1124-60-59 **Andrew Brown** (ab7@g.clemson.edu), Clemson, SC 29634, **Arvind Saibaba*** (asaibab@ncsu.edu), Raleigh, NC 27606, and **Sarah Vallelian** (scvallel@ncsu.edu), Raleigh, NC 27606. *Computationally Efficient Markov Chain Monte Carlo Methods for Bayesian Inverse Problems.* Preliminary report.

Many imaging modalities in neuroscience, such as Computer Tomography (CT) and Electroencephalography (EEG) can be described mathematically as inverse problems. To deal with the ill-posedness associated with the inverse problems, we adopt a Hierarchial Bayesian approach, in which we impose a prior distribution on both the unknowns of interest, as well as on the regularization parameters to make inference on the posterior distribution. Much work has been done on computing the maximum a posteriori (MAP) estimate, but to quantify the reconstruction uncertainty, it is desirable to generate samples from this distribution. The standard approach is to use a Markov Chain Monte Carlo sampling method; however, a straightforward implementation may be computationally expensive. We develop a proposal distribution for a Metropolis-Hastings-within-Gibbs algorithm, that is both computationally efficient to sample from, and also has high acceptance rate. We derive theoretical results that shed light into the acceptance rate and discuss an efficient implementation of the sampler. The performance of our algorithms will be demonstrated on simulated examples from neuroimaging applications in EEG and CT. (Received August 24, 2016)