Artificial Bee Colony (ABC) based Variable Density Sampling Scheme for CS-MRI

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Overview

MRI AND ITS BASIC PRINCIPLE

- MRI (magnetic resonance imaging) is an imaging modality that uses non-ionizing radiation to create diagnostic useful images.
- It exploits the property of directional magnetic field, or moment, associated with charged particles in motion. Nuclei containing an odd number of protons and/or neutrons have a characteristic motion or precession.
- Scan sequences provide excellent soft tissue contrast and high resolution
- Has the ability to provide structural, functional (fMRI) information and useful in several diagnostic studies
- Disadvantage - Data acquisition is sequential and slow, cannot be used on patients with metallic implants

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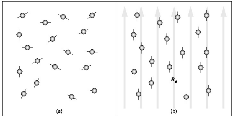
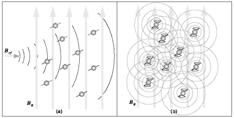
PRINCIPLE



No magnetic field   Strong Magnetic Field B_0



RF pulse   RF Removed

The protons (Hydrogen ions) in the body are spinning clockwise or anti-clockwise in random orientations in steady state.

When a strong magnetic field is B_0 is applied these tiny magnets tend to align with B_0 resulting in a net magnetic moment.

An RF pulse in resonant frequency applied, pushes aligned proton (H+) to a higher energy level

When the RF pulse is turned off, the protons precess and return to original magnetization B_0, emitting a RF signal called free induction decay signal. The FID signal is a measure of proton density in the slice being imaged.

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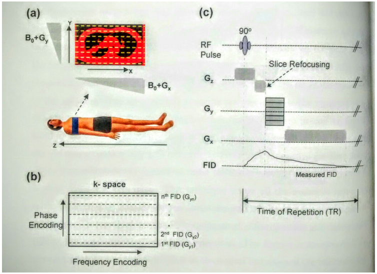
k-SPACE ENCODING

By applying the gradient magnetic field in x and y directions in steps, FID signal can be acquired for each step.

The gradient magnetic field applied in steps varies the precession frequencies of the protons, thus encoding their spatial locations.



A 2D FT is performed on all the FID signals to obtain the image $I(x, y)$ such that

$$I(x, y) = \sum \left[\sum K(x, y) e^{-j\omega_x n} \right] e^{-j\omega_x n} \quad (1)$$

where $K(x, y)$ is the matrix of FID signals and $I(x, y)$ is the proton density image

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Scan Time Reduction Techniques

There are many methods using hardware and scan sequences

- Pulse sequences which use shorter TR
- Pulse sequences allowing reduction in number of RF excitation, ie collecting more than one line of k-space in a single TR
- Methods which improve SNR thus reducing number of signal averaging
- k-space sampling strategies which allow reduction of number of phase encode lines.

These techniques and MRI hardware have enabled faster data collection and faster imaging.

Currently, these techniques have reached a limit where the fundamental physical and physiological effects limit ability to encode and collect data more quickly.

Overview

Compressed Sensing and Undersampling k-space

Compressed sensing (CS) and reconstruction theory, (Candes and Romberg, 2006) works on the principle of acquiring a signal based on its information content (significant samples in some domain) and a non-linear reconstruction algorithm to estimate the signal from the fewer sample.

The main constraints for compressed sensing are

- 1) Sparsity
- 2) incoherence
- 3) Random sampling or encoding

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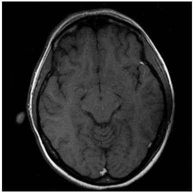
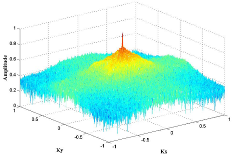
k-space characterstics

- MR images express weak sparsity in Fourier domain.
- They can be reconstructed from random limited k-space samples (Lustig et al 2008, Lustig et al. 2007)
- Generate efficient undersampling matrices Radial, circular, spiral, etc
- Adaptive schemes (F Knoll et al. 2011) and pseudo-random sampling methods have been attempted (Wang et al. 2009)

MRI Image and its k-space



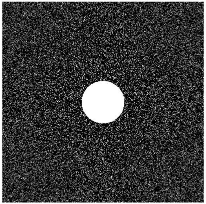
(a) In-Vivo Brain Image



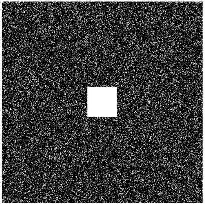
(b) k-space

Variable Density Patterns

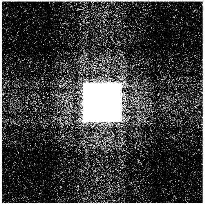
- k-space modeled as a power law distribution with increasing distance (Lustig), or TSP based π distribution, (Chauffert et al 2014)
- Sample k-space with a Deterministic central region and the rest random based on above model.



