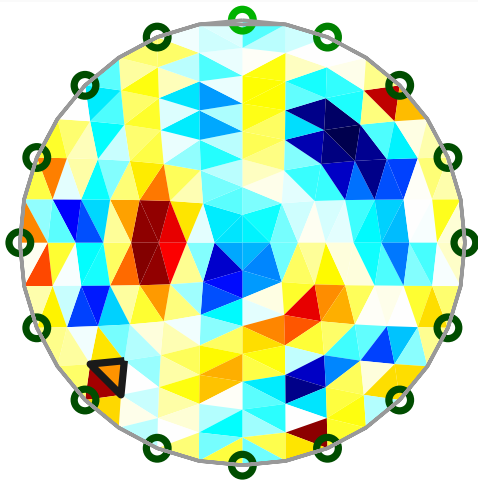


Propagation of Measurement Noise into Images

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EIT2019, July 1-3, 2019

We Choose One Image



$$\lambda_L = 5.9e-02; \quad \lambda_{GCV} = 3.7e-02$$

Measurements are Reconstructed

Single step Gauss-Newton reconstruction

$$\mathbf{x} = (\mathbf{J}^T \mathbf{W} \mathbf{J} + \lambda^2 \mathbf{R})^{-1} \mathbf{J}^T \mathbf{W} \mathbf{b}$$

x: change in conductivity; **b**: difference measurements;
J: Jacobian; **W**: inverse noise covariance;
 λ : hyperparameter; **R**: regularization

Measurements are Reconstructed

Single step Gauss-Newton reconstruction

$$\mathbf{x} = \mathbf{Q}\mathbf{b}$$

\mathbf{x} : change in conductivity; \mathbf{b} : difference measurements;
 $\mathbf{Q} = (\mathbf{J}^T\mathbf{W}\mathbf{J} + \lambda^2\mathbf{R})^{-1}\mathbf{J}^T\mathbf{W}$: reconstruction matrix

Noise is Reconstructed

$$\mathbf{x} = \mathbf{Q}(\mathbf{b} + \eta)$$

x: change in conductivity; **b**: difference measurements;
Q: reconstruction matrix;

η : noise

Additive noise, but of no particular distribution.

Noise is Reconstructed

$$\mathbf{x} = \mathbf{Q}\mathbf{b} + \mathbf{Q}\eta$$

\mathbf{x} : change in conductivity; \mathbf{b} : difference measurements;
 \mathbf{Q} : reconstruction matrix;

η : noise

Noise is not Normal

but if it was...



Sample from the noise distribution, whether normal or otherwise, and linearly combine with other measurement noise samples using \mathbf{Q} .

Noise is not Normal

but if it was...



These are *sums of random variables* (not a mixture distribution). If we have $\mu = 0$ (captured in \mathbf{b}) then we can combine them as a *sum of weighted variances*.

$$c x_1 \sim \mathcal{N}(c\mu, c^2\sigma^2); \quad x_1 + x_2 \sim \mathcal{N}(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2) \text{ for indep } x_1, x_2$$

Use a row of \mathbf{Q} to scale and add measurement distributions into a conductivity distribution/uncertainty on a single voxel of \mathbf{x} .

Central Limit and Bootstrap

Empirical methods for estimating image noise are *bootstrap* or *leave one out*.

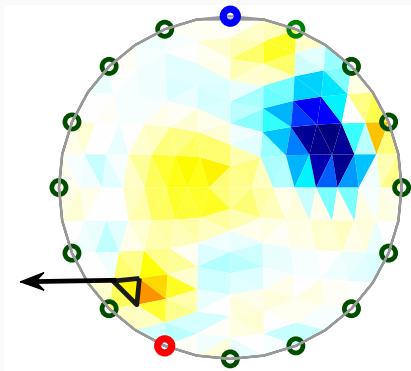
Estimates of the mean are guaranteed to approach a Gaussian distribution, with sufficient sampling, due to the *Central Limit Theorem*.

