

# Regularized fieldmap estimation in MRI

Jeffrey A. Fessler and Desmond Yeo

EECS Dept.  
The University of Michigan

Douglas C. Noll

BME Dept.  
The University of Michigan

ISBI  
Apr. 9, 2006

# Introduction

- Focus: fast single-shot MR imaging, such as echo-planar imaging (EPI) or spiral imaging for fMRI
- Long readout times  
⇒ sensitive to  $B_0$  field inhomogeneity / magnetic susceptibility
- Accurate correction for off-resonance effects requires a **field map**
- Field-corrected MR image reconstruction
  - Pixel-shifting for EPI (Sekihara *et al.*, 1985, IEEE T-MI)
  - Conjugate phase (Macovski, 1985, MRM; Noll *et al.*, 2005, IEEE T-MI)
  - Iterative (Sutton *et al.*, 2003, IEEE T-MI)

# Measurement model

Two reconstructed images with slightly different echo times:

$$\begin{aligned}y_j &= f_j + \varepsilon_j \\z_j &= f_j e^{ix_j} + \eta_j, \quad j = 1, \dots, n_p\end{aligned}$$

- $f_j$ : unknown complex transverse magnetization of the  $j$ th voxel
- $n_p$ : number of voxels
- $x_j = \omega_j \Delta_t$ : accrued phase
- $\omega_j$ : off-resonance of  $j$ th voxel
- $\Delta_t$ : echo-time difference
- $\varepsilon_j, \eta_j$ : e (complex) noise.

**Goal:** estimate **phase map**  $\mathbf{x} = (x_1, \dots, x_{n_p})$  from images  $\mathbf{y}$  and  $\mathbf{z}$ .

The unknown image  $\mathbf{f} = (f_1, \dots, f_{n_p})$  is a nuisance parameter vector.

# Conventional phase estimator

Phase difference of the two images: (Sekihara *et al.*, 1985, IEEE T-MI):

$$\hat{x}_j = \angle(y_j^* z_j) = \angle z_j - \angle y_j$$

- Fieldmap estimate is simply scaled by echo-time difference:

$$\hat{\omega}_j = \hat{x}_j / \Delta_t .$$

- Works perfectly in the absence of noise and phase wrapping, within voxels where  $|f_j| > 0$ .
- Sensitive to noise in voxels where magnitude  $|f_j|$  is small.
- Ignores *a priori* knowledge that fieldmaps tend to be smooth
- Post-filtering works poorly because  $\hat{x}_j$  is severely corrupted in low SNR voxels.

# Maximum-likelihood phase estimation

Maximum likelihood (ML) method based on a statistical model.

Assume independent zero-mean white gaussian complex noise.

Assume  $\mathbf{y}$  and  $\mathbf{z}$  have same variance  $\sigma^2$ .

Joint log-likelihood for  $\mathbf{f}$  and  $\mathbf{x}$  given  $\mathbf{y}$  and  $\mathbf{z}$  is

$$\begin{aligned}\log p(\mathbf{y}, \mathbf{z}; \mathbf{f}, \mathbf{x}) &= \log p(\mathbf{y}; \mathbf{f}) + \log p(\mathbf{z}; \mathbf{f}, \mathbf{x}) \\ &\equiv \frac{-1}{2\sigma^2} \sum_{j=1}^{n_p} \left( |y_j - f_j|^2 + |z_j - f_j e^{ix_j}|^2 \right).\end{aligned}$$

Simultaneous ML estimation of image  $\mathbf{f}$  and phase map  $\mathbf{x}$ :

$$\arg \min_{\mathbf{x} \in \mathbb{R}^{n_p}} \arg \min_{\mathbf{f} \in \mathbb{C}^{n_p}} \sum_{j=1}^{n_p} \left\| \begin{bmatrix} y_j \\ z_j \end{bmatrix} - \begin{bmatrix} 1 \\ e^{ix_j} \end{bmatrix} f_j \right\|^2.$$

## ML solution

Quadratic cost function in  $f_j$ , leading to the following ML estimate:

$$\hat{f}_j = \frac{y_j + e^{-ix_j} z_j}{2}.$$

Substituting back into the cost function and simplifying yields the following minimization problem for ML estimation of  $\mathbf{x}$ :

