

Image Reconstruction in MRI

The Possibilities of Portable, Low-cost MRI Scanners

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Research goal
Outline
Hardware
Modeling the signal
Analysis of the model
Results
Conclusion



Research goal

To develop a sufficiently accurate image reconstruction algorithm that is able to effectively process signals produced by a low-cost MRI scanner.

Research goal

Hardware

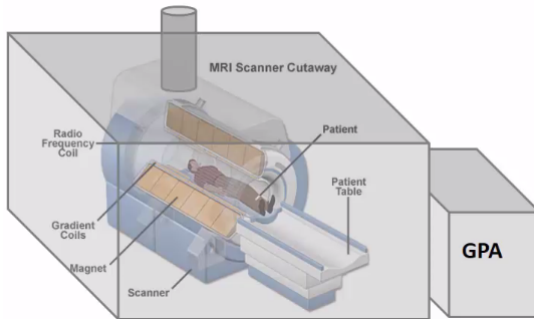
Modeling the signal

Analysis of the model

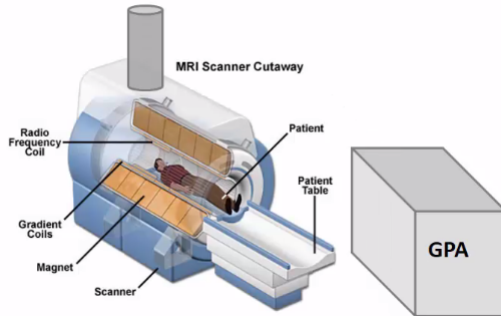
Results

Conclusion

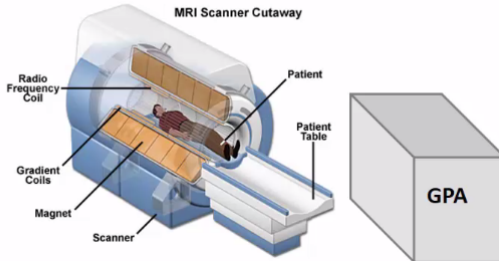
Standard MRI



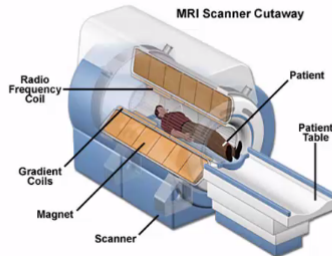
Standard MRI



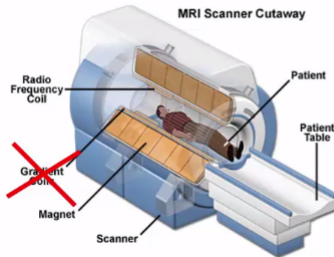
Standard MRI



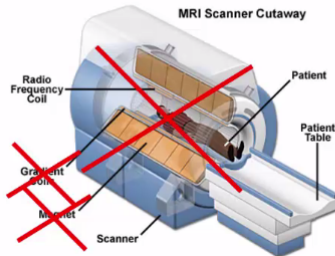
Standard MRI



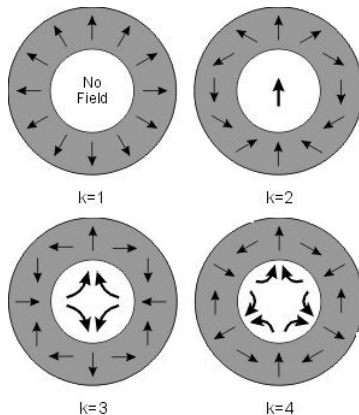
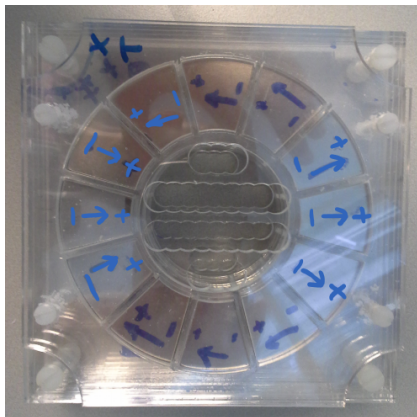
Standard MRI



Standard MRI



Main Magnet



Magnetic Flux Density Field

(Loading video)

Signal Equation

$$S(t) = \int_{\mathbf{r} \in \mathbb{D}} c(\mathbf{r}) \omega_0(\mathbf{r}) e^{-t/T_2(\mathbf{r})} e^{-i\phi(\mathbf{r}, t)} f(\mathbf{r}) d\mathbf{r}$$