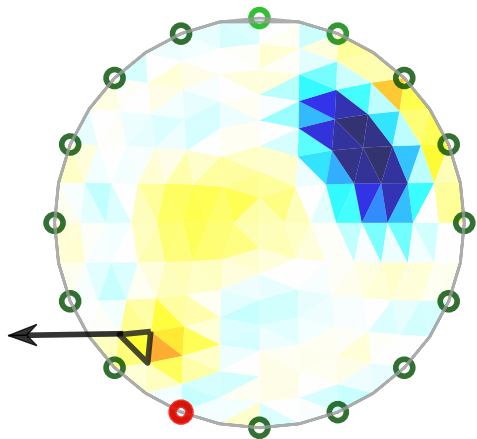
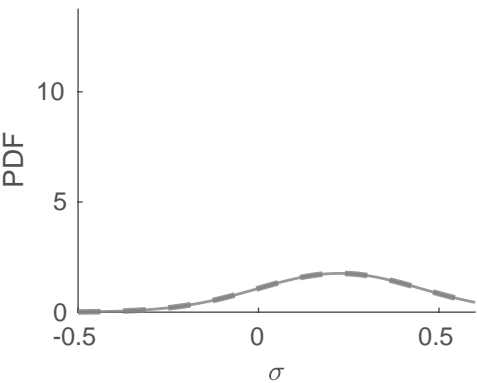
...but we can also just calculate the distribution directly, given our linear reconstruction matrix \mathbf{Q} and a parametric noise distribution η when they're available.

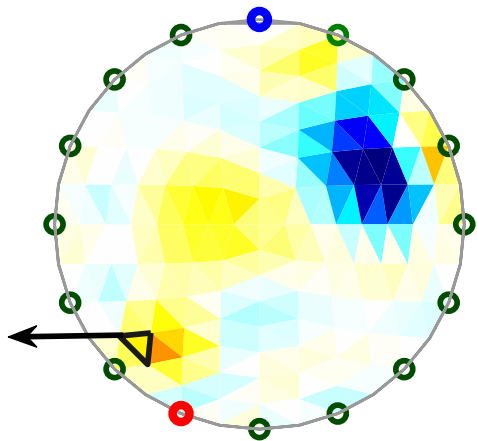
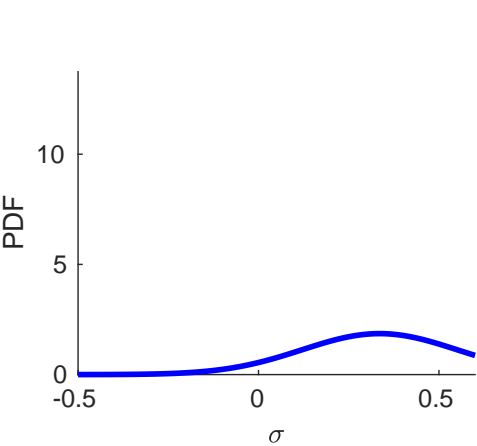
SIMULATIONS

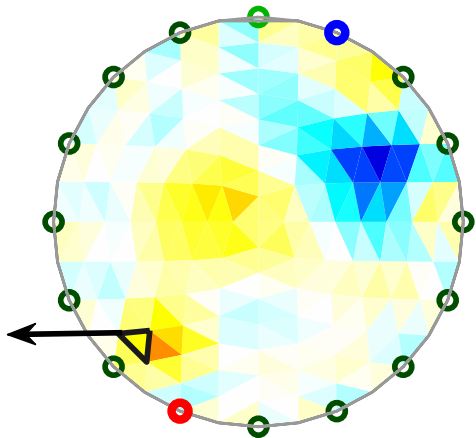
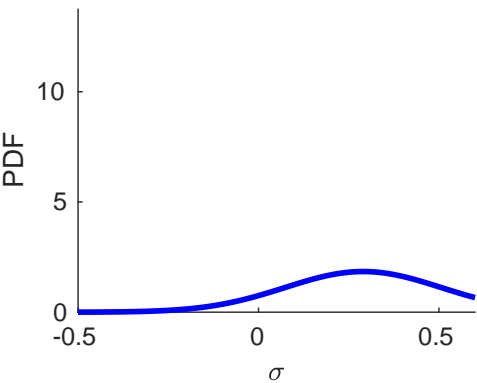
Simulation