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \Psi(\mathbf{x}), \quad \Psi(\mathbf{x}) = \sum_{j=1}^{n_p} \frac{1}{2} |y_j - e^{-ix_j} z_j|^2.$$

After simplifying:

$$\Psi(\mathbf{x}) \equiv \sum_{j=1}^{n_p} |y_j z_j| [1 - \cos(\angle z_j - \angle y_j - x_j)].$$

One ML estimate is the minimizer:

$$\hat{x}_j = \angle z_j - \angle y_j.$$

$\therefore$  Conventional phase estimate  $\equiv$  ML estimate!

# Penalized likelihood phase / fieldmap estimation

ML estimate ignores *a priori* smoothness of fieldmaps.

Penalized-likelihood approach using regularization (aka MAP)

- Regularize phase map  $\mathbf{x}$  with strong roughness penalty
- No regularization of magnetization map  $\mathbf{f}$  (anatomical details)

Regularized cost function:

$$\Psi(\mathbf{x}) = \sum_{j=1}^{n_p} |y_j z_j| [1 - \cos(\angle z_j - \angle y_j - x_j)] + \beta R(\mathbf{x})$$

Down-weights data in voxels where the magnitude  $|y_j z_j|$  is small. In such voxels the phase will be estimated from neighboring voxels, due to the spatial roughness penalty  $R(\mathbf{x})$ :

$$R(\mathbf{x}) = \sum_{n=1}^{N-1} \sum_{m=0}^{M-1} \psi(x[n, m] - x[n-1, m]) \\ + \sum_{n=0}^{N-1} \sum_{m=1}^{M-1} \psi(x[n, m] - x[n, m-1]).$$

Quadratic potential function  $\psi(t) = t^2/2$ . (No “edge” preservation.)

# Minimization algorithm

Optimization transfer approach leads to diagonally preconditioned gradient descent algorithm:

$$\mathbf{x}^{(n+1)} = \mathbf{x}^{(n)} - \text{diag} \left\{ \frac{1}{|y_j z_j| + \beta \cdot 4} \right\} \nabla \Psi(\mathbf{x}^{(n)})$$

- Initialize  $\mathbf{x}^{(0)}$  with conventional (aka ML) phase estimate
- Guaranteed to decrease  $\Psi(\mathbf{x})$  monotonically
- $\Psi$  nonconvex  $\implies$  convergence to a local minimizer of  $\Psi(\mathbf{x})$

(movie in pdf)

# PWLS fieldmap estimator

Echo time difference  $\Delta_t$  usually small enough to prevent phase wrap.

Taylor series approximation  $1 - \cos(t) \approx t^2/2$ .

Penalized weighted-least squares (PWLS) cost function:

$$\Psi(\mathbf{x}) = \sum_{j=1}^{n_p} w_j \frac{1}{2} (\angle z_j - \angle y_j - x_j)^2 + \beta R(\mathbf{x}),$$

where we define a magnitude weighting function:  $w_j \triangleq |y_j z_j|$ .

