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Under-sampling Trajectory Design for Compressed Sensing Based DCE-MRI

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Abstract— **Dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) needs high temporal and spatial resolution to accurately estimate quantitative parameters and characterize tumor vasculature. Compressed Sensing (CS) has the potential to accomplish this mutual importance. However, the randomness in CS under-sampling trajectory designed using the traditional variable density (VD) scheme may translate to uncertainty in kinetic parameter estimation when high reduction factors are used. Therefore, accurate parameter estimation using VD scheme usually needs multiple adjustments on parameters of Probability Density Function (PDF), and multiple reconstructions even with fixed PDF, which is inapplicable for DCE-MRI. In this paper, an under-sampling trajectory design which is robust to the change on PDF parameters and randomness with fixed PDF is studied. The strategy is to adaptively segment k-space into low-and high frequency domain, and only apply VD scheme in high-frequency domain. Simulation results demonstrate high accuracy and robustness comparing to VD design.**

I. Introduction

Accuracy of kinetic parameter derivation is the main consideration in DCE-MRI, and results from high temporal resolution. On the other hand, high spatial resolution which benefits from long acquisition time is also needed to characterize Region of Interest (ROI). With this trade-off importance, both high temporal and spatial resolution in DCE-MRI is highly desirable.

Compressive sensing (CS) [1], as a new signal sampling and recovery framework, has been applied to reduce the number of required data with insignificant resolution loss in MRI. The feasibility of applying CS in DCE-MRI has been proved in some relevant work [2-4]. However, only very few work explored the uncertainty caused by under-sampling trajectory design in parameter estimation using CS. For instance, David et al. did a preliminary work on evaluating that how random under-sampling with acceleration rate two affected the parameter derivation, with the conclusion of no outlier estimation in 1000 randomly generated trajectories[5]. No relevant evaluation on higher acceleration factors and no adaptive scheme for designing robust under-sampling trajectory for DCE-MRI have been proposed previously.

In this paper, we firstly evaluate the effect of VD design scheme on parameter estimation with higher acceleration factor from two aspects: different PDF parameter groups and different random generations with fixed PDF. Then we propose an adaptive scheme of trajectory design for accurate and stable kinetic parameter estimation. For DCE-MRI, trajectory design for different dynamic scan should enforce more phase encodings sampled in central k-space which should be determined by unique characteristic for different subjects since intensity change only occurs in small ROI and remains stable in most of regions during the circulation of contrast agent (CA). In our method, the k-space from the scan without CA for each subject as the pre-scan is partioned into low- and high-frequency domain using Fourier transform of 2D wavelet filters and all the phase encodings in low-frequency domain are full-sampled. VD design is only applied for remainder phase encodings in high-frequency domain. The simulation results demonstrate the stability in parameter estimation using proposed method comparing to conventional design.

II. Proposed Method

Variable Density (VD) random sampling trajectory has been commonly used in CS-MRI [1]. Specifically, phase encodings are sampled densely in central k-space and sparsely in marginal k-space respectively. Under-sampling trajectory is generated according to a one-dimensional Power Density Function (PDF).

$$\begin{cases} PDF = (1-r_i)^p & r_i \in [0,1] \\ PDF = 1 & r_i < r \end{cases} \quad (1)$$

In Eq.(1), r_i is the normalized distance of position i to the k-space center (Fig.1(a)). r is the radius of full-sampled center, determining the range of full-sampled phase encodings. The PDF of position i is defined as 1, when its distance is smaller than r. The larger r leads to more full-sampled phase encodings in the central k-space. p is the power of polynomial controlling the distribution of phase encodings in central and marginal k-space. The larger p means higher probability for phase encodings sampled in the marginal k-space. r and p are adjustable parameters given a fixed acceleration factor. Besides, every random generation trail will generate different

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under-sampling trajectories even with fixed PDF (Fig.1(d)).

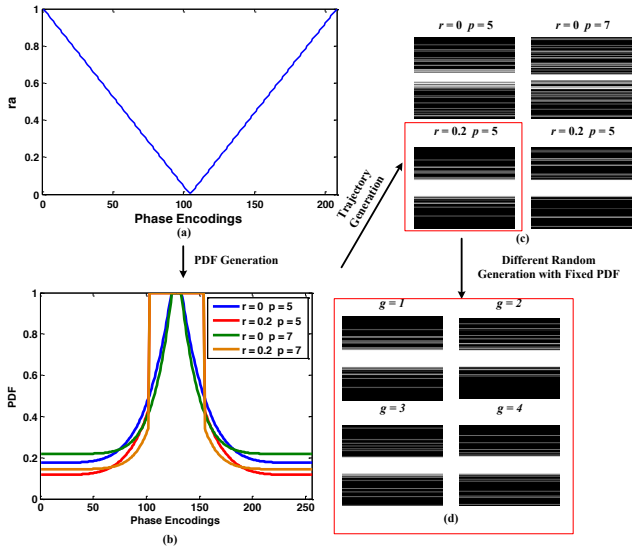

Figure.1 Under-sampling trajectory generation. (a) is a random generated linear vector. (b) PDFs generated from 4 parameter groups ($r = 0$ $p = 5$, $r = 0$ $p = 7$, $r = 0.2$ $p = 5$ and $r = 0.2$ $p = 7$). (c) and (d) are under-sampling trajectories generated from different PDF parameters and fixed PDF ($r = 0.2$ $p = 5$) in different random generation trails, respectively.

