

PARALLEL MRI

RECONSTRUCTION OF IMAGES FROM MULTIPLE COILS

RECONSTRUCTION OF UNDERSAMPLED DATA

IMAGE DOMAIN - SENSE (THIS TIME)

FREQUENCY DOMAIN - SMASH/GRAPPA (NEXT TIME)

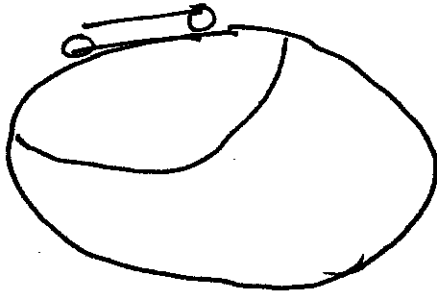
READING

LARDMAN + NUJES PAPER (OUTLINE)

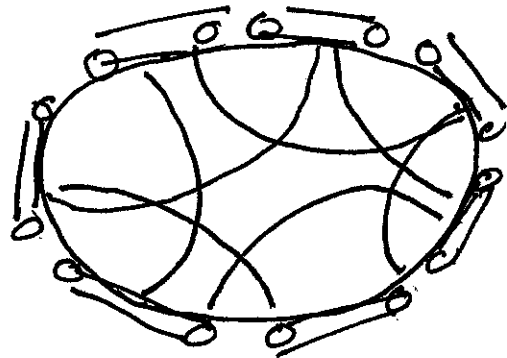
SECTION 13.3 IN BERNSTEIN

RECONSTRUCTION FROM MULTIPLE COILS

ROEMER, 1990



SURFACE COIL



ARRAY COIL

EACH COIL A COMPLETE IMAGE OF WHOLE FOV

EACH COIL HAS AN AMPLITUDE AND PHASE SENSITIVITY

$$C_l(\underline{x}) \quad l = 1..L \quad \text{COILS}$$

COILS ARE COUPLED, SO NOISE IS CORRELATED

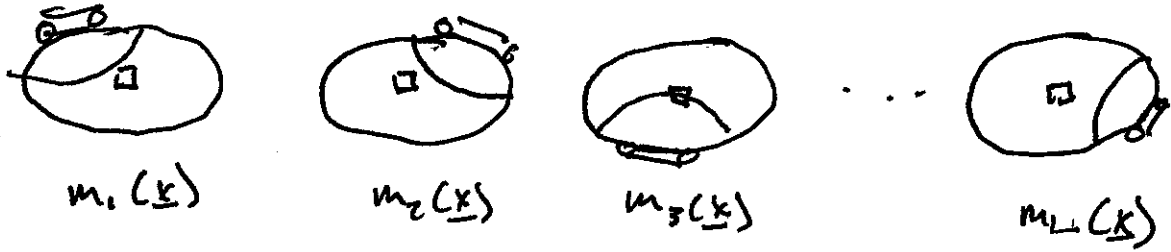
$$E[n_i n_j^*] = \Psi \quad \Psi \text{ IS } L \times L$$

RECEIVED DATA FROM COIL l

$$\underbrace{m_l(\underline{x})}_{\text{MEASURED IMAGES}} = \underbrace{C_l(\underline{x})}_{\text{COIL } l \text{ SENSITIVITY}} \underbrace{m(\underline{x})}_{\text{OBJECT}} + \underbrace{n_l(\underline{x})}_{\text{NOISE FROM COIL } l}$$

GIVEN $m_l(\underline{x})$, HOW DO WE RECONSTRUCT $m(\underline{x})$?