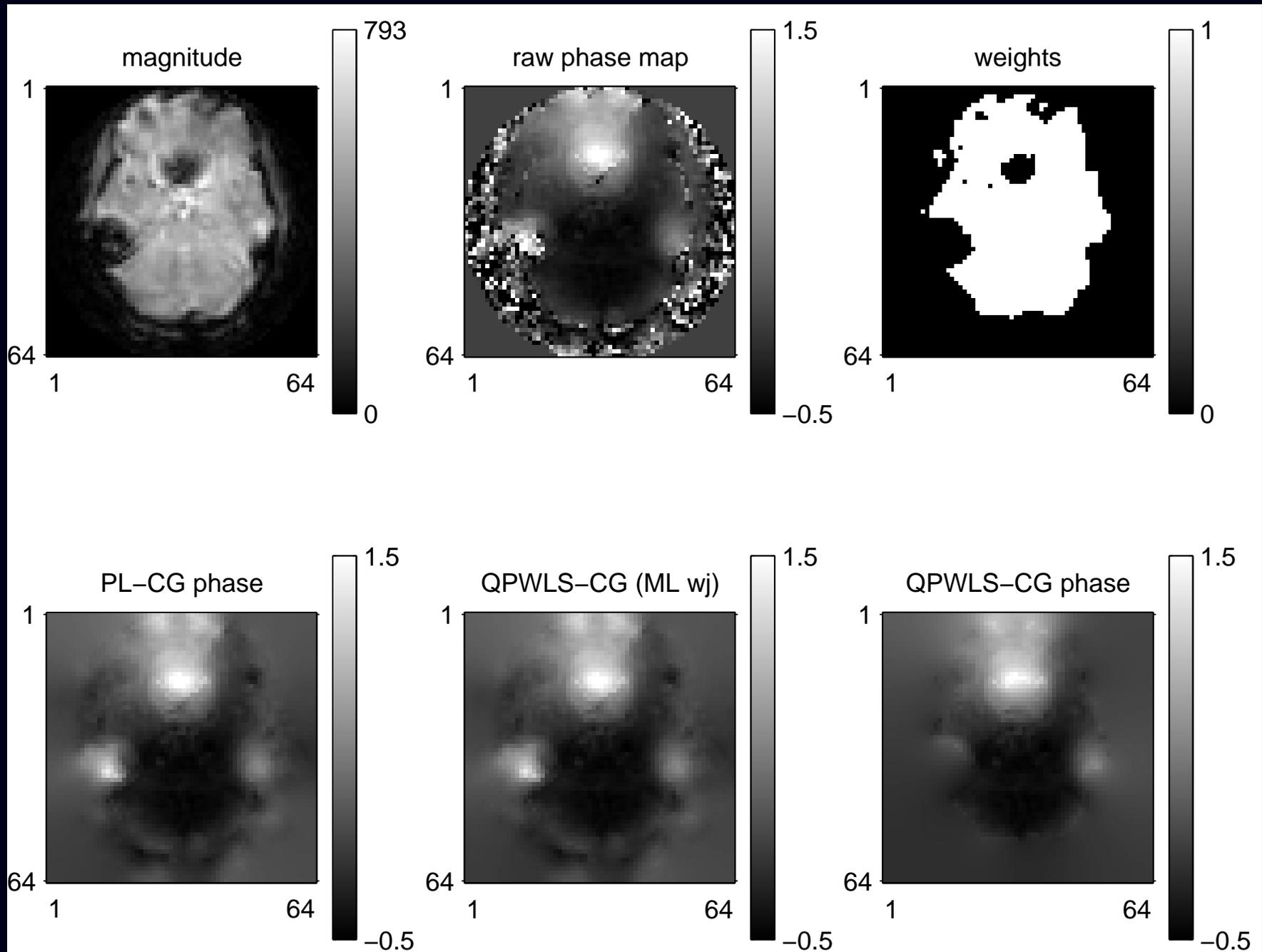
PWLS estimators give more weight to the “good data” and use regularization to control noise.

Alternative: binarize the weights  $w_j$  using a threshold:

$$w_j \triangleq \begin{cases} 1, & |y_j z_j| > \gamma \\ 0, & \text{otherwise,} \end{cases} \quad \text{e.g.,} \quad \gamma = 0.4 \max_j |y_j z_j|.$$

Use conjugate gradient (CG) algorithm for minimization.