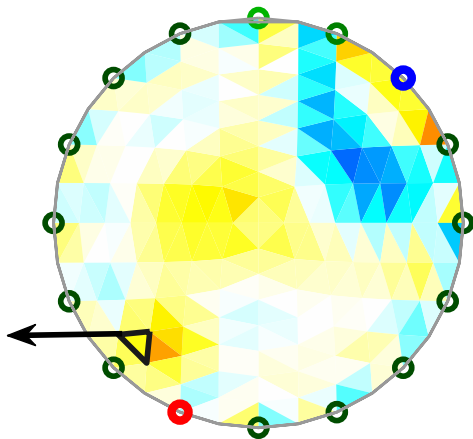
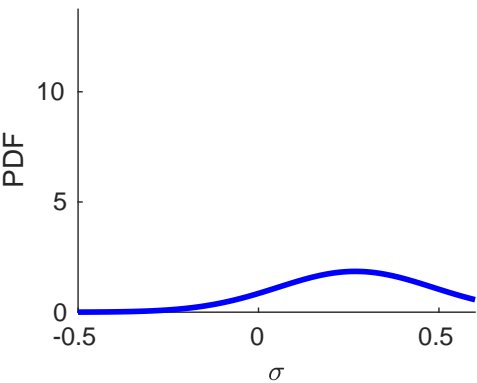
- 2D, 16 electrodes, time difference \mathbf{b}
- ∇ observe distribution of 1 voxel
- measurement noise $\eta \sim \mathcal{N}(0, c/10)$ for $c = \text{var}(\mathbf{b})$
- ● electrode#10 noise $\eta_{10} \sim \mathcal{N}(0, c)$
- ● removed stimulus or measurements using electrode# k

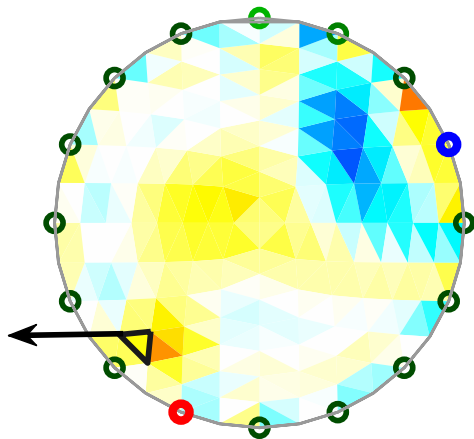
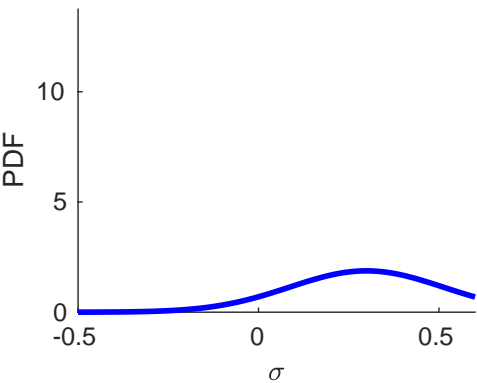


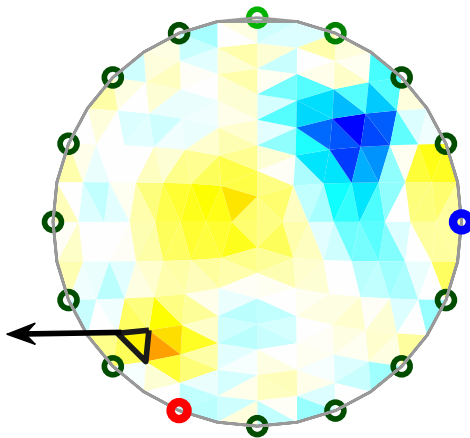
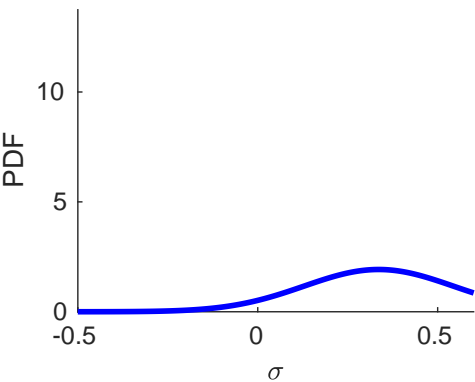