WE HAVE N MEASUREMENTS OF EACH VOXEL



FOR A PARTICULAR VOXEL \underline{x}_p

$$\begin{pmatrix} m_1(\underline{x}_p) \\ m_2(\underline{x}_p) \\ \vdots \\ m_L(\underline{x}_p) \end{pmatrix} = \begin{pmatrix} c_1(\underline{x}_p) \\ c_2(\underline{x}_p) \\ \vdots \\ c_L(\underline{x}_p) \end{pmatrix} m(\underline{x}_p) + \begin{pmatrix} n_1(\underline{x}_p) \\ n_2(\underline{x}_p) \\ \vdots \\ n_L(\underline{x}_p) \end{pmatrix}$$

OR

$$\underbrace{\underline{m}_s(\underline{x}_p)}_{L \times 1 \text{ MEASUREMENTS}} = \underbrace{\underline{C}}_{L \times 1 \text{ SENSORS}} \underbrace{m(\underline{x}_p)}_{1 \times 1 \text{ PIXEL}} + \underbrace{\underline{n}}_{L \times 1 \text{ NOISE}}$$

NOISE DISTRIBUTED AS

$$\underline{n} \sim N(0, \Psi)$$

MINIMUM VARIANCE ESTIMATE

$$\hat{m}(x_p) = \underbrace{(C^* \Psi^{-1} C)^{-1}}_{1 \times 1} \underbrace{C^* \Psi^{-1}}_{1 \times L} \underbrace{m_s(x_p)}_{L \times 1}$$

COVARIANCE (VARIANCE)

$$\text{COV}(\hat{m}(x_p)) = \underbrace{(C^* \Psi^{-1} C)^{-1}}_{1 \times 1}$$

SPECIAL CASE

IF

$$\Psi = \sigma^2 I$$

THEN

$$\begin{aligned} \hat{m}(x_p) &= (C^* (\sigma^2 I)^{-1} C)^{-1} C^* (\sigma^2 I)^{-1} m_s(x_p) \\ &= (C^* C)^{-1} C^* m_s(x_p) \\ &= \frac{1}{\sum_l |c_l(x_p)|^2} \sum_l c_l^*(x_p) m_{s,l}(x_p) \end{aligned}$$

WEIGHTED LINEAR COMBINATION

PHASE CORRECTED ($c_l^*(x_p)$)

WEIGHTING CORRECTED ($\frac{1}{\sum_l |c_l(x_p)|^2}$)

APPROXIMATE SOLUTION

OFTEN WE DON'T KNOW $C_L(x)$

HOWEVER

$$m_L(x) = C_L(x)m(x)$$

SO $m_L(x)$ HAS $C_L(x)$ IMPLICITLY, PARTICULARLY
AMPLITUDE AND PHASE

APPROXIMATE SOLUTION

$$\hat{m}_{SS}(x) = \sqrt{\sum_L m_L^*(x) m_L(x)}$$

THIS PHASE CORRECTS AND WEIGHS THE MEASUREMENTS

SQUARE-ROOT APPROXIMATELY FIXES WEIGHTING
LEAVES SHADING

FOR $\text{SNR} > 20$, WITHIN 10% OF OPTIMAL
SOLUTION (ROEMER)

LONG THOUGHT TO BE ADEQUATE

ACCELERATED IMAGING WITH ARRAY COILS

PARALLEL IMAGING

BASIC IDEA

COIL ELEMENTS PROVIDE SOME LOCALIZATION
 UNDERSAMPLE IN k -SPACE, PRODUCING ALIASING
 SORT OUT IN RECONSTRUCTION

MANY APPROACHES

IMAGE DOMAIN - SENSE

FREQUENCY DOMAIN - SMASH, GRAPPA, SPIRIT

HYBRID - ARC, SPACE-RIP

WE WILL FOCUS ON TWO:

SENSE - OPTIMAL IF YOU KNOW
 COIL SENSITIVITIES

EASY TO VISUALIZE

EASY TO ANALYZE

GRAPPA -

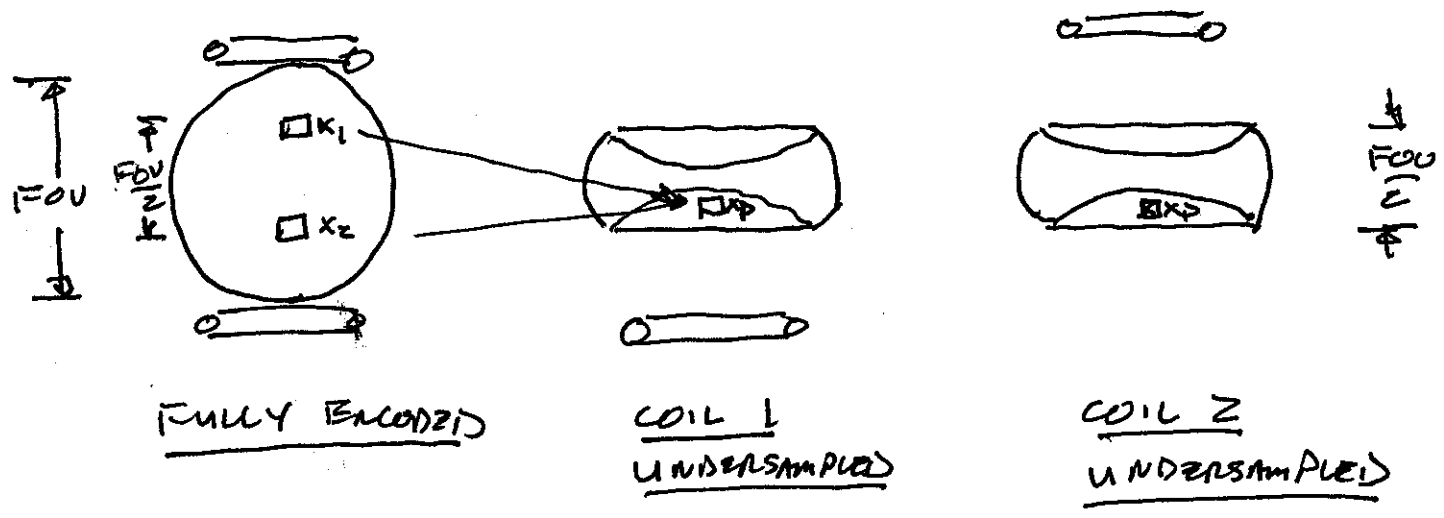
AUTOCALIBRATING

ROBUST

ZDF T SENSE

L' RECEIVING COILS

UNDERSAMPLED IMAGES BY FACTOR OF 2
(R=2)



x_1 AND x_2 ALIAS TO x_p

WE HAVE N MEASUREMENTS OF x_p (i.e. $x_1 + x_2$)
EACH WITH DIFFERENT SENSITIVITIES

$$\begin{matrix} \text{COIL 1} \\ \vdots \\ \text{COIL N} \end{matrix} - \begin{pmatrix} m_1(x_p) \\ m_2(x_p) \\ \vdots \\ m_L(x_p) \end{pmatrix} = \begin{pmatrix} C_1(x_1) & C_1(x_2) \\ C_2(x_1) & C_2(x_2) \\ \vdots & \vdots \\ C_L(x_1) & C_L(x_2) \end{pmatrix} \begin{pmatrix} m(x_1) \\ m(x_2) \end{pmatrix} + \begin{pmatrix} n_1 \\ \vdots \\ n_L \end{pmatrix}$$

ALIASED IMAGES
SENSITIVITY AT SOURCE VOXELS
SOURCE VOXELS

IN MATRIX FORM

$$\underbrace{m_s(x_p)}_{L \times 1} = \underbrace{C}_{L \times Z} \underbrace{m}_{Z \times 1} + \underbrace{n}_{L \times 1}$$

SAME MINIMUM VARIANCE SOLUTION

$$\hat{\underbrace{m}_{Z \times 1}} = \underbrace{(C^* \Psi^{-1} C)^{-1}}_{Z \times Z} \underbrace{C^* \Psi^{-1}}_{Z \times L} \underbrace{m_s(x_p)}_{L \times 1}$$