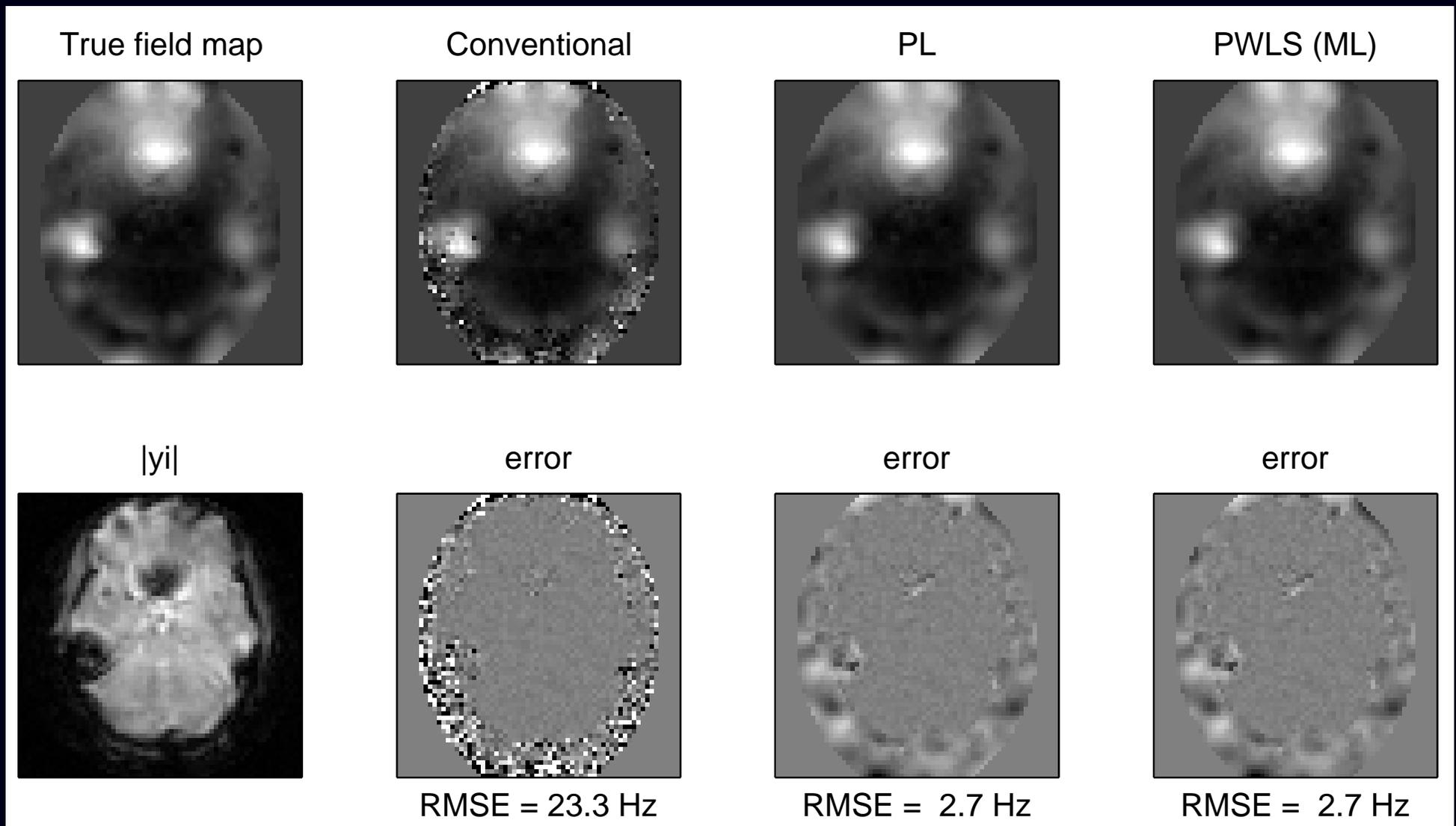
# Example (3T MR scan)