(c) Lustig l_2 pattern



(d) Lustig l_∞ pattern



(e) π Distribution pattern

How to choose the Deterministic Dense Region and Suitable PDF function for k-space ?

- Adaptive Model - Magnitude k-space is the pdf

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Introduction to Bee-Colony

- The Artificial Bee-Colony algorithm, a swarm intelligence algorithm, was introduced by Karaboga et. al [1] for the purpose of numerical optimization.
- The **Four** Essential Components of Bee Colony-
    1. **Food Sources** - They refer to nectars foraged by the bee and are distributed according to a chosen *Fitness Distribution*.
    2. **Scout Bees** - These are *Random Forager* who perform the task of searching for food sources and pass on that information to other bees in the hive.
    3. **Employed Bees** - These are bees which are *associated* with a particular food source.
    4. **Onlooker Bees** - These bees use the information provided by Scout bee and Employed bees *o find a another nectar in the neighbourhood* of already found food source.

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Motivation/ Idea:

- The sample at regions closer to **center of *k*-space** hold information regarding the **overall structure of the image, contrast and SNR** - Hence, needs to be given higher priority.
- By choosing a fitness distribution that **mimics *k*-space** of an MR image, its characteristics can be captured as the bees forage.
- Exploiting the behaviour of the bees to pick only nectars with high quality as they can perform both **Global** and **Local search**.
- Such that sampling scheme obtained in **three phases** satisfies **Randomness** and **Incoherence** properties required for CS-MRI.

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Random Search by Scout-Bees

- The pre-defined number of scout-bees forage for N_k nectars from k^{th} annular regions known as bins.

$$r_k = \begin{cases} r_{k-1} + c_k * \Delta r, & \text{if } k > 0 \\ r_{IN}, & \text{if } k = 0 \end{cases} \tag{2}$$

  where Δr gives the incremental width of the annular region and c_k determines the relative bin width of successive bins.

- The location of food sources in k^{th} bin is given by:

$$x_i^k = (rand(0,1)(r_k - r_{k-1}) + r_{k-1},\ \theta), \forall k \in \{1, 2, ...\} \tag{3}$$

  where $i \in \{1, 2, 3, ...N_k\}$, $\theta \in [0, 2\pi]$ is a randomly chosen angle and $x_i^0 = (rand(0,1)r_{IN},\ \theta)$ gives the location of food sources within r_{IN}.

- The entire k-space is spanned bin-wise according to the aforementioned steps, and information regarding the quality and distance accrued over time.

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Local Search By the Employed-Bees

- A neighbourhood search is performed by M bees moving in concentric circles of varying width r_l until at least one better position is found.
- If the bee fail to update its position in one cycle, they restart the process by searching in circles of larger radii, $r_{l+1} = r_l + l * \Delta r_l$.
- The food selection follows a greedy nectar selection mechanism and is as follows:

$$x^k_{i+N_k} := y^l_j \ , \ i \in \{1, 2, 3, ..., \} \tag{4}$$

subject to the constraint $\nabla f(y^l_j) \geq \nabla f(y^l_{j-1})$

- These newly chosen profitable nectars are added to the N_k food sources already present in the each bin, based on its location in k-space.
- Thus, the effective number of points in each of the bin after updating is $N^e_k \geq N_k$.

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Advance of the Onlooker-Bees

- A designated number of the onlookers move towards the location of E food sources.
- They are chosen from the nectars obtained in (4), if they exceed a threshold, f_{th} defined as follows:

$$x_e^k := x_i^k, \;\; \texttt{if} \;\; f(x_i^k) > f_{th} \;\; \forall\, i \in \{1, 2, ..., N_k^e\} \tag{5}$$

  where $e \in \{1, 2, ..., E\}$ and E was fixed to be 50% of the employed-bee swarm size.
- On reaching the E locations, as only one bee can reach the best position x_e^k, out of S, the remaining bees can best be in only close proximity of x_e^k at the locations $x_{e'}^k$ such that:

$$|x_e^k \text{ - } x_{e'}^k| \; < \; \epsilon \text{ and } f(x_{e'}^k) \leq f(x_e^k).$$

- The net count of samples after the advance of the onlookers is N_k^o.