Matrix form

$$\mathbf{y} = A \mathbf{f}$$

Signal Equation

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Matrix form

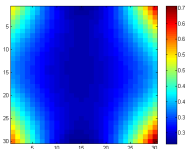
$$\mathbf{y} = A \mathbf{f}$$

Signal Equation

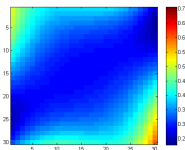
$$S(t) = \int_{\mathbf{r} \in \mathbb{D}} c(\mathbf{r}) \omega_0(\mathbf{r}) e^{-t/T_2(\mathbf{r})} e^{-i\phi(\mathbf{r}, t)} f(\mathbf{r}) d\mathbf{r}$$

Matrix form

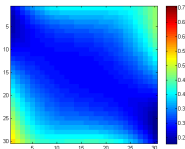
$$\mathbf{y} = \mathbf{A} \mathbf{f}$$



Rotation 1



Rotation 2



Rotation 3

⋮

$$\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} f_1 \\ \vdots \\ f_{n_p} \end{bmatrix} + \begin{bmatrix} n_1 \\ \vdots \\ n_N \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} f_1 \\ \vdots \\ f_{n_p} \end{bmatrix} + \begin{bmatrix} n_1 \\ \vdots \\ n_N \end{bmatrix}$$

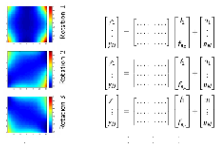
$$\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} f_1 \\ \vdots \\ f_{n_p} \end{bmatrix} + \begin{bmatrix} n_1 \\ \vdots \\ n_N \end{bmatrix}$$

⋮

⋮

⋮

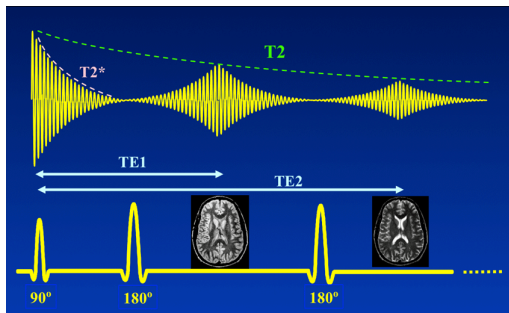
System of equations



$$\begin{bmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_{n_r} \end{bmatrix} = \begin{bmatrix} A_1 \\ \vdots \\ A_{n_r} \end{bmatrix} \mathbf{f} + \begin{bmatrix} \mathbf{n}_1 \\ \vdots \\ \mathbf{n}_{n_r} \end{bmatrix}$$

$\mathbf{y} \in \mathbb{C}^{Nn_r \times 1}$, $A \in \mathbb{C}^{Nn_r \times n_p}$, $\mathbf{f} \in \mathbb{C}^{n_p \times 1}$ and $\mathbf{n} \in \mathbb{C}^{Nn_r \times 1}$.

T_2 relaxation

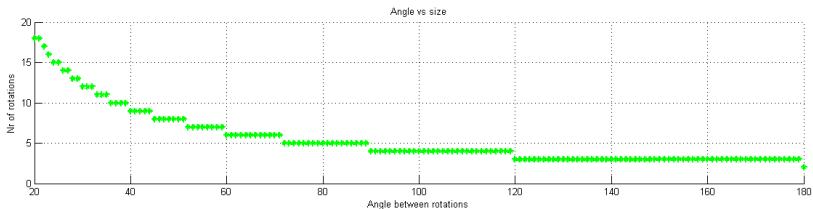
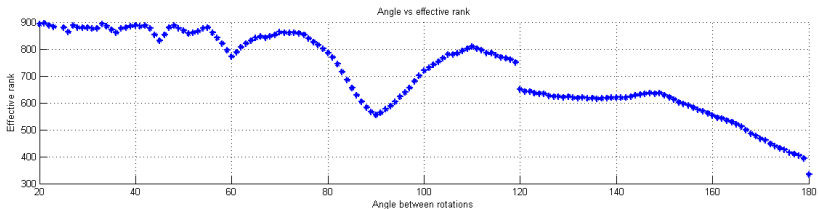


$$\frac{1}{T_2^*} = \frac{1}{T_2} + \frac{1}{T_2'}$$

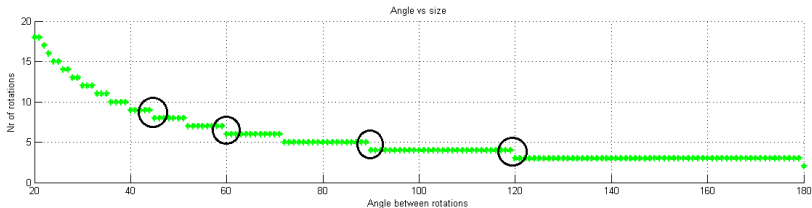
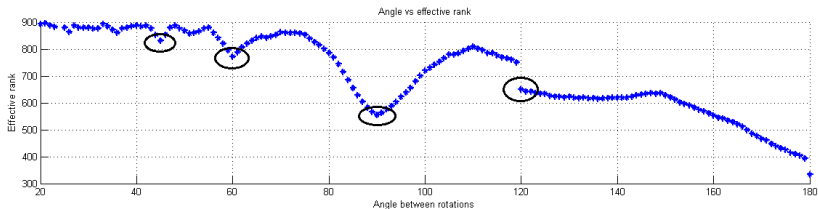
Nyquist