# Results

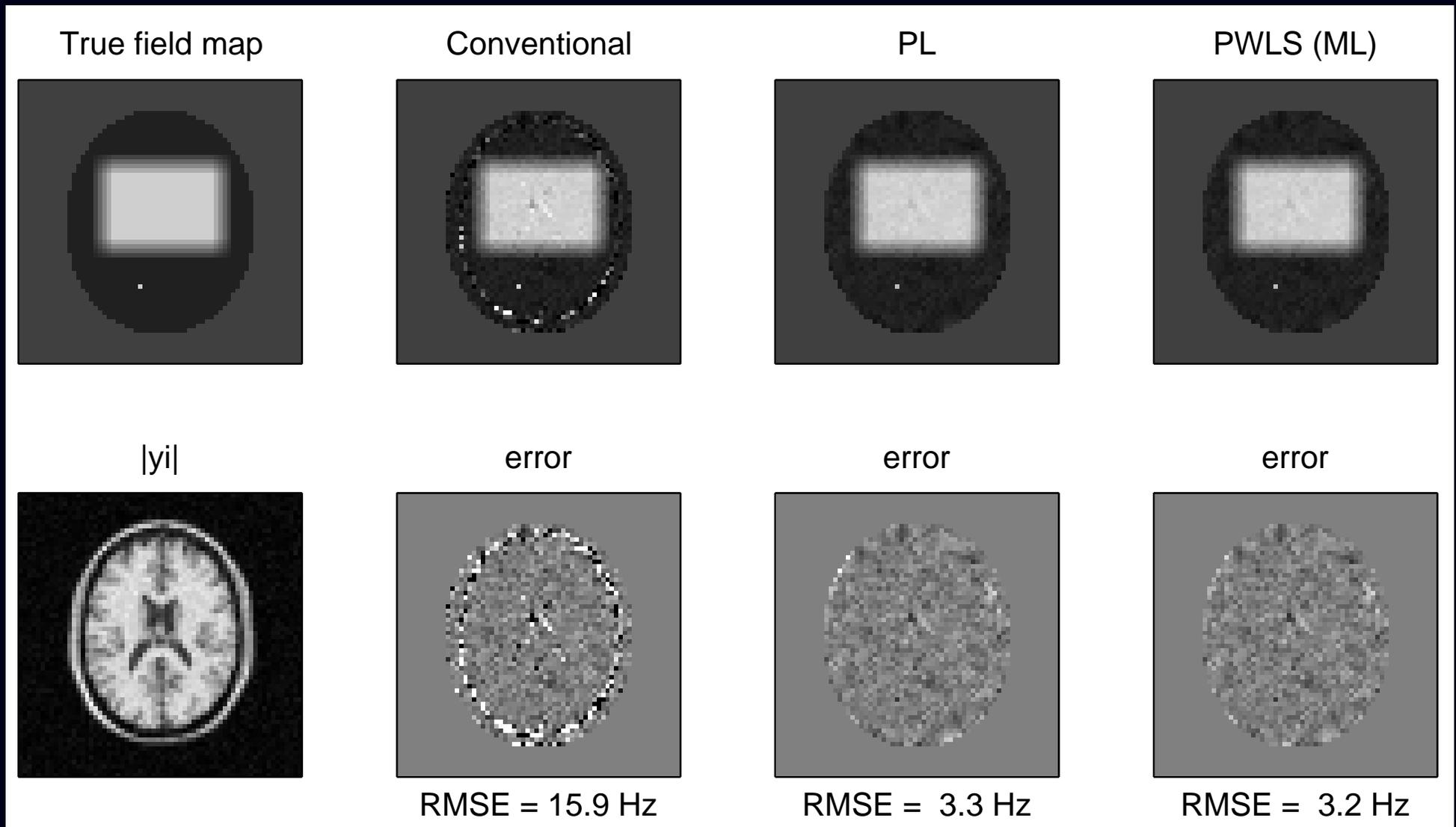
- Real data from a 3T MR scanner.
- 150 iterations for PL: 4.4 s (Matlab on G5)
- 150 iterations for PWLS: 2.2 s
- 3% normalized RMS difference for PL method vs PWLS approximation with ML weights.
- 42% normalized RMS difference for PWLS with binary weights vs PWLS with ML weights.

