Bayesian algorithms in Imaging and Deconvolution

Applications :

Object detection in extended emission (devonvolution+component fitting), calibration, fitting physical models to sky emission patterns...

Method :

- Use a parameter based model : M
  - Image = sum of elliptical gaussian components
- Provide prior information about each type of parameter : P(I|M)
  - Uniform distribution for position,amplitude, Non-uniform for scale
- Use an appropriate goodness-of-fit criterion : P(D|I,M)
  - Chi-Square
- Perform Monte Carlo sampling of a posterior distribution.

$$\mathbf{P(I|D,M)} \;\; \alpha \;\; \mathbf{P(D|I,M)P(I|M)} \;\; \alpha \;\; \mathbf{e}^{-\frac{1}{2}\chi^2}\mathbf{P(I|M)}$$

Goals :

- Obtain estimates for most probable values of all parameters.
- Obtain error estimates on these parameters + other statistics.

Advantages :

- Work directly with the raw visibility data, with no pre-processing.
- Obtain combined error estimates over all intermediate processing steps.

Implementation & Performance

- Deconvolution is a non-linear inverse problem with no unique solution.
- Component fitting (gaussians) to extended emission is likely to be multi-modal.

Some running times for an algorithm that fits elliptical gaussian components to extended emission :

Image size	#-Gaussians	Time
16x16	1	1 min
16x16	1-3	2.5 min
64x64	1-3	20 min
64x64	4-7	60 min
128x128	3-4	5.5 hrs

The running time depends on

Computational factors:

- Image Size – $O(N^2 \log(N))$
- Number of Parameters - O(N)
- Number of Ensembles - O(N)

Algorithmic factors

- Prior information (regularization)
- Signal to Noise Ratio (Chi-Square)
- Area under the clean beam
  (degree of smoothing to be undone +
  complexity of the point spread function.)

Parallelization is certainly necessary, but there could be a trade-off between the efficiency of the sampling algorithm (speed of convergence) and its simplicity.