Sampling rate ($f_s = bw$)	Nyquist rate ($2.2f_s = 2.2bw$)	Upperbound dt
1 MHz	2.2 MHz	$4.5455 \cdot 10^{-7}$ s
2 MHz	4.4 MHz	$2.2727 \cdot 10^{-7}$ s
3 MHz	6.6 MHz	$1.5152 \cdot 10^{-7}$ s

Method of rotating



Method of rotating

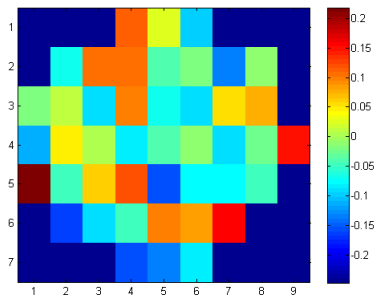


Method of rotating

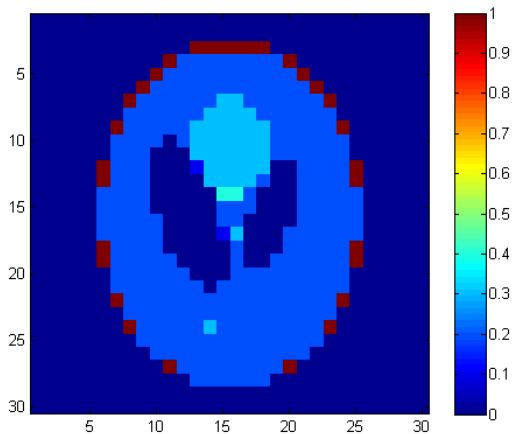
Bandwidth bw	min. number of rotations	max. angles	optimal angles	effective rank
3	5	89	72	860
2	7	59	48	864
1	10	39	33	813

Field perturbations

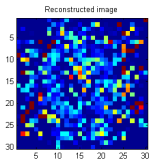
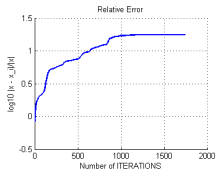
- ▶ 10^{-1} mT: accuracy measuring tool
- ▶ 1 mT: human mistakes



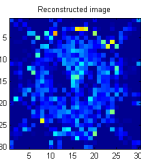
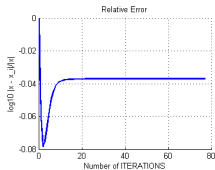
Phantom image



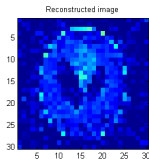
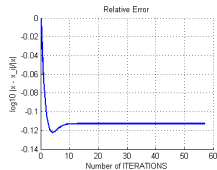
Field perturbations 10^{-1} mT



(a) angles= 70°

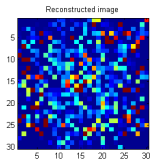
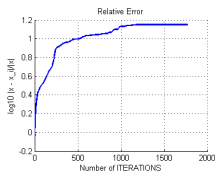


(b) angles= 30°

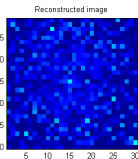
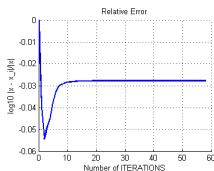


(c) angles= 10°

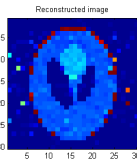
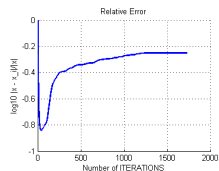
Field perturbations 1 mT and 10^{-2} mT



(a) angles = 70° ,
1 mT

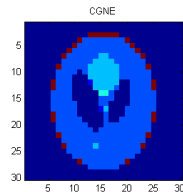
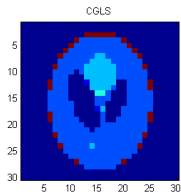
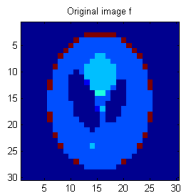
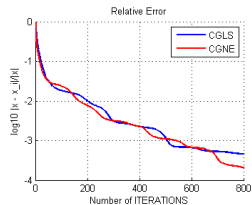
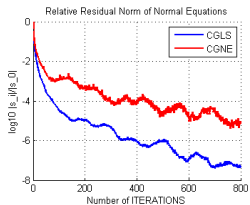
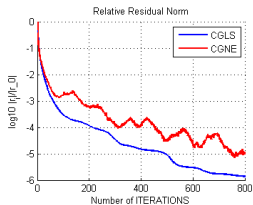


