SCUBA-2: iterative map-making with the Sub-Millimetre User Reduction Facility

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ABSTRACT

The Submillimetre Common User Bolometer Array 2 (SCUBA-2) is an instrument operating on the 15-m James Clerk Maxwell Telescope, nominally consisting of 5120 bolometers in each of two simultaneous imaging bands centred over 450 and 850 μm. The camera is operated by scanning across the sky and recording data at a rate of 200 Hz. As the largest of a new generation of multiplexed kilopixel bolometer cameras operating in the (sub)millimetre, SCUBA-2 data analysis represents a significant challenge. We describe the production of maps using SMURF (Sub-Millimetre User Reduction Facility) in which we have adopted a fast, iterative approach to map-making that enables data reduction on single, modern, high-end desktop computers, with execution times that are typically shorter than the observing times. SMURF is used in an automated setting, both at the telescope for real-time feedback to observers and for the production of science products for the JCMT Science Archive at the Canadian Astronomy Data Centre. Three detailed case studies are used to: (i) explore convergence properties of the map-maker using simple prior constraints (Uranus – a point source); (ii) achieve the white-noise limit for faint point-source studies (extragalactic blank-field survey of the Lockman Hole); and (iii) demonstrate that our strategy is capable of recovering angular scales comparable to the size of the array footprint (approximately 5 arcmin) for bright extended sources (star-forming region M17).

Key words: methods: data analysis – methods: observational – techniques: image processing – submillimetre: general.

1 INTRODUCTION

The Submillimetre Common User Bolometer Array 2 (SCUBA-2, Holland et al. 2013) is a new instrument for the 15-m James Clerk Maxwell Telescope (JCMT) on Mauna Kea, Hawai’i. The camera simultaneously images the sky in two broad bands centred over 450 and 850 μm, with approximately 7.5 and 14.5 arcsec full width at half-maximum (FWHM) point spread functions (PSFs). The focal planes at each wavelength are populated with four rectangular subarrays, consisting of 40 × 32 bolometers each, and together subtend a nearly 7 × 7 arcmin² footprint on the sky (excluding gaps, the continuous solid angle is about 43 arcmin² per focal plane). This paper describes the properties of SCUBA-2 data that are relevant for producing maps of the imaging data, and SMURF (Sub-Millimetre User Reduction Facility), a software package for performing the reduction written using the Starlink Software Environment (Warren-Smith & Wallace 1993; Jenness et al. 2009). The details of the instrument design, performance and calibration are given in two companion papers: Holland et al. (2013) and Dempsey et al. (2013).

Over the last 20 years, observations in the submillimetre band (defined here to be 200–1200 μm) have helped revolutionize several important areas of astrophysics, including: discovering through blind surveys a class of massive dusty star-forming galaxies in the early (z > 2) Universe, now referred to as submillimetre

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galaxies (SMGs); characterizing the early stages of star formation by identifying the dense, cold regions in molecular clouds where stars may eventually form; and identifying debris discs around nearby stars, helping us understand the early stages of planet formation. With 10,240 nominal detectors (of which ~70% per cent work and are typically useful, Holland et al. 2013), SCUBA-2 is presently the largest of a new generation of multiplexed kilopixel (sub)millimetre bolometer cameras, which also includes the camera for the South Pole Telescope (SPT, Carlstrom et al. 2011) and the Atacama Cosmology Telescope (ACT, Swetz et al. 2011), both dedicated experiments for studying anisotropies in the cosmic microwave background (CMB) using similar technology, the latter of which uses the same time-domain multiplexed readout electronics as SCUBA-2 (Battistelli et al. 2008).

Submillimetre imaging cameras generally maximize sensitivity using bolometers, rather than coherent detectors, which are limited by white photon and phonon noise from the instrument and ambient backgrounds. The low-frequency noise, however, is typically dominated by sources which produce slow variations in the background (e.g. thermal variations within the cryostat, and the atmosphere for ground-based cameras), and drifts in the readout electronics. Such noise has a power spectrum of $1/f^\alpha$ ($\alpha > 0$), and the frequency at which it is comparable to the white noise level is called the ‘$1/f$ knee’. Since the low-frequency noise is largely correlated between all, or subsets, of the bolometers in time, it can be suppressed during map-making, since astronomical signals have the distinct property that they are fixed in a sky reference frame (assuming they are not time-varying). If successful, the noise in the resulting map is said to be ‘white noise limited’, meaning that it is uncorrelated spatially, and has an amplitude that scales as $\text{NEFD}/\sqrt{t}$, where the NEFD is the noise equivalent flux density (the white noise level of a bolometer in 1 s of integration), and $t$ is the amount of integration time in a map pixel.

There are numerous ways to attack this map-making problem, both in terms of the data-collection method and in terms of processing. The two most important principles to follow in terms of scan strategy are: (i) to modulate the astronomical signals of interest in such a way that they appear in the lowest noise regions of the bolometer noise power spectrum, i.e. above the $1/f$ knee; and (ii) to provide good ‘cross-linking’, in which each portion of the map is scanned at a range of position angles, again, to help distinguish time-varying noise features from fixed astronomical sources. In the case of SCUBA-2, principle (i) is achieved through fast scanning of the entire telescope (up to 600 arcsec s$^{-1}$), such that a significant drift in the bolometers due to low-frequency noise occurs more slowly than the crossing times for the astronomical scales of interest; and principle (ii) by offering scan patterns that cross the sky at a wide range of position angles. Such methods are now used by virtually all existing ground-based submillimetre cameras (e.g. Glenn et al. 1998; Weterling et al. 2002; Kovács 2008b; Wilson et al. 2008), in preference to ‘chopping’ methods (where the secondary is moved quickly to modulate the signal) that were more appropriate for older instruments that had poorer low-frequency noise performance, and were only sensitive to modest angular scales. We note that under some circumstances cross-linking may not be essential. For example, SPT, which was designed to measure CMB anisotropies, scans entirely in azimuth (Schaffer et al. 2011). While this strategy limits its ability to recover large angular scales transverse to the scan direction, the anisotropic filtering in its maps can be accounted for during analysis to achieve SPT’s focused objectives (in contrast, the similar ACT experiment uses cross-linking to improve its response to large angular scales, Das et al. 2011). This approach is less practical as a general solution for SCUBA-2, however, which must serve a broader range of scientific interests.

There are three general styles of map-making that are relevant to reducing bolometer data in the literature. The simplest ‘direct methods’ involve some basic processing of the data to remove as much noise contamination as possible (e.g. using baseline removal and other simple filters), and then re-gridding these cleaned data into a map. Such was the basic recipe for the reduction of chopped data from SCUBA-2’s predecessor SCUBA (Jenness & Lightfoot 1998; Jenness et al. 2000), and MAMBO (e.g. Omont et al. 2001), another camera from the same generation. A more recent example is the analysis of SPT data (Schaffer et al. 2011). Generally speaking, such methods are fast, although depending on the science goals and noise properties of the data, they may not achieve the best noise performance on the angular scales of interest. A method for reducing data in fields of faint point sources with Bolocam (e.g. Laurent et al. 2005), and its younger sibling the Atzronomical Thermal Emission Camera (AzTEC, e.g. Scott et al. 2008), is principal component analysis (PCA) cleaning. A statistical ‘black box’ removes the most correlated components of the bolometer signals, enabling the detection of point sources close to the theoretical white noise limits of the detectors, with reasonable computation times when small numbers of bolometers are involved (hundreds rather than thousands of detectors). However, PCA cleaning is not a good solution for producing maps of extended structures, since such sources produce correlated signals amongst many detectors, and are removed by this procedure (an exception is the iterative PCA approach of Aguirre et al. 2011). Furthermore, in the case of SCUBA-2, performing PCA on even a single subarray (typically ~900 detectors) can be prohibitively slow.