L ALIASED RECONSTRUCTIONS RESOLVE TWO IMAGE PIXELS

FOR AN $N \times N$ IMAGE, WE SOLVE

$$\frac{N}{Z} \times N$$

$Z \times Z$ INVERSE SYSTEMS

FOR HIGHER ACCELERATIONS, R , WE SOLVE

$$\frac{N}{R} \times N$$

$R \times R$ INVERSE SYSTEMS

MANY SMALL PROBLEMS, VERY FAST

HOW LARGE CAN R BE?

SNR COST

TWO SNR LOSS MECHANISMS

REDUCED SCAN TIME

CONDITION OF THE SENSE DECOMPOSITION

SNR LOSS

$$\frac{SNR_R}{SNR_F} = \frac{1}{g\sqrt{R}}$$

\uparrow GEOMETRY FACTOR \nwarrow REDUCED SCAN TIME

FULLY ENCODED COVARIANCE

$$\chi_F = \frac{1}{n_{KF}} (C_F^* \Psi^{-1} C_F)^{-1}$$

VARIANCE OF ONE VOXEL, SCALAR

REDUCED ENCODING COVARIANCE

$$\chi_R = \frac{1}{n_{KR}} (C_R^* \Psi^T C_R)^{-1}$$

COVARIANCE OF R ALIASED VOXELS

FOR THE j^{th} ALIASED VOXEL

$$\begin{aligned} \frac{SNR_R}{SNR_F} &= \frac{S / \sqrt{[\chi_R]_{j,j}}}{S / \sqrt{\chi_F}} \\ &= \frac{1}{\sqrt{[\chi_R]_{j,j} / \chi_F}} \\ &= \frac{1}{\sqrt{\frac{\chi_{F,F}}{\chi_{R,R}} \sqrt{[(C_R^* \Psi^T C_R)^{-1}]_{j,j}} (C_F^* \Psi^T C_F)}} \\ &= \frac{1}{\sqrt{R} g} \end{aligned}$$

WHERE

$$g = \sqrt{(C_F^* \Psi^T C_F) [(C_R^* \Psi^T C_R)^{-1}]_{j,j}}$$

GEOMETRY FACTOR, $g \geq 1$

OTHER WRITTEN

$$g = \sqrt{[C^* \Psi^T C]_{j,j} [(C^* \Psi^T C)^{-1}]_{j,j}}$$

WHERE $C = C_R$, AND

$$[C^* \Psi^T C]_{j,j} = (C_F^* \Psi^T C)$$

FOR FULL ENCODING OF PIXEL j

GEOMETRY FACTOR IS CRITICAL

DEPENDS ON

ACCELERATION

SPATIAL POSITION

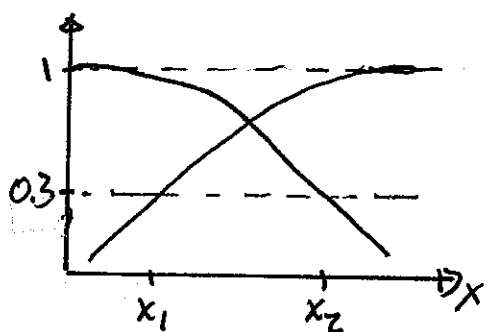
ALIASING DIRECTION

COIL GEOMETRY

MINIMIZING q DRIVES SYSTEM DESIGN

SENSE COILS ARE DIFFERENT FROM TRADITIONAL
ARRAY COILS

EXAMPLE GOOD SENSE COLL



$$\begin{aligned}
 C_1(x_1) &= 1.0 \\
 C_1(x_2) &= 0.3 \\
 C_2(x_1) &= 0.3 \\
 C_2(x_2) &= 1.0
 \end{aligned}$$