# Simulation 1



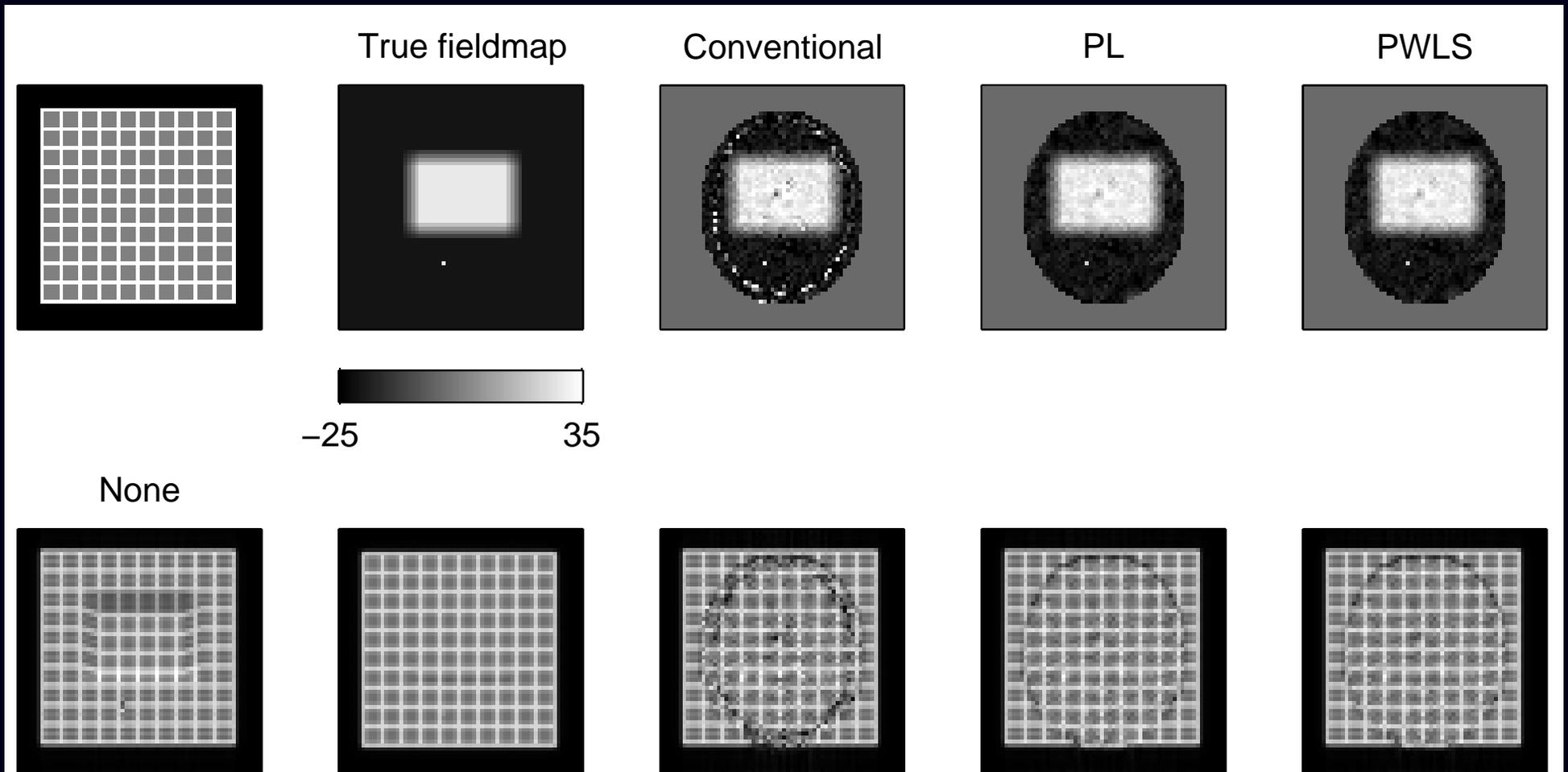
Field map display range: -40 to 120 Hz  
Error map display range: -20 to 20 Hz.

# Simulation 2



Field map display range: -40 to 120 Hz  
Error map display range: -20 to 20 Hz.

# Effect on EPI



30 msec EPI readout.

20 iterations of PWLS-CG field-corrected image reconstruction

# Choosing regularization parameter $\beta$

Spatial resolution analysis of fieldmap estimator (Fessler *et al.*, IEEE T-MI, 1996):

$$E[\hat{\mathbf{x}}] \approx \underbrace{\left[ \mathbf{I} + \beta \text{diag}\{w_j\}^{-1} \mathbf{C}'\mathbf{C} \right]}_{\text{"filter"}} \mathbf{x},$$

where  $\mathbf{C}$  is the 1st-order or 2nd-order differencing matrix.