The best existing map-making strategies for recovering information on all angular scales are maximum-likelihood techniques, in which the time-series data are expressed as a sampling of the ‘true’ map of the sky plus noise, and then the equation is inverted to estimate the map as some weighted linear combination of the data that minimizes the variance. The first good description of this method appears in Janssen & Gulkis (1992) for the production of maps from the Cosmic Background Explorer (the description is relevant despite the fact that it used a differential radiometer instead of bolometers). Other descriptions in the experimental CMB literature include Tegmark (1997) and Stompor et al. (2002), and an application to data from SCUBA is described in Borys et al. (2004). The downside to such methods is that they can be both computationally expensive and have large memory requirements. While for some experimental designs fast iterative methods for the inversion do exist without requiring excessive amounts of memory, such as that of Wright, Hinshaw & Bennett (1996) (which was later implemented for SCUBA by Johnstone et al. 2000), for the more general map-making problem, involving many detectors, matters are significantly complicated both by the need to measure the cross-spectra for all unique pairs of bolometers and performing the inversion itself. A maximum-likelihood method was successfully used to make maps from ACT data using approximately the same number of detectors as a single SCUBA-2 subarray at a single wavelength. However, the calculation is extremely resource intensive and requires a large cluster in order to run; a single map can take 10 CPU years (Fowler et al. 2010). Perhaps the most promising maximum-likelihood method that may one day be applied to SCUBA-2 data is ‘SANEPIC’, which produced maps from Balloon-borne Large-Aperture Submillimeter Telescope (BLAST) data, involving hundreds of bolometers, while correctly incorporating inter-bolometer noise correlations (Patanchon et al. 2008).
The third approach adopted here for SCUBA-2 is a compromise between the previous two methods. Under the assumption that a significant portion of the (predominantly low-frequency) non-white noise sources can be modelled, an iterative solution is obtained for both the astronomical image and the parameters of the noise model. Since the remaining (non-modelled) noise sources are assumed to be white, a single scalar rms may be calculated for all of the data points from a given bolometer to characterize its noise distribution (since the noise at any instant in time is uncorrelated with others, and with the data from other bolometers), greatly simplifying the inversion step that is so complicated in the maximum-likelihood methods. In the iterative approach, memory usage scales linearly with \( N_t \), the product of the number of bolometers, \( N_b \), with the number of samples in time, \( N_s \). The computation time is the product of the number of iterations, \( N_{\text{iter}} \), with the time per iteration, \( t_{\text{iter}} \). For the algorithm described in this paper, \( N_{\text{iter}} \) is typically in the range \( 5-100 \) [depending on the signal-to-noise ratio (S/N) of large-scale structures, and the size of the map], and \( t_{\text{iter}} \) scales as \( N_b \log N_t \), since fast Fourier transforms (FFTs) of the time series are typically performed. By comparison, the fastest maximum-likelihood methods that account for inter-bolometer correlations have an execution time with an \( N_b^2 \) dependence, although it is possible to limit memory usage to be linear in \( N_t \) (e.g. Patanchon et al. 2008).

Iterative approaches to map-making have a long history in the submillimetre, such as the pipeline recipe for fitting and removing baseline drifts in SCUBA-2 scan-map data as the astronomical image estimate improved (Jenness & Economou 1999). The closest modern relatives are CRUSH (Comprehensive Reduction Utility; Kovács 2008a) for the Submillimeter High-Angular Resolution Camera II (SHARC-II), the pipeline developed for the Bolocam Galactic Plane Survey (Aguirre et al. 2011), and BoA (Bolometer Array data analysis software) for the Large APEX Bolometer CAmera (Schuller 2012).

A reasonable model for correlated noise in SCUBA-2 is a single ‘common mode’ signal seen by all of the bolometers. Iterative estimation and removal of this signal significantly lowers the \( 1/f \) knee, without compromising structures on angular scales smaller than the array footprint. Residual independent drifts at lower frequencies are removed with an iterative high-pass filter. This strategy enables SMURF to reduce data on time-scales commensurate with the observing times (or significantly faster), on single, high-end desktop computers. For reference, all of the data analysis in this paper was performed on a machine with a 64-bit 8-core CPU operating at 2.7 GHz, and 48 Gb of memory. SMURF has been successfully used as part of a real-time pipeline (based on the ORAC-DR (Observatory Reduction and Acquisition Control – Data Reduction) system, Gibb et al. 2005; Cavanagh et al. 2008) offering feedback to observers at the telescope. The pipeline is also used to generate products for the JCMT Science Archive (Economou et al. 2011) hosted by the Canadian Astronomy Data Centre (CADC).

This paper is organized as follows. We first describe the properties of SCUBA-2 data, including a PCA to reveal correlated noise features, in Section 2. Next, the details of the SMURF algorithm (pre-processing steps and the iterative solution) are given in Section 3. This paper is concluded in Section 4 with three detailed test cases that span the majority of observation types likely to be undertaken with SCUBA-2, with an emphasis on the mitigation of divergence problems, and characterizing the output maps: (i) Uranus, a bright, compact source (Section 4.1); (ii) the Lockman Hole, a blind survey of faint point-like sources (Section 4.2); and (iii) the star-forming region M17, including bright, extended emission (Section 4.3). All of the data analysed in this paper are publicly available through the CADC SCUBA-2 raw-data queries page for the dates and observation numbers given in the text.\(^1\) All of the analysis was performed using the Starlink KAPUASH release from 2012.

## 2 SCUBA-2 DATA PROPERTIES

In this section, we summarize how SCUBA-2 works (Section 2.1), give examples of typical bolometers signals (Sections 2.2), discuss the impacts of magnetic field pickup (Section 2.3) and sky noise (Section 2.4), and finally use of PCA to explore the correlated noise properties of SCUBA-2 data (Section 2.5).

### 2.1 Description of SCUBA-2

While the details of how SCUBA-2 works are described in Holland et al. (2013), and its calibration in Dempsey et al. (2013), we summarize the basic concepts relevant to map-making here.

Incoming light passes through a beam splitter, and then bandpass filters, providing simultaneous illumination and wavelength definition of both the 450 and 850 \( \mu \)m focal planes. Each focal plane is populated by four ‘subarrays’ (labelled s4a–s4d at 450 \( \mu \)m, and s8a–s8d at 850 \( \mu \)m), each consisting of 32 columns and 40 rows of bolometers. The bolometers are thermal absorbers (with a response time constant of \( \tau \sim 1 \text{ ms} \)) coupled to superconducting transition-edge sensors (TESs) for thermometry. Temperature variations in the TESs produce changing currents, and therefore varying magnetic fields, which are detected and amplified using chains of superconducting quantum interference devices (SQUIDs), before the larger output currents are digitized. Each detector has its own SQUID for the first stage of the amplification, but the remaining stages occur within a common chain of SQUIDs for each of the 32 columns. All 40 rows are read out in sequence at a row-visit frequency of about 12 kHz. Such a high sample rate is unnecessary to produce maps, so the data are re-sampled to approximately 200 Hz before writing to disc. This rate provides a sample every 3.0 arcsec, or approximately one-third of the 450 \( \mu \)m diffraction-limited FWHM – a typical rate for thumb for adequately sampling a Gaussian PSF – at the maximum scanning speed of 600 arcsec s\(^{-1}\). There is an additional 41st row of SQUID readouts that are not connected to TESs. These ‘dark SQUIDs’ track non-thermal noise sources that are common to each column’s output current. The relationship between the output digitized current, \( I \), and the input power, \( P \), or \( df/dP \), is established using flat-field observations immediately prior to science observations, in which the output signal is measured throughout a ramp of the pixel heaters (which provide a known input power) (see section 2.1 in Dempsey et al. 2013 and section 5.3 in Holland et al. 2013 for more details). Finally, the conversion to astronomical flux units from power involves a correction for atmospheric extinction [primarily using the 183 GHz (1.6 mm) JCMT Water Vapour Monitor (WVM) to track line-of-sight opacity variations, see section 3 in Dempsey et al. 2013], and the application of a flux conversion factor (FCF) which is established from regular measurements of calibrators such as Uranus (section 5 in Dempsey et al. 2013).