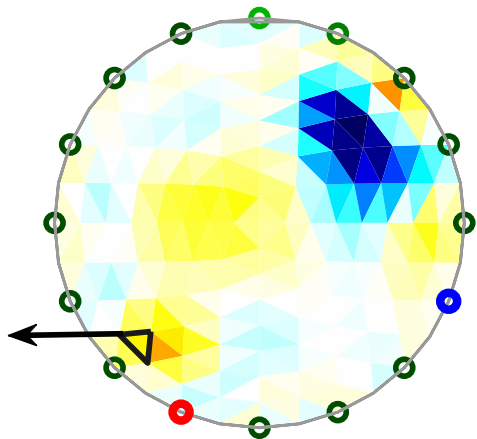
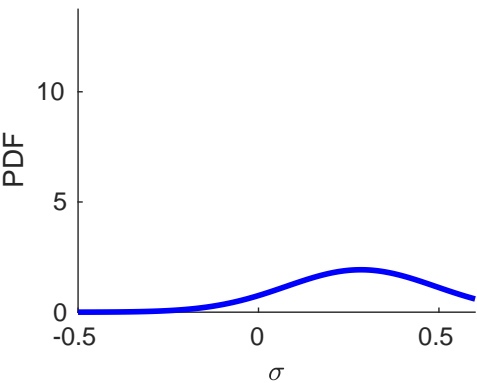


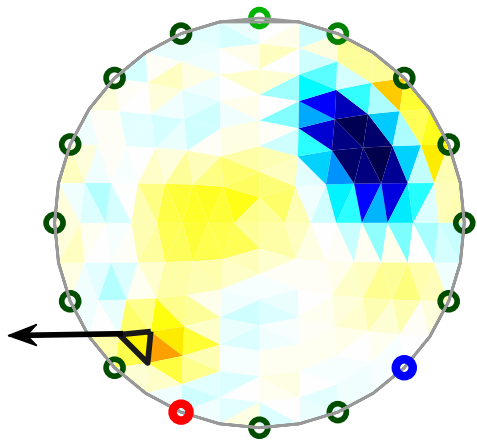
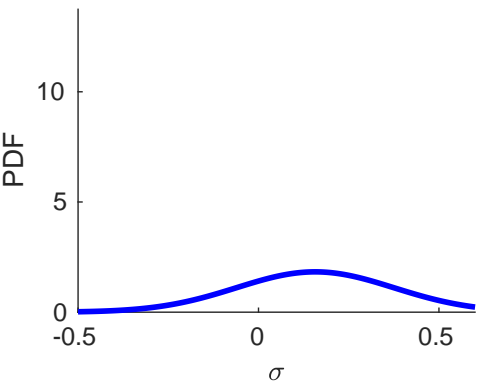


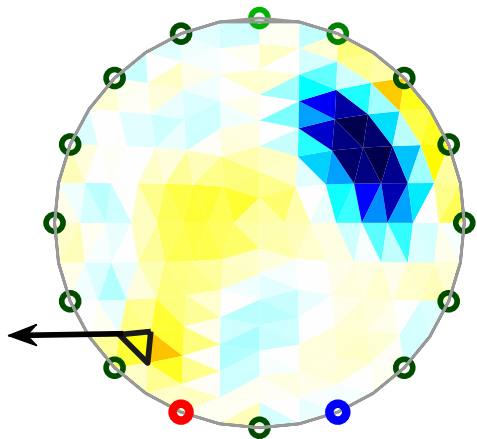
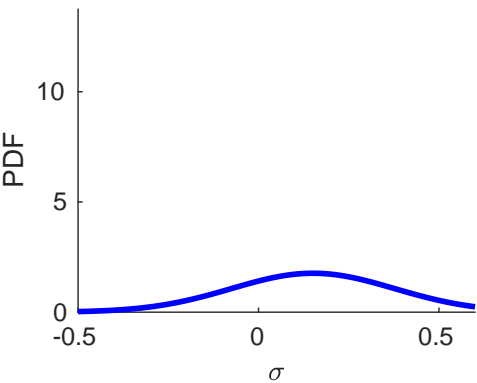


