

Simulation of the analysis of interferometric microwave background polarization data

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Abstract. We present results from an end-to-end simulation pipeline of interferometric observations of cosmic microwave background polarization. We use both maximum-likelihood and Gibbs sampling techniques to estimate the power spectrum. In addition, we use Gibbs sampling for image reconstruction from interferometric visibilities. The results indicate the level to which various systematic errors (e.g., pointing errors, gain errors, beam shape errors, cross polarization) must be controlled in order to successfully detect and characterize primordial B modes and achieve other scientific goals. In addition, we show that Gibbs sampling is an effective method of image reconstruction for interferometric data in other astrophysical contexts.

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Measurement of cosmic microwave background (CMB) anisotropy has become one of the most powerful tools in cosmology. In recent years, researchers have built on the success of these anisotropy measurements by studying linear polarization in the CMB. In particular, considerable attention has been focused on the search for “B-mode” polarization, which has the potential to measure the energy scale of inflation, along with probing cosmology in a variety of other ways (Hu & Dodelson 2002). BICEP2 has measured a B-mode polarization signal in the microwave sky (Ade *et al.* 2014), which if confirmed will represent a major advance in cosmology. The field eagerly awaits other measurements at different frequencies and with different instruments.

Because the *B*-mode signal is expected to be very faint, control of systematic errors is of paramount importance. An argument can be made (Timbie *et al.* 2006, Bunn 2007) that interferometers provide better control of systematics than imaging telescopes. This is one of the reasons that, for instance, the QUBIC collaboration (Ghribi *et al.* 2013) is constructing an instrument based on the novel approach of bolometric interferometry.

Whether or not interferometers have *better* systematic error properties than imagers, it is clear that they have *different* sensitivity to systematics. Interferometric systematic issues have not received as much attention as systematics in imaging systems. Given the importance of a robust characterization of CMB *B* modes, it seems worthwhile to study these effects in detail. For these reasons, we have performed detailed simulations of interferometric observations of CMB polarization, in order to characterize the effects of various systematic errors on the reconstruction of the polarization power spectra (Karakci *et al.* 2013a, Karakci *et al.* 2013b, Zhang *et al.* 2013).

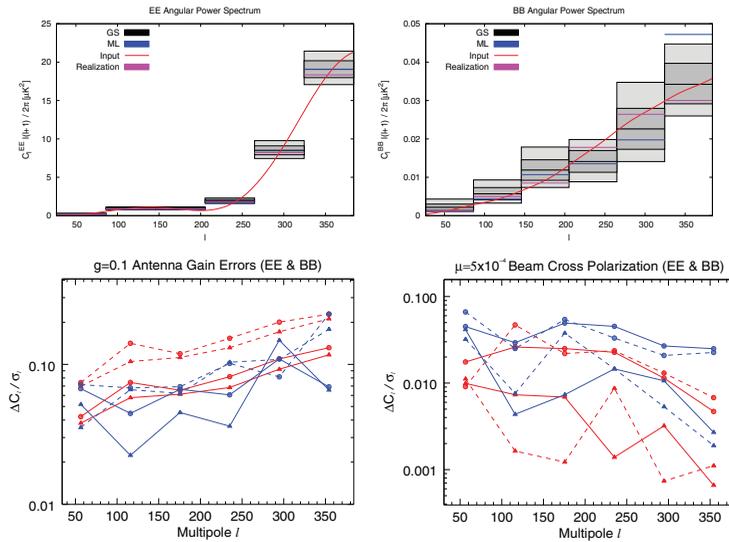


Figure 1. *Top:* Mean posterior band powers obtained by Gibbs sampling (GS) are shown in black. The maximum-likelihood (ML) band powers are shown in blue. Dark and light grey indicate 1σ and 2σ uncertainties on the Gibbs sampling results. Binned power spectra of the signal realization and input power spectra are shown in pink and red. *Bottom:* Examples of the effects of systematic errors, obtained by both ML (triangles) and GS (dots) are shown. Solid and dashed lines correspond to experiments that interfere linear and circular polarization states respectively. Results are shown for the EE (red) and BB (blue) power spectra. For further details, see Karakci *et al.* (2013b).