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SUMMARY: PARAMETERS REQUIRED

- The are **five** parameters and distribution to be passed to the algorithm are :
  - Initial Food sources N_0
  - Initial search radius r_{IN}
  - Swarm size of the employed-bees M
  - Bin Width Δr
  - Maximal radius for neighborhood search r_s
  - Fitness distribution $f(x)$.
- The optimal parameters were found by **Monte-Carlo Simulations** using standard fitness distribution that mimics k-space - Gaussian Distribution.

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Algorithm

Input : N_0, r_{IN}, M, Δr, h r_s and $f(x)$.
Output: k-ABC based VDS scheme

1. Initialize with N_0 food sources within the radius r_{IN}.
2. Pick N_k food sources randomly from each bin.
3. Pass the information regarding the M best nectars within r_s of k-space to the employed-bees and evaluate them.
4. The employed-bees perform a neighborhood search to find better nectars locally.
5. Evaluate these nectars and perform greedy-selection which results in N_k^e samples/bin.
6. The onlooker-bees choose the E best nectars, from the available N_k^e nectars, based on distance criterion and settle in their vicinity. Memorize the locations of all food sources selected by scout, employed and onlooker-bees in the bin, N_k^o.
7. Repeat the steps **2-7** for all bins.
8. Peform logical OR of N_k^o over k bins to obtain sampling scheme.

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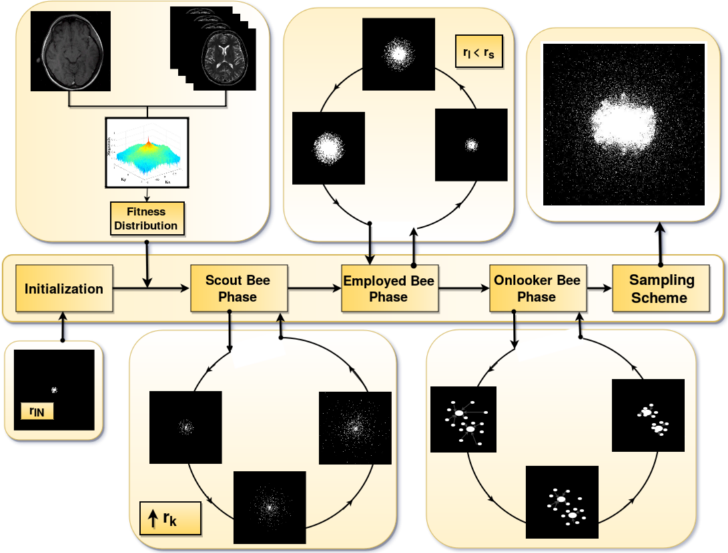
k-ABC - A Visual Representation



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Parameters chosen for DLMRI Reconstruction

- DLMRI [2] simultaneously learns an image patch based dictionary and reconstructs the image iteratively using undersampled data.
- Key parameters used in DLMRI are:
  - K-SVD itrations = 20,
  - Reconstruction Iterations = 10,
  - Patch size = 36,
  - Overlap Stride = 1.

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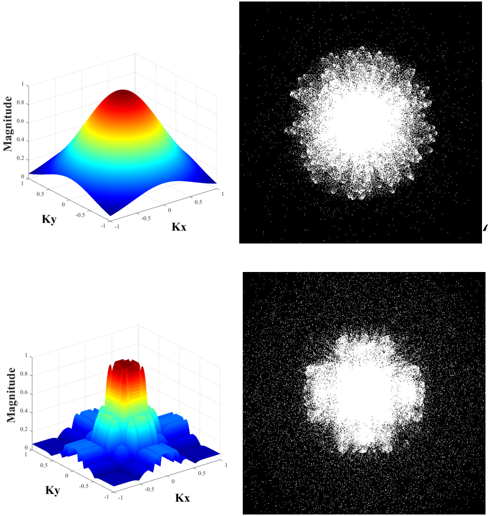
k-ABC based VDS scheme given a Fitness Distribution

Top row: Gaussian Distribution, *Bottom row*: π-Distribution



Parameters and Reconstruction Results - Gaussian Distribution

Table: Image Quality of Reconstruction Results for Brain Image for different under-sampling percentages (R)

Parameters			**Quality Measures**						
N_0	r_s	M	R%	**PSNR**	PSNR(μ/σ^2)	**HFEN**	HFEN(μ/σ^2)	**SSIM**	SSIM(μ/σ^2)
1500	0.67	75	20	**43.71**	43.66/0.009	**0.30**	0.28/0.001	**0.97**	0.96/1.93e-06
1400	0.60	45	15	42.39	42.48/0.004	0.52	0.49/0.007	0.95	0.95/1.01e-05
1200	0.50	35	10	40.86	40.85/0.013	0.80	0.80/0.002	0.94	0.93/7.57e-05
900	0.40	10	5	37.13	36.28/0.478	1.88	2.04/0.060	0.90	0.89/0.004