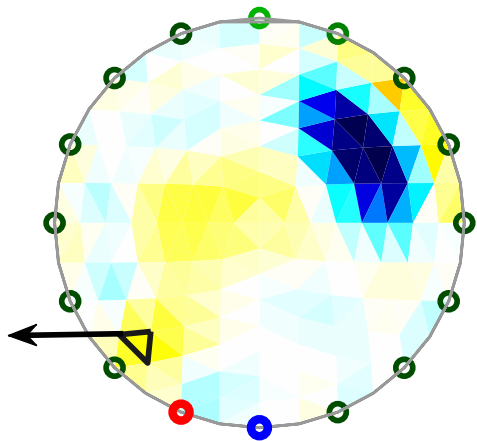
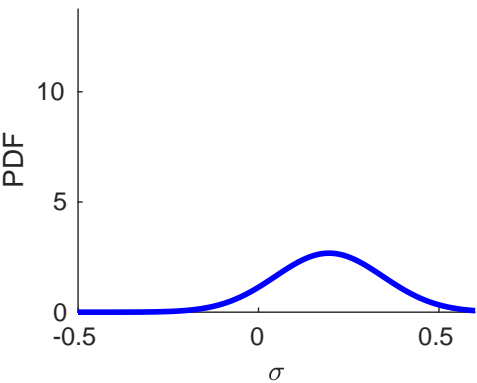


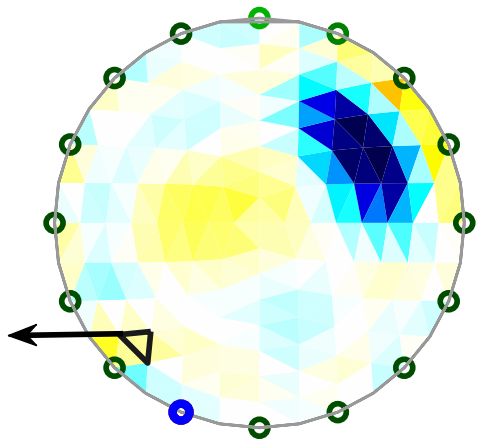
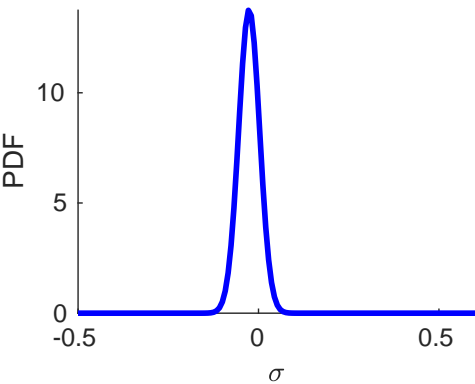


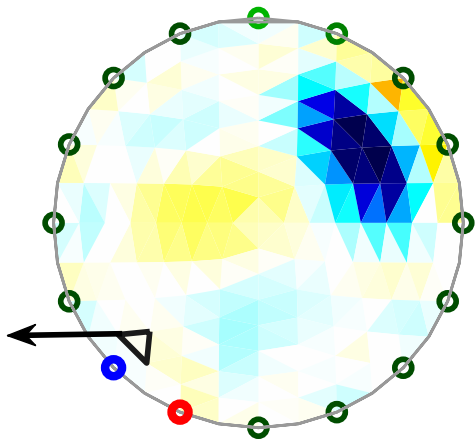
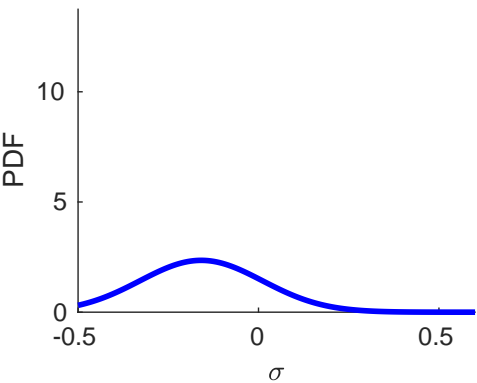