In addition to uncorrelated white noise, and low-frequency (and often correlated from bolomer to bolometer) \( 1/f \)drifts, bolometer power spectra exhibit a roll-off at frequencies approaching Nyquist, which is due to the anti-aliasing filter that forms part of the 200Hz re-sampling stage. This anti-aliasing filter also introduces an effective lag of \( \sim 6 \text{ ms} \). Adding this lag to the \( \sim 1 \text{ ms} \) thermal time

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\(^1\) http://www.cadc-ccda.hia-iha.nrc-cnrc.gc.ca/jcmt/search/scuba2
constant, as well as a negative shift of about \(-2.5\) ms caused by a half-sample offset due to the synchronization between the pointing and bolometer data, yields a net lag of approximately \(4.5\) ms. There are also line features in the spectra that are thought to be produced primarily at frequencies far above the final \(200\) Hz sample rate, which are aliased to lower frequencies during the multiplexed readout stage before they can be removed by the anti-aliasing filter.

We note that the noise performance of SCUBA-2 has evolved over time. An initial ‘SCUBA-2 shared-risk observing’ period (S2SRO) took place during 2010 February and March, during which each of the 450 and 850 \(\mu\)m focal planes was populated with single subarrays, s4a and s8d, respectively. In addition to having significantly fewer available bolometers than the current fully commissioned instrument (and therefore a mapping speed reduced by a factor of \(~4\)), instabilities in the fridge led to a large oscillating signal with a period of about \(25\) s that was correlated amongst the detectors. After upgrading and commissioning the instrument, a servo using newly added thermometers in the focal planes has effectively mitigated this problem (section 2.5 in Holland et al. 2013). In addition, there were improvements to the magnetic shielding (reducing magnetic field pickup, as described in Section 2.3), as well as more effective removal of aliased noise sources (which has reduced both the presence of line features and the mean white noise level).

In order to reduce the impact of low-frequency noise on the final maps, SCUBA-2 scan strategies have been designed to provide: (i) good cross-linking (visiting every point of the mapped area at different scan angles); and (ii) minimal accelerations to reduce turnaround overheads (which could be quite large, given the area at different scan angles); and (ii) minimal accelerations to reposition the subarray. We have calculated a common mode signal, \(c(t)\), as the average time series of all the working bolometers. We then fit the amplitude of \(c(t)\) at each wavelength to the signals shown in Fig. 1 and remove it, yielding the grey residual signals. These residuals are nearly white, although still with noticeable long-time-scale variations. The white noise is greater at 450 \(\mu\)m as one would expect from the larger backgrounds compared to 850 \(\mu\)m.

Data from the fully commissioned instrument, observation 38 on 2011 November 12, are shown in Fig. 1(b). Having solved the fridge oscillation problem, these data no longer exhibit a correlation with the mixing chamber (however, note that variations are still seen in the mixing chamber signal; such variations do not necessarily reflect changes in the focal plane temperature). There is minimal correlated low-frequency noise in these 450 \(\mu\)m data, resulting in a little difference between the raw and common mode subtracted data. The 850 \(\mu\)m channel, however, exhibits a much greater signal that is obviously correlated with the telescope motion. It is also correlated amongst many of the detectors, and common mode removal corrects it to a large extent. Part of the reason that this is seen here, and not in the S2SRO data set shown, is that the amplitude of the scan pattern is larger. This ‘scan-synchronous’ noise is attributed to a combination of magnetic field pickup, as described in Section 2.3, and sky brightness variations due to changes in elevation (not to be confused with underlying changes in the atmosphere; a homogeneous atmosphere will appear brighter with increasing air-mass). Also similar to the S2SRO data, an anticorrelation between the opacity and elevation is apparent.

Next, in Fig. 2 we produce power spectral density (PSD) plots for four of the most sensitive bolometers from both focal planes, using the same two data sets. To produce this figure, we follow the convention that the PSD as a function of frequency, \(P(f)\), is normalized such that the integral over frequency gives the same variance as the time-series variance across the full time series. In other words, given a bolometer signal \(b(t)\),

\[
\langle b^2(t) \rangle = 2 \int_0^{f_N} P(f) \, df,
\]

where we only integrate over the positive frequencies up to \(f_N\), the Nyquist frequency, and the factor of 2 accounts for the (equal) power that appears at negative frequencies in the discrete Fourier transform. The units of the PSD written in this form are \(\text{pW}^2\text{Hz}^{-1}\).

The dotted coloured lines in Fig. 2 show the PSDs for raw, though flat-fielded and step-corrected (Section 3.1.3) data. At each wavelength, and in both data sets, there are clear \(1/f\) knees at frequencies ranging from roughly 1 to 2 Hz, followed by a predominantly white spectrum punctuated by line features at higher frequencies, and finally a roll-off caused by the anti-aliasing filter above \(70\) Hz. The correlation between the low-frequency components of the different bolometer signals is large. The solid black lines in Fig. 2 indicate the PSDs of the common modes \(c(t)\) at each wavelength, which reproduce much of the low-frequency structure, as well as some of the higher frequency line features. The \(c(t)\) otherwise drop substantially below the individual bolometer PSDs at high frequency, as expected if the bolometers are dominated by uncorrelated white noise in that part of the spectrum. The common mode signals are fitted to each bolometer time series and removed as in Fig. 1, and the resulting PSDs are shown
as the solid coloured lines. For reference, the top horizontal axes have been converted to angular scale assuming the scan speeds of each observation (120 arcsec s$^{-1}$ in Fig. 2a, and 190 arcsec s$^{-1}$ in Fig. 2b). The power spectra of unresolved point sources are also shown as the dashed lines in each band (arbitrarily normalized), showing that the smallest features resolvable by the telescope are only minimally affected by the excess noise in the line features at these scan speeds (this may not be the case at higher scan speeds).

In the S2SRO data (Fig. 2a), the low-frequency noise is very correlated between the detectors (note the tight scatter in the dotted coloured lines, and their resemblance to the common mode), due to it being dominated by the fridge oscillations. Common mode subtraction is very effective, reducing the 1/f knees in both wavelengths by about a factor of 5.

Raw data from the fully commissioned instrument (Fig. 2b) generally have less significant 1/f noise as compared with the S2SRO

Figure 1. A comparison between single bolometer time series in each of the 450 and 850 µm bands with the mixing chamber temperature, the line-of-sight 450 µm opacity derived from the JCMT WVM, and azimuth/elevation pointing offsets, before and after upgrading the instrument. The grey signals overplotted in the top two panels show the residual time series after removing the common mode signals. (a) Data taken during the S2SRO period, observation 29 on 2010 March 13. There is a strong correlation between the bolometers and the roughly ∼25 s oscillation in the fridge, but only a minor correlation with the opacity and telescope motion. The nearly-flat common mode subtracted signals show: (i) that most of the low-frequency signal is common to all of the bolometers; and (ii) the non-correlated and predominantly white noise at 450 µm is significantly larger than at 850 µm. (b) Data taken with the fully commissioned instrument, observation 38 on 2011 November 12. Unlike the S2SRO data, there is no strong signal produced by variations in the fridge temperature. The 450 µm data have minimal correlated low-frequency noise (as evidenced by the lack of a difference between the raw and common mode subtracted signals), although the 850 µm data show a common signal correlated with the opacity and telescope motion (note that this scan has a significantly larger amplitude than the S2SRO data set), mostly likely caused by a combination of changing airmass (anticorrelated with opacity) and magnetic field pickup (see Section 2.3 and Fig. 3).
data, and it is considerably less correlated amongst detectors (larger spread in the dotted coloured lines, particularly noticeable in these 450 μm data), leading to a less drastic improvement upon common mode removal. However, since the data are less dominated by low-frequency noise to begin with, the signals generally require less aggressive high-pass filtering to produce maps, and therefore retain larger scale structures than with the S2SRO data. Furthermore, there are generally fewer line features in the PSDs of bolometers in the fully commissioned instrument. Finally, these two data sets illustrate that the white noise performance (NEFD) is in fact similar before and after the upgrades for these two subarrays (s4a at 450 μm and s8b at 850 μm). The main improvements are a reduction in correlated and line noise features mentioned above, the larger number of working bolometers and the field of view (approximately a factor of 4).

2.3 Magnetic field pickup

An additional noise source that is significant primarily for wide-area scans (and more so during the S2SRO period) is magnetic field pickup. Since the bolometer signals are detected through the amplification of magnetic fields, any additional changing fields within the instrument will add to the noise.