In quantitative DCE-MRI, kinetic parameters are estimated from the fitted curve of the mean signal intensity (mean SI) in ROI of dynamic image sequence. The observation that intensity change only occurs in small ROI and remains stable in most of regions during the circulation of CA, infers that trajectory design in DCE-MRI should enforce more phase encodings sampled in central k-space. However, PDF parameters in VD design scheme can not accurately differentiate the number of phase encodings distributed in central and marginal k-space respectively. Besides, the definition of PDF parameters are all based on experience and independent of characteristics for different subjects. Therefore, multiple adjustment on PDF parameters will lead to large computational complexity.

Inspired by work in [6], we used 2D wavelet filters (Eq.(2)) to segment k-space into low-and high-frequency domain in our method (shown in Fig.2 (a)), where phase encodings with normalized intensity below than 0.05 were regarded as belonging to the low-frequency domain, and were full-sampled. Unlike the method in [6] with purely random sampling in high-frequency domain, VD design was applied in high-frequency domain in our method shown in Fig.2 (e). Fig.2 shows the detailed design procedure in low-and high-frequency domain.

$$\begin{cases} y_{LL} = FT(\varphi(x,y) \otimes W_{LL}) \\ y_{LH} = FT(\psi^H(x,y) \otimes W_{LH}) \\ y_{HL} = FT(\psi^V(x,y) \otimes W_{HL}) \\ y_{HH} = FT(\psi^D(x,y) \otimes W_{HH}) \end{cases} \quad (2)$$

$\varphi(x,y)$, $\psi^H(x,y)$, $\psi^V(x,y)$, $\psi^D(x,y)$ and W_{LL}, W_{LH}, W_{HL}, W_{HH} are 2D wavelet filters and corresponding wavelet coefficients. $\otimes$ and FT mean convolution and 2D Fourier transform. y_{LL}, y_{LH}, y_{HL} and y_{HH} are localized k-space data.

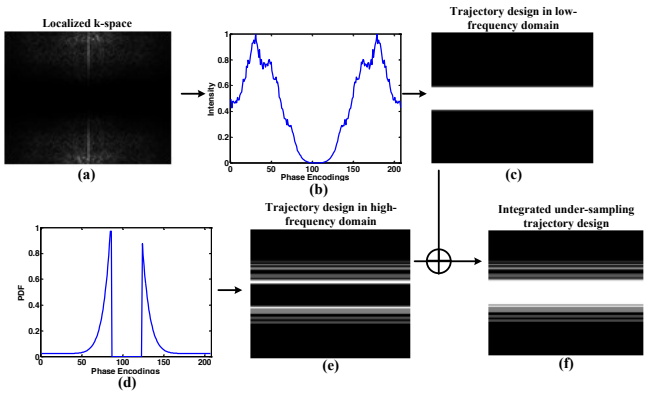

Figure.2 Under-sampling trajectory design procedure. (a-c) and (d-e) show the design procedure in low- and high-frequency domain respectively. (f) is the integrated under-sampling trajectory. The zero region in (d) corresponds to the phase encodings already full-sampled in recognized low-frequency domain.

III. SIMULATION RESULTS

Fully sampled DCE-MRI datasets of 5 subjects with histologically confirmed high grades of gliomas were acquired on a 1.5T MRI system (Sonata, SIEMEN, Germany) using a 2D Turbo Flash sequence, after giving written informed consent. Based on Tofts' model [7], uptake rate and trace kinetic parameter (K^{trans}) calculated from the reconstructions with acceleration factor as 3.6 by different PDF parameter groups were evaluated. All slices and time points for one subject were sampled with the same under-sampling trajectory and split Bregman [8] was used as reconstruction algorithm. Statistical analysis for estimated kinetic parameters was based on analysis of variance (ANOVA) and dunnett t-test (post hoc). Large P-value correlates to minor kinetic parameter difference between the DCE parameters derived from under-sampled and full-sampled data.

For evaluation on VD design, we randomly chose four PDF parameter groups ($r = 0$ $p = 5$, $r = 0$ $p = 7$, $r = 0.2$ $p = 5$ and $r = 0.2$ $p = 7$) and 4 under-sampling trajectories were generated for each parameter group (Fig.3).