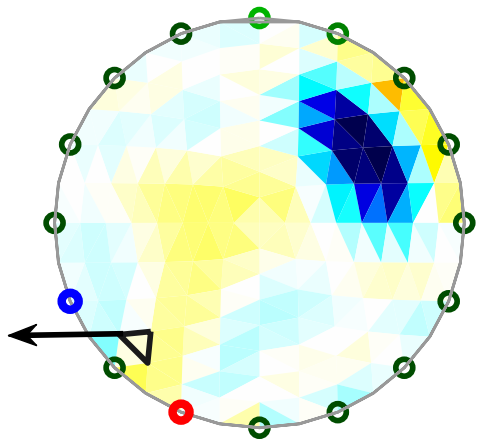
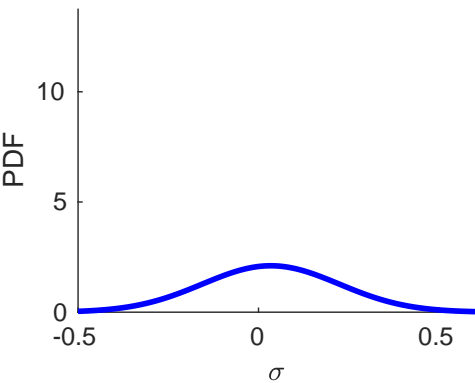


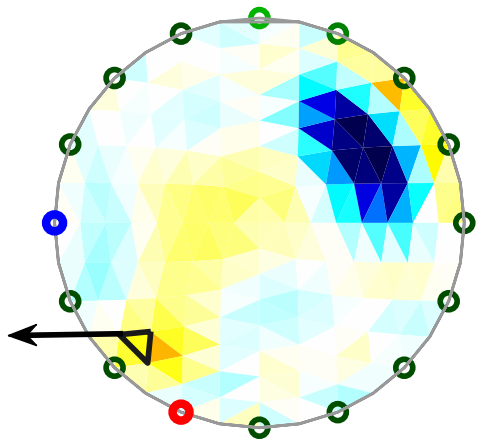
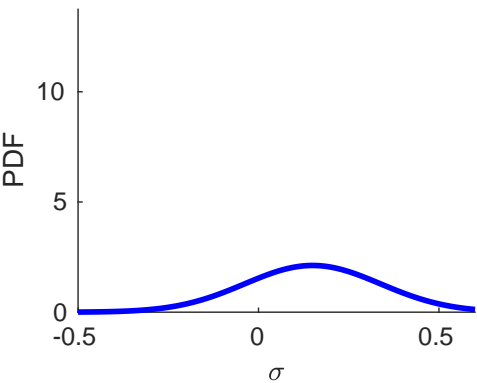


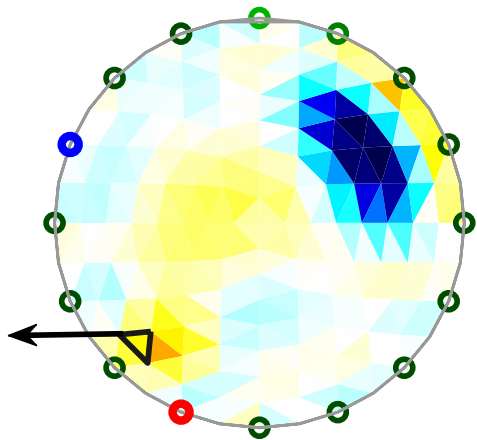
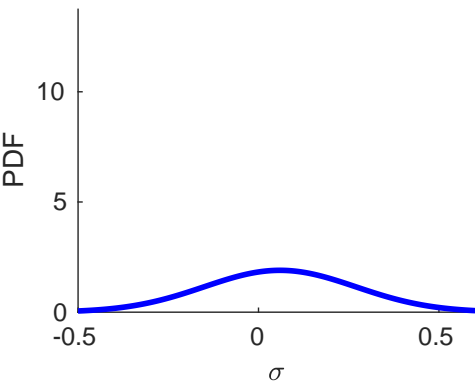