Example data from the 450 μm subarray s4a where pickup appears to be significant (observation 16 on 2010 February 28) are shown in Fig. 3. The time series for two bolometers in the same column (not flat-fielded) show that there is a strong signal with a similar shape, but opposite signs. This behaviour is seen across the entire array. The dark SQUID signal for the same columns exhibits a similar shape and amplitude. Since the dark SQUID has no thermal absorber or TES attached to it, this observed signal is not likely to be optical or thermal in nature (although there can be some cross-talk with the bolometers). Due to the fact that the sign of the gain in each stage of SQUID amplification is random (although the combined gain is constrained to be negative), and since magnetic field pickup is only seen at the input to the second stage, the pickup can appear with random signs for bolometers along a column, giving it a distinct signature from other common signals that always appear with the same sign.

The telescope pointing offsets for this approximately 0.5 diameter scan are also shown in Fig. 3. Since the phase of the azimuth offsets from the map centre in this scan pattern slowly drifts with respect to the elevation offsets, it is clear that the bolometer and dark SQUID signals are detecting a noise source that is correlated only with the azimuthal motion and not the elevation. This behaviour would be expected if if there were a strong magnetic field fixed with respect to the telescope dome (i.e. the Earth’s magnetic field). Since SCUBA-2 is mounted on a Nasmyth platform, only azimuthal motion will change the direction of such a field with respect to the cryostat. Tests have shown that, as in this example, large scans in

Figure 2. Bolometer PSDs for the same two data sets (before and after upgrades) as used in Fig. 1. The PSDs have been boxcar smoothed with a width of 0.1 Hz to reduce the noise slightly and clarify some features. Four of the most sensitive bolometers have been selected at each wavelength, and the flat-fielded and step-corrected (but otherwise raw) PSDs are shown as the coloured dotted lines (the blue signals are for the same time series as those shown in Fig. 1). The solid black lines are the PSDs of the common mode signals at each wavelength, and the solid coloured lines show the PSDs of the bolometers once the common mode is removed. Finally, the dashed black lines show the spectral shape produced by a point source, given the scan speeds for the two observations [120 arcsec s⁻¹ in (a) and 190 arcsec s⁻¹ in (b); for reference, the top horizontal axes show the conversion from frequency to angular scale]. The horizontal dotted lines at 10⁻⁷ and 10⁻⁸ pW Hz⁻¹ at 450 and 850 μm, respectively, are provided as a visual reference for the white noise levels. In addition to 1/f and white noise components, and line features, all of the PSDs exhibit the gradual roll-off of the anti-aliasing filter just below the Nyquist frequency. (a) For the S2SRO data, particularly at 450 μm, there are broad line features in the PSDs at both wavelengths above ~35 Hz. At lower frequencies, the bolometer signals exhibit clear 1/f knees at approximately 2 and 3 Hz at 450 and 850 μm, respectively. Common mode subtraction removes most of the correlated fridge oscillation signal, lowering the 1/f knees to approximately 0.6 and 1.0 Hz at 450 and 850 μm, respectively. (b) Data from the fully commissioned instrument tend to have lower 1/f knees, and fewer line features. For this example, the improvement is most striking at 450 μm where the PSD is approximately two orders of magnitude lower in the fully commissioned data at 0.1 Hz. The white noise performance, however, is similar for the two subarrays (s4a and s8b) that were used both before and after the upgrades.
azimuth generically produce pickup. In contrast, and as expected, changes in elevation result in pickup that is approximately three orders of magnitude smaller.

2.4 Sky noise

The data shown in Figs 1 and 2 were taken during fairly stable weather conditions (although with different 450 μm line-of-sight opacities ~0.9 and 6.5 in the S2SRO and post-upgrade data sets, respectively), and are dominated at low frequencies (≤2 Hz) by scan-synchronous noise, rather than underlying variations in the atmosphere, or ‘sky noise’. However, only ~100 s of data were analysed. In Fig. 4, an order-of-magnitude longer (fully commissioned) data set is plotted from observation 18 on 2011 March 24, during highly variable weather conditions (450 μm line-of-sight opacities ranging from 3.6 to 7.7, scaled from the WVM data which are shown as a black line). Unlike the earlier plots, it is clear that the bolometer baseline drifts on time-scales ≥100 s are closely correlated with the atmospheric opacity, which serves as a proxy for atmospheric emission. The weaker correlation between the WVM and the 450 μm bolometers is probably due to the atmosphere being more transmissive at 850 μm; therefore, the emission detected at 450 μm comes from water vapour that is closer to the telescope than that observed at the longer wavelengths.

While the relative importance of sky noise at low frequencies is highly time-dependent and scan-pattern-dependent, in general it does not have a major impact on map-making. Upon common mode removal (which is an integral part of our map-making strategy) uncorrelated noise remains (e.g. solid lines in Fig. 2). As we will see in Sections 2.5 and 3.2.6, this remaining noise does not have a smoothly varying correlation pattern across the focal plane as one might expect if it were due to resolved ‘clouds’ of atmospheric emission. A high-pass filter with an edge frequency in the range ~0.1–1.0 Hz is usually employed to remove this residual noise (Section 3.2), and will also remove any sky noise that is not already subtracted by the common mode.

2.5 Principal component analysis

A method that has been used to remove correlated noise as part of the map-making procedure for Bolocam and AzTEC is PCA (Laurent et al. 2005; Perera et al. 2008; Scott et al. 2008). Here we use PCA to further explore correlated signals in SCUBA-2 data.

The basic method is as follows: (i) a covariance matrix is built up for all pairs (i, j) of the N bolometer time series, bi(t), bj(t); and (ii) a singular value decomposition identifies a new set of statistically uncorrelated basis vectors, ξi(t) (i.e. whose covariance matrix is diagonal), such that each of the bolometer time series is a linear combination of the basis vectors, or components, i.e. bi(t) = ξiλiT, where each row of the matrix ξi is a basis vector, and λiT is a column vector containing the corresponding amplitudes. The ξi are normalized by [∑ξi2(t)]1/2, such that the amplitude of each component in a given bolometer signal is proportional to its rms. In the earlier analyses mentioned, the low-frequency noise is assumed to be encapsulated in those components with the largest eigenvalues. Removing the projection of the time series along those components then significantly reduces 1/f noise while retaining most of the (higher frequency) signal in point-like sources.

A novel feature of our SCUBA-2 analysis is that we can perform PCA with 450 and 850 μm data simultaneously, potentially helping us to differentiate thermal and optical noise signals (e.g. from the atmosphere) that might appear in both wavelengths, from other noise sources that are restricted to single subarrays (such as readout noise). In Fig. 5, we show the results for a combined

Figure 3. Evidence for significant magnetic field pickup for observation 16 on 2010 February 28 at 450 μm (s4a subarray). The top panel shows two un-flat-fielded (but mean subtracted and step corrected) bolometer time series from the same column, with a 200 sample box-car smoothing (approximately 1 s), illustrating that they are dominated by a similar signal with opposite signs. The second panel shows the dark SQUID signal for the column, also mean subtracted and with the same box-car smoothing. The bottom panel shows the azimuthal and elevation offsets from the map centre (mean azimuth and elevation 171.9 and 68.0, respectively). Only the azimuthal signal is obviously correlated with the dark SQUID and bolometer signals, which suggests a magnetic field stationary with respect to the telescope dome as the source, since its direction with respect to the cryostat only changes with azimuthal motion.