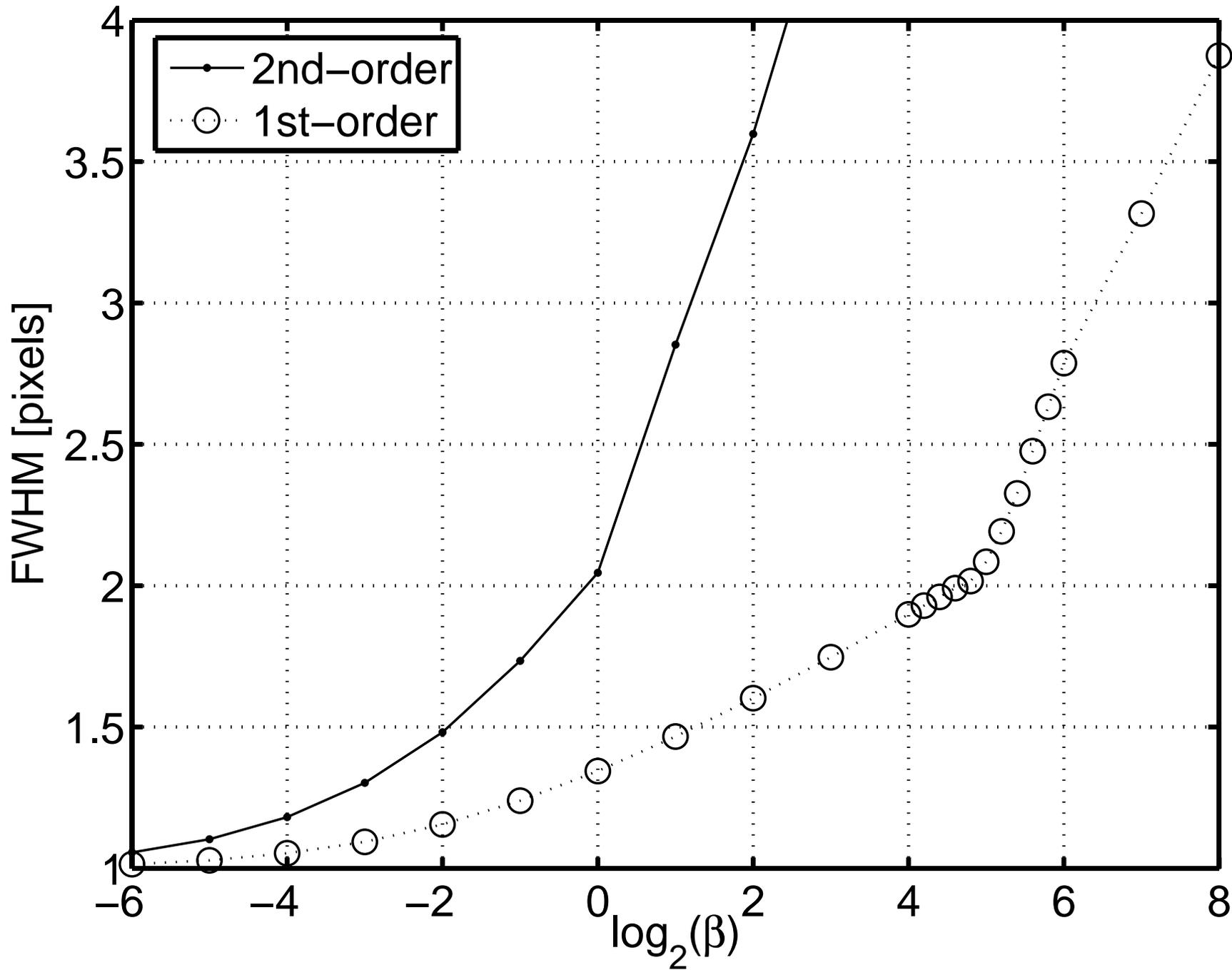
Local frequency response of the “filter” is: (Unser *et al.* IEEE T-SP 1991)

$$H(\omega_1, \omega_2) \approx \frac{1}{1 + (\beta/w_j)(\omega_1^2 + \omega_2^2)^p},$$