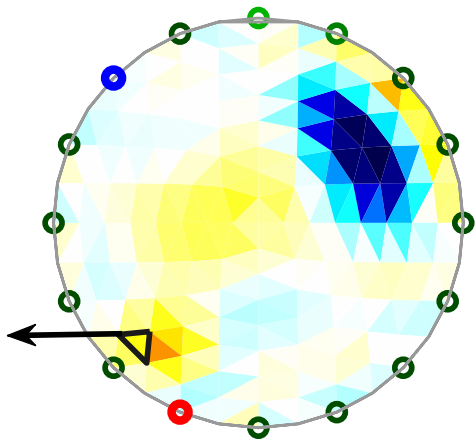
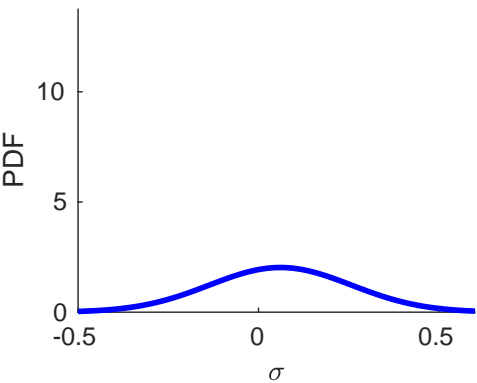


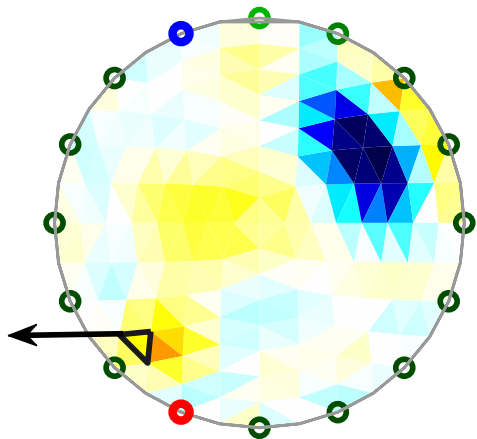
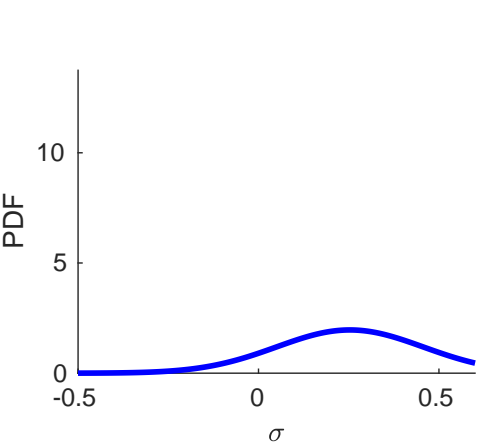


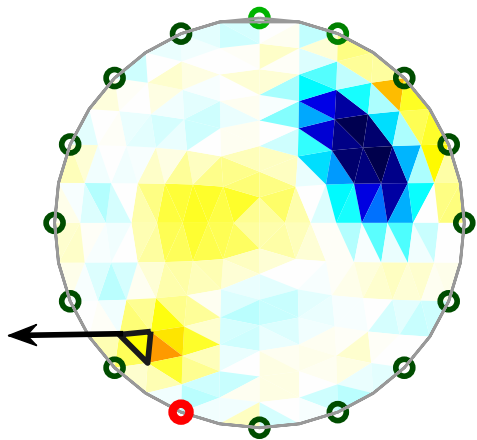
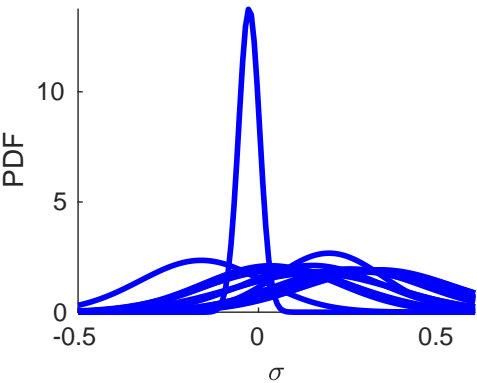