Figure 4. Illustration of the dominance of atmospheric variations on long time-scales using 35 min of data taken in highly-variable weather conditions (line-of-sight 450 μm opacity ranging from 3.6 to 7.7) from the fully commissioned instrument, observations 18 on 2011 March 24. The red and blue lines show the 850 and 450 μm common mode signals, corresponding to the left- and right-hand vertical axes, respectively. The black line shows the line-of-sight opacity from the WVM as a proxy for atmospheric emission (arbitrary scale). Bolometer baseline drifts on time-scales ≥100 s are clearly correlated with the atmosphere in this case.
Figure 5. The first nine components from a PCA, ranked by the mean amplitudes of combined 450 (s4a subarray) and 850 μm (s8b subarray) time series bolometer data, for the same observation as that used in Figs 1(b) and 2(b). For each component, the top plot shows the time series of the basis vectors normalized by their rms, the middle plot its PSD, and the bottom coloured plots the amplitudes for the bolometers at each wavelength (the contribution of the basis vectors to the time series). For reference, both the mean, \( \bar{\lambda} \), and rms, \( \lambda_{\text{rms}} \), amplitudes for the bolometers in each subarray are also shown. Most of the correlated 1/f signal is encapsulated in Component 1, and appears to be dominated by scan-synchronous noise (compare with the scan pattern in Fig. 1b). Some of this signal also appears in Component 3. Component 2 is another 1/f signal that is dominant in the 850 μm subarray. Most of the remaining components consist of weaker 1/f noise and line features predominantly above \( \sim 30 \) Hz. The amplitude maps show correlated patterns along columns, suggesting pickup in their common amplifier chains.
analysis of the s4a and s8b subarrays for the first ~100 s of the same observation that was used in Figs 1(b) and 2(b). The nine most significant components are shown (ranked by the mean amplitudes across all working bolometers in both bands). The top and middle panels for each component show the time series and PSDs of the normalized basis vectors. The bottom panels are maps indicating the significance (amplitudes) of the component across the focal plane (with the mean $\lambda$ and and rms, $\lambda_{\text{rms}}$, of the amplitudes for all of the bolometers calculated separately at each wavelength also shown).

The majority of the correlated signal at both wavelengths in Fig. 5 is produced by Component 1, in which the basis vector time series exhibits a roughly periodic signal that resembles the scan pattern in Fig. 1(b). While this correlated signal appears at both wavelengths, referring to the maps of amplitudes, they are considerably stronger at 850 μm (consistent with the visual appearance of the bolometer signals in Fig. 5). Also note that the PSD for this basis vector exhibits nearly a pure 1/f signature with minimal line features, and no white noise plateau (suggesting that these are high-S/N measurements of a purely low frequency drift). Component 3 is weaker, yet also shows evidence of the scan-synchronous noise, combined with high-frequency line features that appear primarily in columns 26, 29 and 30 of the 450 μm subarray. Unlike Component 1, it is generally more dominant at 450 μm.

Why are there two components that seem to be dominated by scan-synchronous noise (which is presumably a mixture of magnetic field pickup and brightness variations in the atmosphere)? First, the smoothly varying gradients in the amplitude maps (primarily at 850 μm) suggest that this noise has a different response across the focal plane; in this case, the PCA has identified two orthogonal shapes that, when mixed in different quantities, can reproduce most of the signal in each bolometer. It is also likely that the atmospheric contribution is stronger at 450 μm (i.e. predominantly Component 3).

Like Component 1, Component 2 is a purely 1/f signal, with an amplitude comparable to Component 3, that appears almost exclusively at 850 μm. Since it is not obviously correlated with the telescope motion, yet has an amplitude that varies smoothly across the 850 μm subarray, it may represent the PCA’s attempt to reproduce some non-linear response to magnetic field and/or atmospheric pickup.

The remaining, weaker, Components 4–9 share some common features. They all have some degree of 1/f noise, suggesting further residual noise related to the telescope motion and/or other slow baseline drifts. All of them also exhibit line features in their spectra, which in many cases appear at random amplitudes along columns (e.g. columns 15, and 26–30 at 450 μm in Component 4), or in a sampling of isolated bolometers (e.g. column 13, row 19 at 850 μm in Component 6). The signals that appear along columns are probably related to magnetic field pickup. Other sources of lines are thought to be aliased high-frequency noise, and also the 60 Hz mains which appear in some bolometers.

This example illustrates some of the types of correlated signals and patterns that PCA can identify in SCUBA-2 data. While there are typically one or two strong signal components detected, in general, the details can vary significantly from data set to data set, and the lengths of the time series analysed. The reason for this is that many of the noise sources are not stationary in time (e.g. scan-synchronous noise which obviously depends on the scan pattern, and the tuning of the subarrays). It should also be clear from this example that while PCA offers some helpful insight into the various sources of noise, it does not necessarily identify clean patterns that can easily be modelled. For example, while there are clearly correlation patterns along columns as expected from the common amplification chain, the intensities of these high-frequency signals appear random in the eigenvalue maps, and a simple common mode signal estimated from the data for each column would not remove it. Regardless, the dominant noise in excess of the fundamental white noise limit, in all cases, is at low frequencies. This conclusion is central to our data reduction strategy described in Section 3.

3 PRODUCTION OF MAPS

The approach taken by SMURF to reducing SCUBA-2 data is to model (and remove) predominantly low-frequency noise sources that are correlated amongst detectors, and to iterate this process along with estimates of the map. Significant experimentation with different models for noise sources during SCUBA-2 commissioning required a highly flexible software framework, and a configurable user interface. To achieve this goal, while minimizing development time, it was decided to build SMURF as a Starlink package (Jenness et al. 2009), which provides access to a large suite of libraries (including a commanding and messaging interface, astrometric coordinate conversions and generation of standard WCS information, file formats, etc.). Furthermore, Starlink is open source3 (distributed under the GNU General Public Licence v3), and already used extensively at the Joint Astronomy Centre (host of the JCMT) for many other systems (Jenness & Economou 2011), which helps with interoperability. Though originally written in FORTRAN, many of the core Starlink libraries are now ported to native C, or at least have a C interface. It was therefore decided to develop SMURF in C as well (rather than C++, for example, which would have required adding further dependencies to Starlink), although we have taken an object-oriented approach. For example, all of the data for a given signal component model are encapsulated in a C structure, and there is a standard interface for all functions that handle models (member data and functions for the class, respectively). In this way, it is easy to extend SMURF with new models. Parallelization is incorporated in the most time-consuming low-level routines using threads (e.g. performing FFTs, re-gridding the data), usually handling independent blocks of bolometers or blocks of time, in each thread, depending on the nature of the calculation. We have found that for typical data sets the processing time scales well with the number of CPU cores, although beyond eight the returns are diminished due to tasks that cannot be parallelized (e.g. reading the data from disc).

As we have seen in Sections 2.2–2.5, SCUBA-2 data are dominated at low frequencies (<2 Hz) by highly correlated signals. While it can be significantly reduced using simple common mode removal (subtracting the average signal from all bolometers at each time-step), the more complicated correlated residuals at these low frequencies are difficult to model. Ultimately, a very simple approach has been taken to handle both components, for which the main steps in a typical reduction are shown in Fig. 6.

First, the raw data are passed through a pre-processing stage which corrects some of the more significant glitches, applies flatfield corrections, etc. Next, the iterative process begins (dashed box). Most of the low-frequency noise is removed using common mode subtraction (COM, GAT, Section 3.2.1). Then, the extinction correction (EXT, Section 3.2.2) is applied. At this point, the data resemble the grey bolometer traces in Fig. 1, with some residual baseline

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3 http://www.starlink.ac.uk

1 https://github.com/Starlink
In general, SMURF is highly configurable, including many options for both the pre-processing stage and the iterative model components (which models are used, what order they are calculated in, how they are calculated). In Sections 3.1 and 3.2 we describe the data pre-processing steps and iterative algorithm in detail. Section 3.3 explores convergence tests and degeneracies between model components. Finally, Section 3.4 summarizes the mapping performance of SCUBA-2 using SMURF.

3.1 Data pre-processing

Prior to executing the iterative part of the algorithm, the data must undergo several pre-processing steps. First, the data files are read into memory and concatenated into continuous arrays (SCUBA-2 data are broken up and written to disc every \( \sim 30 \) s regardless of the observation length during data acquisition). As the data are loaded, they are multiplied by the flat-field correction (see section 2.1 in Dempsey et al. 2013). Next, a series of configurable data cleaning and filtering procedures are applied; these include the removal of large glitches that may hinder the iterative solution from converging, or simply tasks that do not need to be iterated. All of the data that are flagged as bad are ignored when estimating the map.