(b) angles = 10° ,
1 mT

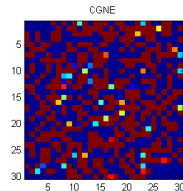
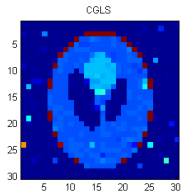
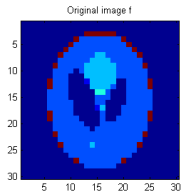
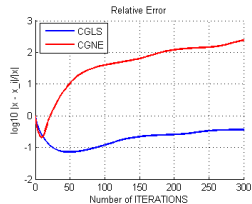
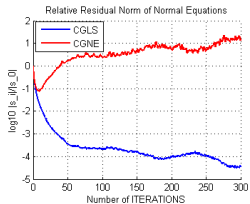
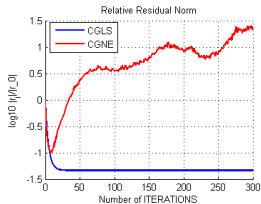


(c) angles = 70° ,
 10^{-2} mT

CGLS vs CGNE without noise



CGLS vs CGNE with noise



CGLS with regularisation

$$\arg \min_{\mathbf{f}} \|\mathbf{y} - \mathbf{A}\mathbf{f}\|_2 + \lambda^2 R(\mathbf{f}), \quad R(\mathbf{f}) = \|\mathbf{L}\mathbf{f}\|.$$

CGLS with regularisation

$$\arg \min_{\mathbf{f}} \|\mathbf{y} - \mathbf{A}\mathbf{f}\|_2 + \lambda^2 R(\mathbf{f}), \quad R(\mathbf{f}) = \|\mathbf{L}\mathbf{f}\|_2.$$

CGLS with regularisation

$$\arg \min_{\mathbf{f}} \|\mathbf{y} - \mathbf{A}\mathbf{f}\|_2 + \lambda^2 R(\mathbf{f}), \quad R(\mathbf{f}) = \|\mathbf{L}\mathbf{f}\|_2.$$

CGLS with regularisation

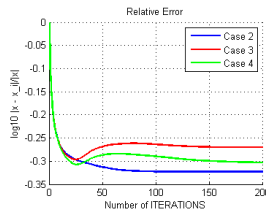
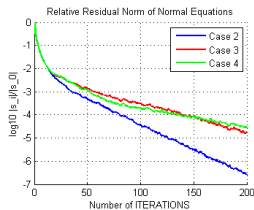
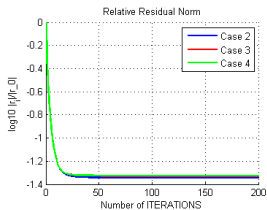
$$\arg \min_{\mathbf{f}} \|\mathbf{y} - A\mathbf{f}\|_2 + \lambda^2 R(\mathbf{f}), \quad R(\mathbf{f}) = \|\mathbf{L}\mathbf{f}\|_2.$$

CGLS with regularisation

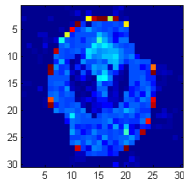
$$\arg \min_{\mathbf{f}} \|\mathbf{y} - \mathbf{A}\mathbf{f}\|_2 + \lambda^2 R(\mathbf{f}), \quad R(\mathbf{f}) = \|\mathbf{L}\mathbf{f}\|_2.$$

1. regularisation type 0: $L = I$,
2. regularisation type 0 with air constraint:
 $L = [I \quad \text{constraint}]^T$,
3. regularisation type 1 with air constraint:
 $L = [L_1 \quad \text{constraint}]^T$,
4. regularisation type 2 with air constraint:
 $L = [L_2 \quad \text{constraint}]^T$,

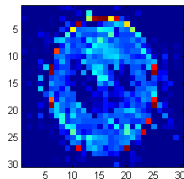
Regularisation, case 2,3,4



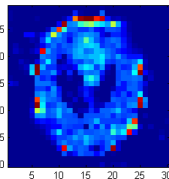
Case 2: Regularisation $L=L_1$ with constraint



Case 3: Regularisation $L=L_1$ with constraint



Case 4: Regularisation $L=L_2$ with constraint



- ▶ Analysis of the model (Nyquist rate, rotations, frequency bandwidth, perturbations)
- ▶ T_2^*
- ▶ CGLS, Tikhonov, $L = I$

Future research

- ▶ Analysis encoding methods
- ▶ modeling coil sensitivity and T_2 or T_2^*
- ▶ 2D to 3D

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