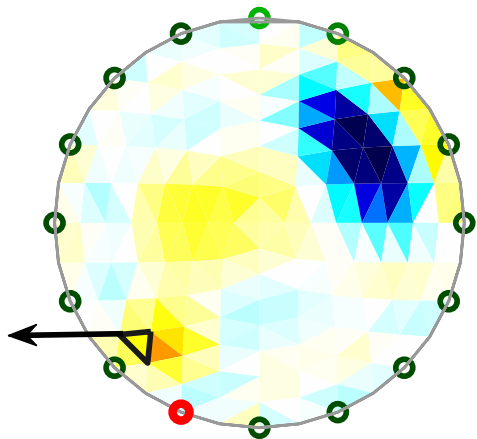
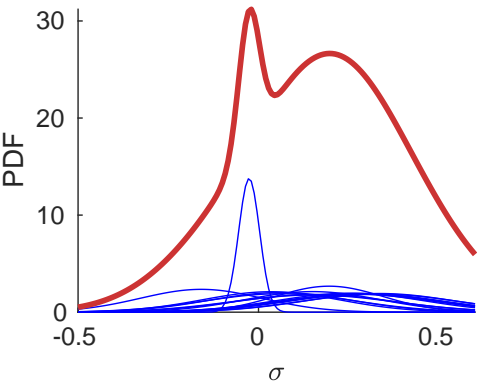


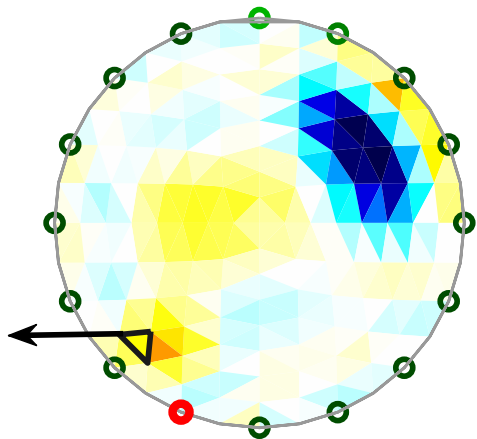
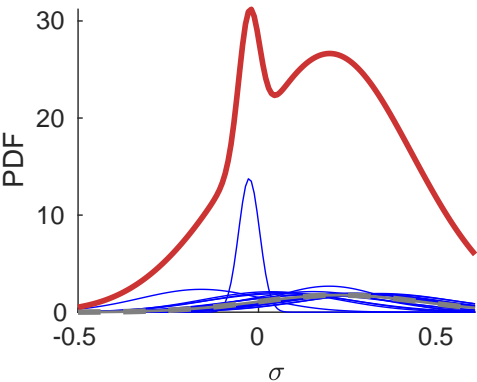


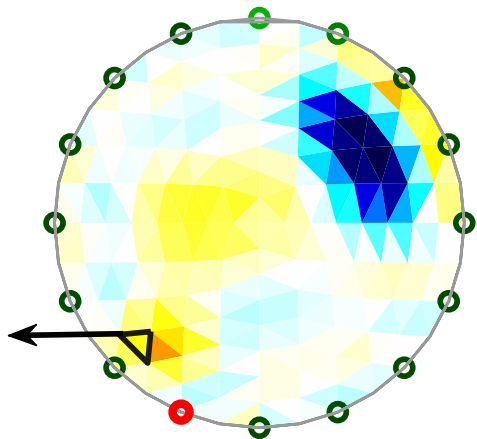
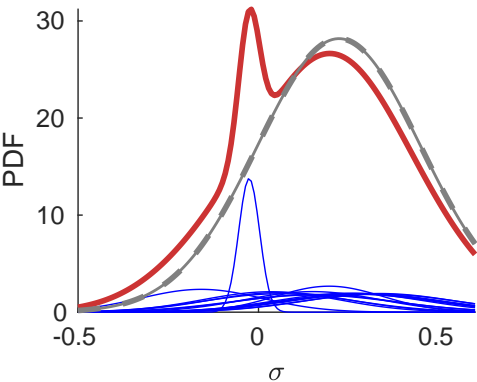












OBSERVATIONS

What can we observe?

- λ_{GCV} tests leaving out a single measurement...doesn't help here
- drop large variance measurements...
- offers a method for efficient calculation of simulated noisy images
- regularization suppresses the effect of measurement variance

