coil encoded data. Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine, 53(6), 1383-1392.