3.1.1 Time-series downsampling and map pixel size

The highest useful frequency in the nominally 200 Hz sampled SCUBA-2 data is that which corresponds to the smallest angular scale that the instrument is sensitive to. As mentioned earlier, the usual rule of thumb for a Gaussian beam is to provide at least three samples for each FWHM, or roughly 2.5 arcsec for the 7.5 arcsec, 450 \( \mu \)m channel, and 5 arcsec for the 14.5 arcsec, 850 \( \mu \)m channel. For a typical scan speed of 300 arcsec s\(^{-1}\), the maximum useful sample rate is therefore about 120 Hz at 450 \( \mu \)m, and 40 Hz at 850 \( \mu \)m. In order to save execution time and memory usage (both of which scale linearly with data volume), it is clearly advantageous to re-sample the data to these lower rates. In practice, the default map pixel sizes are set to 2 and 4 arcsec at 450 and 850 \( \mu \)m, respectively (slightly oversampled), and downsampling occurs as the data are loaded to match this spatial sampling, given the slew speed.

The method used by SMURF is to average together multiple samples from the original time series, \( x_i \), to estimate the lower frequency output time series, \( y_j \). In general there will not be an integer number of samples from \( x_i \) in each of the \( y_j \), so fractional samples from \( x_i \) are used at the \( y_j \) time boundaries: \( y_j = (\sum w_i x_i) / (\sum w_i) \), where \( i \) runs over all the samples from \( x \) that land within, or partially overlap, \( y_j \), and the weights, \( 0 < w_j \leq 1 \), indicate the fractions of each \( x_i \) that land within \( y_j \). The algorithm is fast since each sample in \( x_i \) needs only be visited once. From a spectral point of view, this boxcar average is equivalent to applying a sinc-function low-pass filter. Such behaviour is desirable since it serves as an anti-aliasing filter; most non-white features above the Nyquist frequency in \( y_j \) that could contaminate the output data are removed.

As an alternative, we also investigated an algorithm in which the FFT of \( x_i \) is simply truncated to the target sample rate before transforming back to the time domain (i.e. applying a hard-edged
low-pass filter). In practice, the noise performance was indistinguishable, and required slightly longer execution time compared with the previous method, and is therefore not used.

### 3.1.2 Time-domain despiking

Spikes of short duration and high amplitude are often seen in the time-series data. If not removed, they can cause ringing when filtering the data. Two alternative approaches may be used to remove these spikes. This section describes the detection and removal of spikes within the time series of each bolometer, and Section 3.2.4 describes the iterative detection and removal of spikes as part of map estimation. In practice, map-based despiking usually gives superior results, and so time-domain despiking is switched off by default.

Each one-dimensional bolometer time series is processed independently. At each time slice, the median value of the current bolometer is found in a box centred on the time slice, and containing a specified number of time slices (typically 50). If the residual between the time slice value and the median value is greater than some specified multiple (typically 10) of the local noise level, the time slice is flagged as a spike.

If the local noise level were estimated within the same box used to determine the median value, a spike in the box would cause the local noise level to be overestimated severely. For this reason, the local noise level is taken as the standard deviation of the values within a neighbouring box on the ‘downstream’ side of the median box (i.e. the side that has already been checked for spikes). In other words, the high end of the noise box is just below the low end of the median filter box. This introduces a slight asymmetry in the noise, but this should not matter unless the noise varies significantly on a time-scale shorter than the box size.

This simple algorithm is not very good at distinguishing between spikes and bright point sources, and so the threshold for spike detection is usually raised when making maps of bright point sources.

### 3.1.3 Step correction

Sudden steps can occur in the time-series data from each bolometer, with the most likely cause being cosmic-ray events (see section 3.5.3 in Holland et al. 2013). The black curves in Fig. 7 show examples of such steps in the time series for two bolometers. If not removed, these steps can cause severe ringing when filtering, and visible streaks in the final map, corresponding to the paths of individual bolometers over the sky.

Steps occur with a wide range of heights and shapes. The ratio of step height to noise can vary from less than 10 to several hundreds. Some steps occur over a single sample, such as the step close to sample 5000 in Fig. 7(b), but others happen more gradually, such as the step close to sample 5300. In addition, a step can be preceded or followed by a short period of instability, as is visible at the bottom of the step in Fig. 7(a) (this is probably due to the response of the SCUBA-2 anti-aliasing filter; the sudden large step occurs prior to the 200 Hz resampling). Further problems are caused by steps that occur close together in time, such as the large downward step followed by a smaller upward step close to sample 5000 in Fig. 7(b).

Detecting and correcting such a wide variety of steps reliably has proved to be a challenge. In outline, the following stages are involved in detecting steps in a single bolometer time series:

1. Median smoothing the whole time series;
2. Finding the gradient of the median-smoothed time series at each sample;
3. Smoothing the gradient values to determine the local mean gradient and subtract this local mean from the total gradient to get the residual gradient;
4. Finding residual gradient values that exceed 25 times the local rms of the residual gradients;
5. Grouping these high residual gradients into contiguous blocks of samples;
6. Merging blocks that are separated by less than 100 samples.

The above process produces a list of candidate steps in each bolometer time series. Each candidate step is then verified, measured and corrected using the following procedure:

1. The above process can misinterpret the edges of a bright source as a step, so we ignore blocks that occur close to bright sources.
2. If the block passes the above test, a least-squares linear fit is performed to the median-filtered bolometer data just before the block, and this fit is extrapolated to predict the data value expected at the centre of the block.

![Figure 7](https://academic.oup.com/mnras/article-abstract/430/4/2545/1096175)

Figure 7. Examples of steps in time series data. Steps occur with a wide range of heights from the large steps shown in (a) to the small steps shown in (b). Large steps are often followed by a brief ‘overshoot’ as shown in (a) which is ringing caused by the anti-aliasing filter. In both plots, the black curve is the uncorrected time series, and the red curve is the corrected time series. Samples close to a step are omitted in the corrected time series. In (b) the blue curve is the uncorrected time series for a nearby bolometer. The similarity between the red and blue curves shows that the step correction is performing well.
(iii) A least-squares linear fit is performed to the median-filtered bolometer data just after the block, and this fit is extrapolated to predict the data value expected at the centre of the block.

(iv) The difference between these two expected data values is taken as the step height.

(v) The preceding three steps are repeated several times, each time including a different selection of samples in the two least-squares fits, with the mean and standard deviation of the corresponding set of step heights found.

(vi) If the mean step height is small compared to the standard deviation of the step heights, or compared to the noise in the bolometer data, then the step is ignored.

(vii) If the above checks are passed, all subsequent bolometer samples are corrected by the mean step height.

(viii) Bolometer samples within the duration of the step, and a few samples on either side, are flagged as unusable.

Once all steps have been corrected within a bolometer time series, a constant value is added to all samples in the time series to restore its original mean value.

The results of step correction are shown by the red curves in Fig. 7. For comparison, the blue curve shows the uncorrected time series from a nearby bolometer that does not suffer from steps. The agreement between the red and blue curves confirms that the step correction algorithm is working satisfactorily.

3.1.4 Gap filling/apodization

SMURF uses FFTs of the bolometer data extensively for filtering. Data that have been flagged as bad for any reason (for instance, due to the presence of spikes, steps, or unusual common mode signal) need to be excluded. For this reason, each contiguous block of bad data samples is filled with artificial data before taking the FFT. A least-squares linear fit is performed to the 50 samples preceding the block, and a similar fit is performed to the 50 samples following the block. These are used to estimate the expected values at the start and end of the block of bad values. The bad values are then replaced by linear interpolation between the expected start and end values. Gaussian noise is added with a standard deviation equal to the mean of the rms residuals in the two fits. These flagged and filled portions of the data are then given a weight of zero when estimating the map.

