Map-making for the Next Generation of Ground-based Submillimeter Instruments

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Abstract. Current ground-based submillimeter instruments (e.g. SCUBA-2, SHARC-2 and LABOCA) have hundreds to thousands of detectors, sampled at tens to hundreds of hertz, generating up to hundreds of gigabytes per night. Since noise is correlated between detectors and in time, due to atmospheric signals and temperature oscillations, naive map-making is not applicable. In addition, the size of the data sets makes direct likelihood based inversion techniques intractable. As a result, the data reduction approach for most current submm cameras is to adopt iterative methods in order to separate noise from sky signal, and hence effectively produce astronomical images. We investigate how today’s map-makers scale to the next generation of instruments, which will have tens of thousands of detectors sampled at thousands of hertz, leading to data sets of challenging size. We propose strategies for reducing such large data sets.

1. Introduction

The large data volumes expected from upcoming submillimeter (submm) instruments will pose a challenge for current strategies for map-making. We begin by describing the map-making problem. We then discuss solutions to it, and how they apply to current and future instruments.

2. Map-Making

2.1. The Map-Making Equation

To describe the process of making a map, we begin with the following model for the data:

\[ d_t = A_{ti} s_i + n_t. \] (1)

The notation is: \( d_t \) is the data, with \( t \) indexing both time and detectors; \( A_{ti} \) is the projection operator, associating each time sample with a map pixel; \( s_i \) is the pixelized (and beam-smoothed) map of the sky, with \( i \) indexing the map pixels; and \( n_t \) is the noise in each sample. This is a linear equation, with the least-squares solution (dropping the
Figure 1. Flow chart reproduced from Chapin et al. (2013) illustrating an example configuration of the iterative map-maker SMURF, the SCUBA-2 map-maker. COM, GAI, EXT and FLT are noise models. AST represents the sky model and NOI is used to measure the white noise levels used in data weighting.

indices): $$s = (A^TN^{-1}A)^{-1}A^TN^{-1}d,$$ (2) where $N$ is the data noise covariance matrix, $x^T$ is the transpose and $x^{-1}$ is the inverse of matrix $x$. See, e.g., Tegmark (1997) for more details.

2.2. Solutions to the Map-Making Equation

The noise covariance matrix encodes noise correlations between all samples, both in time and between detectors. It is a very large matrix, $N_d \times N_d$, where $N_d$ is the product of the number of detectors and number of time samples. When taking into account the full data covariance matrix, Equation 2 is not directly solvable for even moderate-sized data sets. However, several approaches exist for approximating the full solution.

Simple Re-binning. If the noise correlations can be ignored (or high-pass filtered so that correlations are insignificant), $N$ is diagonal and the map-making equation becomes a weighted mean of all samples that fall in each pixel. This is also known as “naive” map-making.

Direct Solutions. The noise covariance matrix is not directly invertible, but approximations can be made so that the map-making equation can still be solved for certain data sets (e.g. Patanchon et al. 2008; Dünner et al. 2013). These methods work well for
Table 1. Data volume scaling from SCUBA-2 to Next-Gen Instrument

|                      | SCUBA-2 | Next Gen |
|----------------------|---------|----------|
| No. of detectors     | 5120    | 30,000   |
| Data rate            | 170 Hz  | 2000 Hz  |
| No. of samples in 15 min | $0.8 \times 10^9$ | $54 \times 10^9$ |
| Memory to store data | 6 GB    | 430 GB   |
| Scaling factor       | 1       | 70       |

Instruments with order 100–1000 detectors, but have yet to be successfully applied to larger data sets.

Iterative Solutions. An approach more tractable for large data sets is to iteratively solve for noise models (e.g. common mode, atmosphere, 1/f noise) along with the sky model. Current ground-based large-format submillimeter instruments which use iterative map-makers include: CRUSH for SHARC-2 (Kovács 2008); BoA for LABOCA (Schuller 2012); and SMURF for SCUBA-2 (Chapin et al. 2013). The iterative model used by SMURF is illustrated in Figure 1. A key feature of the map-maker is that it is modular, allowing it to adapt to the particular instrument and data set at hand.

3. Scaling SMURF/SCUBA-2 to Next-Generation Instruments

The next generation of ground-based submm instruments (such as CCAT: Jenness et al. 2014) will make use of Kinetic Inductance Detectors (KIDs; e.g. Day et al. 2003), allowing for 10,000s of detectors in the focal plane. As a concrete example, we consider an instrument with 30,000 detectors sampled at 2 kHz. The data volume scaling from SCUBA-2 to the example Next-Gen instrument is listed in Table 1. A SMURF reduction of 16 minutes of SCUBA-2 450 µm data takes about 7 minutes on a modern server with 8 cores at 2.67 GHz, using 33 GB of memory. Assuming linear scaling (non-linear components are sub-dominant), reducing the Next-Gen data volume on the same machine would require 2.3 TB of memory and would take 8 hours. In five years, we might imagine a 32-core machine with 2 TB memory, and modest improvements in CPU speed. Such a machine can reduce the 15 minutes of Next-Gen data in about an hour.

To further decrease runtime, distributed-memory parallel processing will be required. SMURF is written to take advantage of multi-core systems, using a shared-memory model; certain modules are trivially distributed, while others will require inter-node communication. See Figure 2.

4. Conclusions

Rigorous map-making inversions will be infeasible for next generation instruments, so some approximate solution, using iterative methods, will be necessary. Scaling to a

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1 Note that this includes memory for the noise models, some using memory equal to the data size, and is thus several times larger than the memory needed to store the raw detector data.
real example of SCUBA-2 data reduction by SMURF, we see that reducing 15 minutes of data on a single machine should be possible using existing software. These individual maps can be co-added for longer observations. Should reducing the data in 15 minute chunks not be sufficient for recovering the angular scales of interest, distributed-memory parallelization should be possible.

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