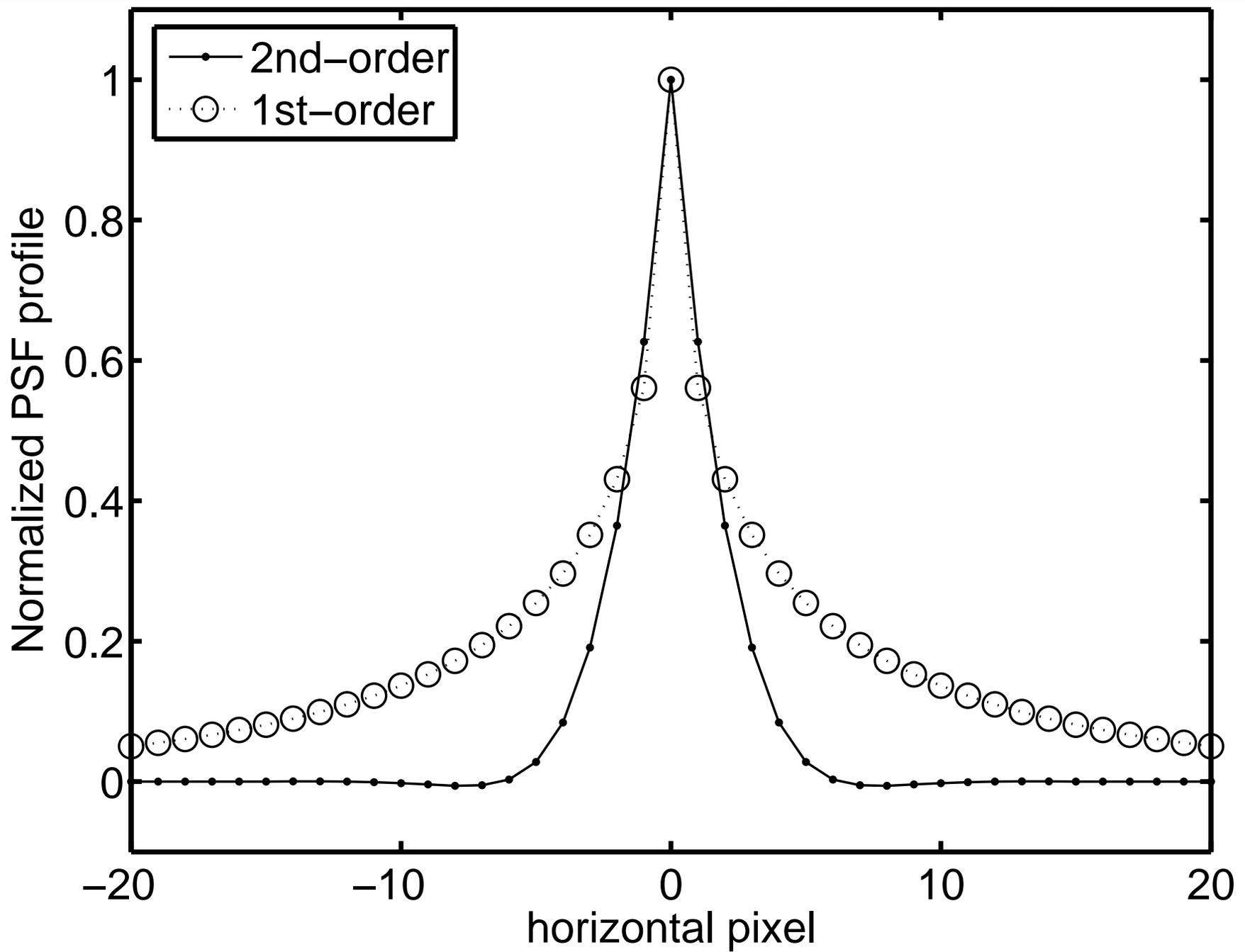
for regularization based on  $p$ th-order differences, where  $p = 1$  or  $2$ .

- Inverse 2D DSFT yields PSF  $h[n, m]$ .
- Tabulate FWHM of PSF vs  $\beta/w_j$ .
- Select required  $\beta$  based on desired spatial resolution (FWHM).

# PSF FWHM vs $\beta/w_j$



# PSF Shape (2nd-order preferable)



# Summary

- Conventional phase estimate equivalent to joint ML estimate
- Penalized-likelihood estimation reduces fieldmap error
- PWLS estimator performs similarly:  
preferable due to simplicity in absence of phase wrap

# Future work

- Accelerate by preconditioning or multi-resolution
- Regularized estimation from k-space data
- Illustrate effects of phase errors on real EPI and spiral scans