In addition to replacing bad samples before the FFT, it is also necessary to ensure that the data values at the start and end of the time series are similar. Since an FFT treats the data as a single cycle in an infinitely repeating waveform, any large difference between starting and ending values will effectively introduce sudden steps at the start and end of each cycle, causing unwanted oscillations (ringing) in the transform. Another consequence of the cyclic nature of the FFT is that features at one end of the time series can affect the filtered values at the other end of the time series. Two methods are available to avoid these two problems:

(i) Apodization. A number of samples at the start and end of each bolometer time series are multiplied by a cosine function in order to roll the data values off smoothly to zero. The default number of samples modified at each end of the time series is given by half the ratio of the sampling frequency to the lowest retained frequency, the edge frequency of the high-pass filter (Section 3.2.3). In addition, each end of the time series is padded with double this number of zeros. This method is illustrated in Fig. 8. It is not used by default as it reduces the amount of data available for the map, and can significantly hinder very short observations (e.g. of calibrators when focusing the telescope).

(ii) Padding with artificial data. Instead of padding with zeros, each time series is padded with artificial data which connects the two ends of the data stream smoothly and includes Gaussian noise. No apodization is performed. The number of samples of padding at each end is again equal to the ratio of the sampling frequency to the lowest retained frequency. This is illustrated in Fig. 9. See Stompor et al. (2002) for a thorough discussion of this procedure within the context of CMB map-making. This method is used by default.

3.1.5 Bolometer filtering

Despite the ability of the map-maker to iteratively remove many noise components, under some circumstances it may be desirable to filter the data once during the pre-processing step. Three main filtering options are available:

(i) The most commonly used pre-processing filter is polynomial subtraction. A polynomial of the requested order is fitted and removed from each bolometer time series. At a bare minimum, the mean is removed from all of the bolometers (order 0) in all reductions described in this paper.
(ii) All of the filters available as part of the iterative Fourier transform filter (Section 3.2.3) can also be applied once during pre-processing.

(iii) As an alternative to the iterative map-making procedure, cleaning by PCA is available as an experimental pre-processing option (Section 2.5). The most significant components in the analysis are identified, and the projection of each bolometer time series along their basis vectors is removed. A single parameter specifies the threshold on the amplitude of the components to be removed, as a number of standard deviations away from the mean value. Subarrays are then cleaned independently, once, for the full length of each continuous chunk of data. Given the computational expense of this method, and initial tests which showed little improvement over simple high-pass filtering, this method has not yet been explored in detail with SCUBA-2 data. However, since systematic effects seem to come and go, it is possible that PCA could be useful for particular data sets.

### 3.1.6 Additional data rejection

Despite the cleaning operations described in the previous sections, the data from a given bolometer may be unusable due to it being poorly biased, having an incorrect flat-field correction applied, or having some other particularly pathological noise contamination. Most of these bolometers can be flagged simply by identifying outliers in the distribution of bolometer white noise levels. By default, SMURF measures the PSD of all bolometers between 2 and 10 Hz, after all other pre-processing steps have been run (identical to the measurement in Section 3.2.5). Despite having significant low-frequency noise (and possibly bright astronomical source) contamination, this higher frequency portion of the PSD is generally quite flat. Furthermore, even if there is contamination, the purpose of this measurement is to identify outliers, rather than provide a meaningful absolute measurement of a given bolometer’s white noise level. Both high and low (e.g. due to an incorrect and very small flat-field correction being applied) outliers from the centre of the logarithm (to reduce the impact of outliers) of the bolometer noise distribution are flagged.

Finally, data that are taken while the telescope is either moving extremely slowly, or extremely fast, are flagged and ignored when estimating the map. When the telescope is moving slowly, astronomical signals appear at low frequencies in the bolometer data that are dominated by 1/f noise (in the extreme case of no motion, the bolometers have zero sensitivity). When the telescope is moving significantly faster than 600 arcsec s$^{-1}$, both the thermal response of the bolometers and the anti-aliasing filter in the readout electronics (Section 2.1) can significantly distort signals. The default allowable range of speed is 30–1000 arcsec s$^{-1}$. These thresholds primarily reject short periods when the telescope is stationary prior to commencing the scan pattern (generally speaking the speed is constant once the scan begins). The scan speed can also briefly exceed the upper limit when approaching the maximum requested speed of 600 arcsec s$^{-1}$ as the pointing system struggles at high elevation.

### 3.1.7 Impact of lags

In principle, the effects of the bolometer thermal response, anti-aliasing filter and data acquisition lags should be accounted for; together they produce a net lag in the bolometer signals of about 4.5 ms with respect to the pointing data (Section 2.1). This can be modelled by convolving the ‘pure’ bolometer signals with a single system response function. Similarly, this effect could be removed using deconvolution as a pre-processing step. The impact of this lag is primarily a reduction in point source sensitivity since scans at different position angles will detect the source at slightly different positions (and therefore reduce the peak signal once averaged together). This attenuation is most significant at 450 μm, given the smaller beam size, and at the greatest scan speeds. For reference, at a speed of 150 arcsec s$^{-1}$ (typical for CV daisies of calibrators and deep fields) the attenuation is negligible <1 per cent at 850 μm, and ~1 per cent at 450 μm. However, at the maximum speed of 600 arcsec s$^{-1}$ (for the largest, and typically shallowest maps), this attenuation grows to about 5 and 15 per cent at 850 and 450 μm, respectively. It is unlikely that this response has had a significant impact on observations taken to date, since such scans have been used primarily for shallow cosmology fields for which only the 850 μm data are expected to be useful, or Galactic fields of extended structures (which are less sensitive to this effect). In the present Starlink KAPUAHI release, there is no option to deconvolve the system response. However, it is presently being added and will be present in future releases.

### 3.2 Iterative model calculation

Once the data have been cleaned, and the worst data flagged, the iterative solution for the map and contaminating noise signals begins.

First, we describe the basic model for SCUBA-2 data. We express the digitized signal observed by the $i$th bolometer as a function of time,

$$b_i(t) = f_i [e_i(t) a_i(t) + n_i(t)],$$

(2)

where $a(t)$ is the time-varying signal produced by scanning the telescope across astronomical sources, $e_i(t)$ is the time-varying extinction, which is a function of the telescope elevation and atmospheric conditions, and $n_i(t)$ represents sources of noise. The two terms in square brackets, as written, have units of power delivered to the detectors (pW). The scalefactor $f_i$ converts this effective power to the digitized units recorded on disc – the flat-field multiplied by a digitization constant (applied once during pre-processing) – which in this formulation is assumed to be constant in time.

We then express the noise, $n_i(t)$, as the sum of several components,

$$n_i(t) = n_i^{\text{wh}}(t) + g_i n_i^{\text{en}}(t) + n_i^\text{c}(t),$$

(3)

where $n_i^{\text{wh}}(t)$ is uncorrelated white noise, $n_i^{\text{en}}(t)$ is a correlated or common mode signal (with an optional scalefactor $g_i$ for each bolometer) and $n_i^\text{c}(t)$ is (predominantly low-frequency) noise in excess of the white noise level, which is either uncorrelated from bolometer to bolometer, or at least does not have a simple correlation relationship that would lead to it being included in $n_i^{\text{wh}}(t)$.

During pre-processing, the map-maker divides by $f_i$ once. Then, in each iteration, the map-maker models and removes $g_i n_i^{\text{en}}(t)$, divides by $e_i(t)$, and applies a high-pass filter to remove $n_i^\text{c}(t)$ from the bolometer time series. This procedure isolates the astronomical signal and white noise, $a_i(t) + n_i^{\text{wh}}(t)$, for estimating the map. Finally, once the map is estimated it is projected into the time domain and removed from the bolometer time series leaving $n_i^{\text{wh}}(t)$, in which the bolometer noise can be measured. This is the most typical sequence; in practice, the user can select an arbitrary order, although the solution converges much faster when the strongest components are estimated first, and then subtracted, leaving a cleaner signal for subsequent model estimates.
Table 1. Summary of the model components that can be fitted to SCUBA-2 time series data with SMURF. Only the first group of models are typically fitted to the data (COM–NO1) in the indicated order. The remaining models (DRS–PLN) are usually omitted, although they are available as options.