AT x_1

$$C_F = \begin{pmatrix} 1 \\ 0.3 \end{pmatrix} \quad C_R = \begin{pmatrix} 1 & 0.3 \\ 0.3 & 1 \end{pmatrix}$$

LET $\psi = I$

$$g = \sqrt{(C_F^* C_F) [(C_R C_R)^{-1}]_{1,1}}$$

$$C_F^* C_F = (1 \ 0.3) \begin{pmatrix} 1 \\ 0.3 \end{pmatrix} = 1.09$$

$$\chi_F = \frac{1}{n_{KF}} \frac{1}{1.09} = \frac{1}{n_{KF}} 0.91$$

$$\begin{aligned}
 C_R^* C_R &= \begin{pmatrix} 1 & 0.3 \\ 0.3 & 1.0 \end{pmatrix} \begin{pmatrix} 1 & 0.3 \\ 0.3 & 1 \end{pmatrix} \\
 &= \begin{pmatrix} 1.09 & 0.6 \\ 0.6 & 1.09 \end{pmatrix} \quad \text{SAME AS } C_F^* C_F
 \end{aligned}$$

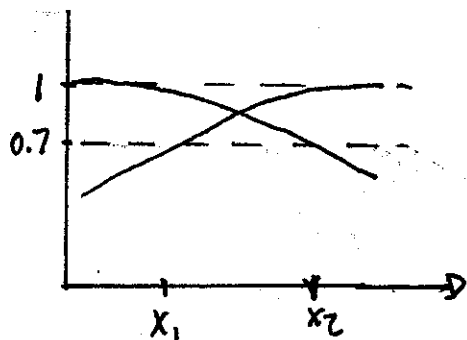
$$(C_R^* C_R)^{-1} = \begin{pmatrix} 1.316 & -0.724 \\ -0.724 & 1.316 \end{pmatrix}$$

$$g = \sqrt{\underbrace{(1.09)}_{MC \text{ LOSS}} \underbrace{(1.316)}_{CONDITION \text{ LOSS}}} = 1.20 \quad \text{20\% LOSS } L8$$

$$\frac{SNR_R}{SNR_F} = \frac{1}{\sqrt{2}(1.20)} = 0.59$$

40% SNR
LOSS

EXAMPLE GOOD ARRAY COIL



$$\begin{aligned} C_1(x_1) &= 1 \\ C_1(x_2) &= 0.7 \\ C_2(x_1) &= 0.7 \\ C_2(x_2) &= 1 \end{aligned}$$

AT x_1

$$C_F = \begin{pmatrix} 1 \\ 0.7 \end{pmatrix} \quad C_R = \begin{pmatrix} 1 & 0.7 \\ 0.7 & 1 \end{pmatrix}$$

$$C_F^* C_F = 1.49$$

$$C_R^* C_R = \begin{pmatrix} 1.49 & 1.4 \\ 1.4 & 1.49 \end{pmatrix}$$

$$(C_R^* C_R)^{-1} = \begin{pmatrix} 5.72 & -5.38 \\ -5.38 & 5.72 \end{pmatrix}$$

$$g = \sqrt{(C_F^* C_F) ((C_R^* C_R)^{-1})_{1,1}}$$

$$= \sqrt{\underbrace{(1.49)}_{\text{MC LOSS}} \underbrace{(5.72)}_{\text{CONDITION}}} = 2.92$$

3X Lower
SNR

$$\frac{SNR_R}{SNR_F} = \frac{1}{\sqrt{2} \cdot 2.92} = 0.24$$

4X Lower
SNR

SENSE COILS SHOULD BE DESIGNED FOR

LOCAL SENSITIVITY

AS ORTHOGONAL AS POSSIBLE

OPTIMIZE SNR IN RECON

ARRAY COILS

LARGER SENSITIVITIES

APPROXIMATELY UNIFORM WITH SQUARE-ROOT

OF SUM OF SQUARES RECON.