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k-ABC Sampling Schemes - Gaussian Distribution

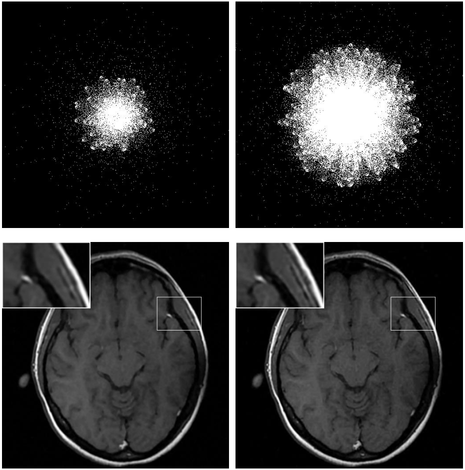

Figure: **VDS Schemes and Reconstructed Images:** *Top row*: Sampling patterns k-ABC , *Bottom row* : Reconstructed In-Vivo Brain image for R=5% and 20%. Inset shows magnification of fine structures

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Intensity Profile Comparison - R= 5% and 20%

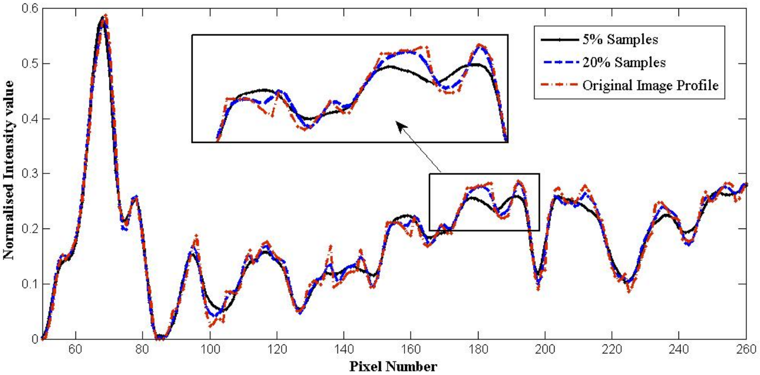

Figure: Image Profile of Reconstructed In vivo Brain MR image

Comparison between Other Sampling Schemes

Table: Reconstruction Quality of Spinal Image for different VDS schemes for under-sampling (R) of 20% and 5%

VDS Scheme	**PSNR**	**HFEN**	**SSIM**
k-ABC (Gaussian distribution)	**41.21 (31.59)**	**0.54 (3.49)**	**0.98 (0.89)**
k-ABC (π-distribution)	40.44 (31.14)	**0.64** (3.75)	**0.98 (0.88)**
Independent π-distribution[3]	36.93 (29.19)	1.72 (4.98)	0.94 (0.84)
Power Law based distribution [4]	32.64 (26.23)	3.25 (6.61)	0.89 (0.76)

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Comparison between Other Sampling Schemes

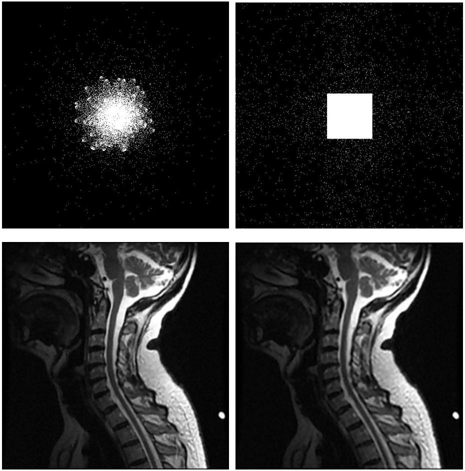

Figure: **VDS Schemes and Reconstructed Images:** *Top row*: Sampling patterns for R=5% - k-ABC and Independent pi-distribution, *Bottom row* : Corresponding Reconstructed T2-Weighted Spinal image.

Conclusion

- The image quality parameters **PSNR, HFEN, SSIM** fare better in the k-ABC Sampling method on retrospective reconstruction.
- The inset embedded inside the reconstructed images show magnification of the fine features.
- From the visual as well as image quality metrics an improvement is observed.
- Thus one can conclude that the proposed k-ABC method yields significantly better results when compared to the other state of the art patterns, at even very low undersampling percentages.

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[2] S. Ravishankar and Y. Bresler, "Mr image reconstruction from highly undersampled k-space data by dictionary learning," *Medical Imaging, IEEE Transactions on*, vol. 30, no. 5, pp. 1028–1041, 2011.

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Thank You