We have developed tools that generate visibilities for interferometers with arbitrary antenna placement, beam shape, etc., from HEALPix sky maps. We can include the effects of a wide variety of systematic errors, including beam shape and pointing errors, cross-polarization, gain errors, *etc.* We then estimate power spectra from these visibilities in two independent ways, via maximum-likelihood estimation (Hobson & Masinger 2002) and Gibbs sampling (Larson *et al.* 2007, Sutter *et al.* 2012).

Fig. 1 shows the results of simulations that are described in detail in Karakci *et al.* (2013a), Zhang *et al.* (2013), and Karakci *et al.* (2013b). These results are for a simulated interferometer consisting of a 20×20 close-packed array of feedhorns with a Gaussian beam width of 5° and separation $D = 7.89\lambda$. We include sky rotation for observations from the South Pole, with average noise per visibility of $0.015 \mu\text{K}$. Fig. 1 shows that we correctly reconstruct the power spectra and illustrates the effects of introducing some systematic errors. Order-of-magnitude agreement is found between the results of these simulations and a simple semi-analytic approach (Bunn 2007). Far more detailed results may be found in the papers cited above.

Gibbs sampling provides simultaneous samples of the power spectrum and the signal map. We have shown that these signal map samples provide excellent image reconstruction from visibility data in other (non-CMB) contexts (Sutter *et al.* 2014). Fig. 2 shows some of the results of this work.

On the left of Fig. 2 we show sample images taken from the CASA user guide (Jaeger 2008). These images were then “observed” with a simulated interferometer consisting of 12 randomly-placed antennas, each with a beam size of 0.075 times the image width. We assumed 6 hours of observation with a signal-to-noise ratio of 10 per visibility. The center panel shows the mean reconstructed image calculated via Gibbs sampling, multiplied by the primary beam. The right panel shows the result of ℓ_1 reconstruction in the pixel

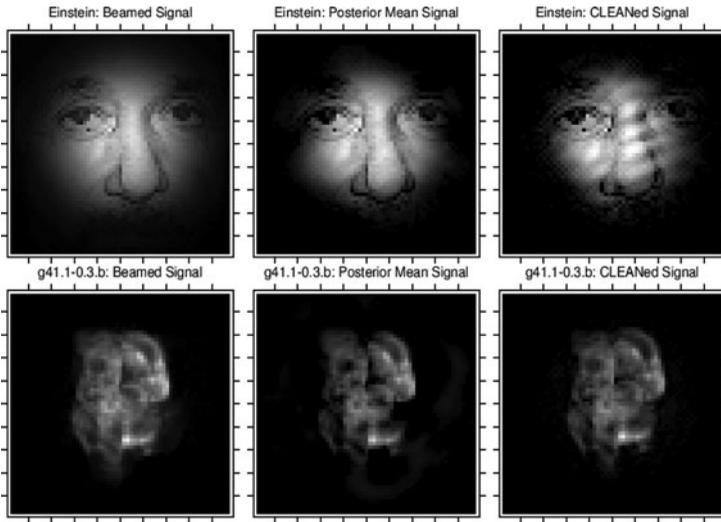


Figure 2. Examples of image reconstruction. The left panel shows test images from the CASA user guide, multiplied by the primary beam of our simulated observations. The center panel shows the result of image reconstruction using Gibbs sampling, and the right shows ℓ_1 reconstruction. Adapted from Sutter *et al.* (2014).

basis, which has been shown (Wiaux *et al.* 2009) to have similar performance to the widely-used CLEAN algorithm (Högbom 1974). By a variety of quantitative measures, Gibbs reconstruction performs better than this proxy for CLEAN reconstruction (Sutter *et al.* 2014).

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