Fig.4 (a) demonstrates the instability of reconstructions using trajectories generated in different random trials with fixed PDF ($r = 0.2$ $p = 5$) for subject 2. The blue curve, representing the fitted curve of mean SI in ROI using generation 2 has a large bias ($K^{trans} = 1.42$) from the fitted curve from full-sampled data ($K^{trans} = 0.88$). In contrast, the red curve using generation 3 has a good match ($K^{trans} = 0.89$) with the original one. Then, we transplant these two trajectory generations from subject 2 to subject 4. From Fig.4 (b), we can see perfect match of the fitted curves using two transplanted trajectories ($K^{trans} = 0.59$ and $K^{trans} = 0.61$) with the original one ($K^{trans} = 0.60$).

From the statistical graph and P-value for 5 subjects shown in Fig.5 and Table.1, the semi-quantitative parameter (Uptake) is robust to the PDF parameters and random generations. However, the quantitative parameter (K^{trans}) is

greatly affected by PDF parameters and shows apparent variance for different random generations with fixed PDF.

In general, the simulation results suggest that the trajectory designed by VD design scheme is instable for each generation trial with fixed PDF and can not be effectively transplanted from one subject to another.

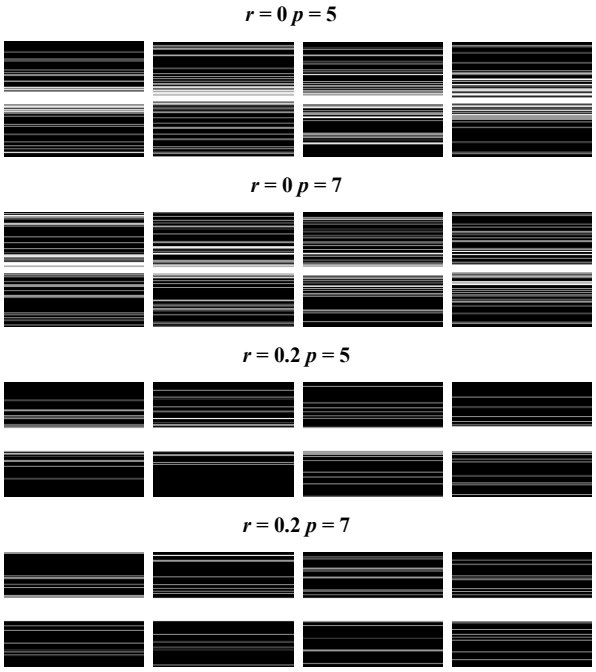

Figure.3 Designed under-sampling trajectories in different random generations with fixed PDF.

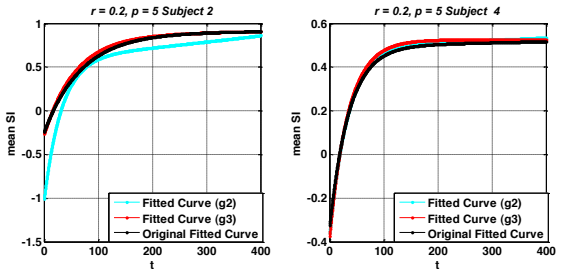

Figure.4 (a) and (b) show the fitted curve of mean SI in ROI with different random generations with fixed PDF ($r = 0.2$ $p = 5$) for subject 2 and 4 (g2 and g3 represents 2nd and 3rd generations, respectively).

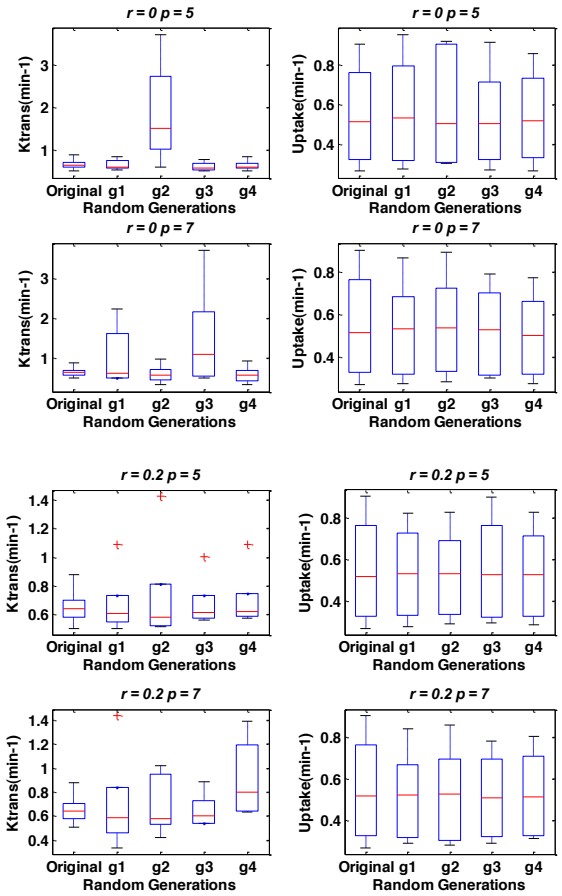

Figure.5 Statistical analysis on K^{trans} and uptake. Each graph represents the dependence of K^{trans} and uptake on different random generations with fixed PDF. Original means the kinetic parameters derived from reconstruction with full k-space datasets.

Table.1 P-value of Dunnett t-test for K^{trans} and uptake between the reconstructions using under-sampling trajectories from different random generations with the full-sampled datasets. The values with bold mean outliers.

P-value	generation	$p = 5$ $r = 0$	$p = 7$ $r = 0$	$p = 5$ $r = 0.2$	$p = 7$ $r = 0.2$
K^{trans}	g1	0.878	0.273	0.865	0.826
	g2	**0.057**	0.705	0.695	0.716
	g3	0.486	**0.189**	0.806	0.945
	g4	0.785	0.565	0.701	**0.136**
Uptake	g1	0.915	0.883	0.924	0.841
	g2	0.829	0.984	0.895	0.870
	g3	0.944	0.858	0.981	0.824
	g4	0.954	0.754	0.907	0.886

Our method used 2D Daubechies-6 wavelet filters to segment low-and high-frequency domain from the image without any CA injection. These five subjects share the same protocol and the images scanned without CA have minor difference. The number of phase encodings in localized

low-frequency domain is about 37. The remainder phase encodings are localized in high-frequency domain where VD scheme was used. r was defined as 0 since the full-sampled phase encodings in low-frequency domain have already been determined by 2D wavelet filters. Therefore, we only tested 2 parameter groups ($r = 0, p = 9$ and $r = 0, p = 11$). The choice of p is under the control of acceleration factor.

From the statistical graph and P-value shown in Fig.7 and Table.2, we can see that the robustness on random generations and PDF parameters is significantly improved for both semi-quantitative and quantitative parameters estimation.

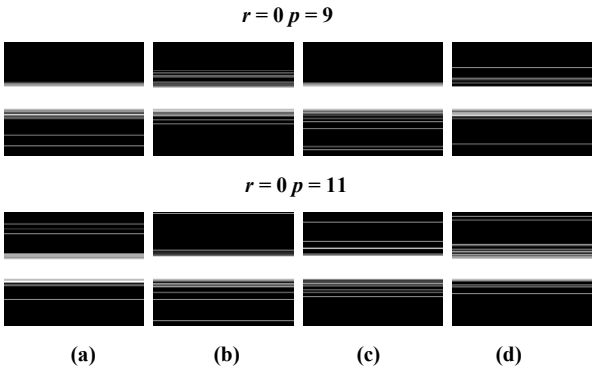

Figure.6 Under-sampling trajectory design in different random generations with fixed PDF.

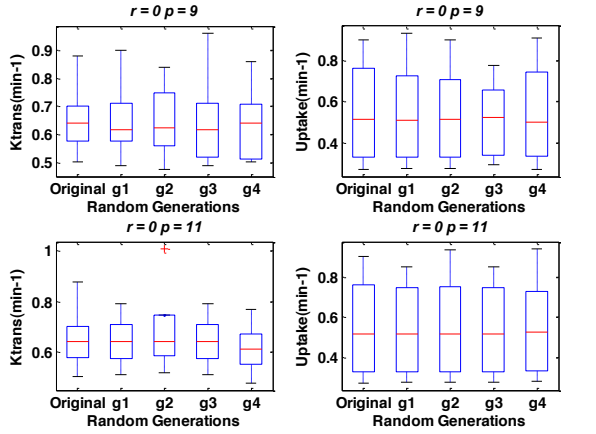

Figure.7 The dependence of k^{trans} and uptake on different random generations using our proposed method.

Table.2 P-value of Dunnett t-test for K^{trans} and uptake between the reconstructions using our proposed under-sampling trajectory design from different random generations with the full-sampled datasets.

P-value	generation	$p = 9$ $r = 0$	$p = 11$ $r = 0$
K^{trans}	g1	0.992	0.906
	g2	0.959	0.754
	g3	0.939	0.907
	g4	0.848	0.631
Uptake	g1	0.977	0.954
	g2	0.939	0.983
	g3	0.807	0.954
	g4	0.985	0.998

IV. Conclusion

In this paper, an adaptive design scheme for under-sampling trajectory was proposed for CS-based DCE-MRI. The simulation results show that our design scheme improves the robustness for the change of PDF parameter and random generations. In the future, we will focus on developing a parameter-free design scheme specific for DCE-MRI.

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