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>COM</td>
<td>Remove common mode signal</td>
</tr>
<tr>
<td>GAI</td>
<td>Common mode scaled to each bolometer</td>
</tr>
<tr>
<td>EXT</td>
<td>Extinction correction</td>
</tr>
<tr>
<td>FLT</td>
<td>Fourier transform filter</td>
</tr>
<tr>
<td>AST</td>
<td>Map estimate of astronomical signal</td>
</tr>
<tr>
<td>NOI</td>
<td>Noise estimation</td>
</tr>
<tr>
<td>DRS</td>
<td>Dark SQUID cleaning along columns</td>
</tr>
<tr>
<td>PLN</td>
<td>Two-dimensional time-varying plane removal</td>
</tr>
<tr>
<td>SMO</td>
<td>Time-domain smoothing filter</td>
</tr>
<tr>
<td>TNP</td>
<td>Pointing as baseline template</td>
</tr>
</tbody>
</table>

After the first iteration, there will almost certainly be correlated errors between the model estimates. For example, the presence of a bright astronomical source will contaminate $n^i(t)$ (which is a simple average of all of the bolometer time series at each instant in time), leading to an oversubtraction, and in turn, negative bowls in the map.

Subsequent iterations, however, diminish such problems. Each additive model component is re-estimated in the same sequence, after first adding the previous estimate back into the time series (but importantly, not the other components). In this case, much of the astronomical signal will have been identified and removed in the previous calculation of $a_i(t)$, and therefore there will be less contamination in $n^i(t)$, and less negative bowling in the map. Any multiplicative models [e.g. $e_i(t)$] are inverted immediately prior to the start of a new iteration to preserve the units of the data. The iterative solution will thus converge, barring degeneracies between model components.

The full set of model components available, and the parameters that control them, are described in the following sections. Table 1 shows the typical order in which they are calculated. For a discussion on convergence tests and degeneracies, see Section 3.3.

3.2.1 COM, GAI: common mode estimation

Fig. 10 shows the time series from a selection of typical bolometers. The similarity between most bolometers is evident, and forms the common mode signal — assumed to be a consequence of variations in the atmospheric emission and fridge temperature. This common mode usually dominates the astronomical signal for all but the brightest sources, and swamps faint extended structure. The purpose of the COM and GAI models is to remove this common mode signal.

The COM model is the common mode signal itself [$n^c(t)$ in equation 3]. It is a single time series that is estimated by finding the mean of all bolometers at each time-step. Bolometer values that have been flagged as unusable are excluded from the mean.

Even after flat-fielding, bolometers may have slightly varying sensitivities and so the amplitude of the common mode variations will also vary from bolometer to bolometer. Comparing each bolometer time series with the common mode signal allows an estimate of the relative bolometer sensitivity to be obtained. In practice, a least-squares linear fit is performed between the bolometer time series and the common mode to determine a gain ($g_i$ in equation 3) and offset for each bolometer. The gain and offset for each bolometer is known as the GAI model. Each bolometer value can then optionally be scaled and shifted using these values so that all bolometers share a common (but as yet unknown) calibration. This provides an alternative (or additional) flat-fielding strategy to that described in Section 2.1.

An option exists to cater for time-varying sensitivities. In principle, the gain of the bolometers should be constant in time. However, there is evidence that there are slight variations, and this option does tend to slightly improve the noise in maps. If used, the least-squares fit described above is performed on short blocks of contiguous time slices, providing multiple gain and offset values for each bolometer (one pair for each block of time slices). The gain and offset at any required time slice can then be found by interpolation between these values.

It can be seen from Fig. 10 that some bolometers depart radically from the common mode, indicating some problem with the bolometer. Such bolometers are identified by calculating the Pearson correlation coefficient between each bolometer time series and the common mode. Bolometers for which the correlation coefficient is below a specified limit, or which have unusually high or low gains compared to the other bolometers, are flagged as bad in order to omit them from the final map. If the option described above for handling

\footnote{The data have been flat-fielded and each time series has been adjusted to a mean value of zero.}
time-varying sensitivities is used, then a correlation coefficient can be determined for each individual block of time slices. This allows individual bad blocks to be rejected from a bolometer time series, rather than rejecting the whole bolometer. As a warning, rejecting data based on outlier gain values can be misleading in cases where the data are dominated by magnetic field pickup. For example, the common mode signal for the data in Fig. 3 would resemble the azimuthal scan pattern, but clearly the gains will have opposite signs (such that one or the other bolometer would be erroneously flagged). Experimental models that were investigated for magnetic field pickup removal are described in Section 3.2.6.

The common mode value at each time slice is calculated as the unweighted mean of the values of all bolometers that have not previously been flagged as bad for some other reason. Bolometer values that were flagged as bad simply because they were poorly correlated with the common mode on the previous iteration are, however, included in the new common mode estimate. If such samples are excluded, there is a strong possibility of discontinuities appearing in the common model at block boundaries. These in turn can lead to ringing when filtering, and instabilities in the convergence process.

Any astronomical sources that are smaller than the array size will contribute signal to some bolometers but not other bolometers, thus biasing the simple mean used to estimate the common mode. However, on each iteration of the map-making algorithm illustrated in Fig. 6, a large fraction of the remaining astronomical signal is extracted from the bolometer time series and transferred to the output map, resulting in subsequent estimates of the common mode being more accurate. It is also for this reason that the previously described step of (re-)flagging outlier portions of the data is generally performed iteratively, rather than once as a pre-processing step, since bright/compact astronomical sources can be the cause of rejection in early iterations.

Any extended astronomical emission on a scale comparable to or larger than the spatial extent of the area used to estimate the common mode will contribute a similar signal to all bolometers. Therefore, such extended emission is indistinguishable from the other sources of common mode signal (e.g. atmosphere variations) and will be removed by the common model. This places a limit on the spatial extent of astronomical structure that can be recovered.

For this reason, the usual practice is to estimate a single common model by examining data from all four subarrays in each waveband, since this allows spatial structure on the scale of the whole focal plane to be recovered. However, sometimes there is evidence that the common mode differs from one array to another, and so an option exists to estimate a separate common model for each individual subarray, with a consequent lowering in the scale of spatial structure that can be recovered.

3.2.2 EXT: extinction correction

The extinction correction is a multiplicative factor that is normally derived using the WVM, and is not considered to be a free parameter in the solution \( [e(t)] \) in equation 2. However, it is applied as part of the iterative solution, rather than a pre-processing step, since any small errors will be amplified by the large low-frequency drifts in the raw bolometer time series. For example, if the bolometer drift is 1000 times greater than an astronomical source of interest, a 1 per cent error in the flat-field will produce stripes of the order of 10 times the astronomical signal amplitude in the final map! If EXT is applied after the bulk of the low-frequency noise has been removed (e.g. COM, GAI), then there is little potential for such small errors to affect the final map. For details on how it is calculated, see Dempsey et al. (2013). Note that its numerical value is calculated only once, and simply applied as a scalefactor in the iterative solution. Unlike the additive model components, it is inverted at the start of each iteration to preserve the amplitude of the data before the re-calculation of other model components.

3.2.3 FLT: Fourier transform filter

This model takes the FFT of the bolometer time series data, and can apply both high- and low-pass filters, as well as notch filters, at hard frequency edges specified by the user. Alternatively, the frequency edges of the filters may be defined in terms of an angular scale, but converted into a frequency through knowledge of the mean telescope slew speed. The time series are generally gap filled (Section 3.1.4) before the transform to avoid ringing (primarily caused by wrap-around discontinuities at the ends of the time series). Finally, a whitening filter may also be applied in which a simple form, \( 1/\sigma^2 + \text{constant} \), is fitted to the power spectrum of each bolometer, and then the bolometer FFT is multiplied by the square root of its inverse (though normalized to preserve the white noise level). The signals that are removed from the time series by this process are stored in the FLT container array. Typically, this model is used purely as a high-pass filter to remove most of the residual 1/f noise following common mode removal \( [n(t)] \) in equation 3. Low-pass filtering is redundant for two reasons: (i) SMURF already low-pass filters and resamples to a lower sample rate, as described in Section 3.1.1; and (ii) the act of re-gridding the data to produce map estimates effectively low-pass filters the data below a frequency that corresponds to the inverse of the crossing time of a single map pixel. Notch filters have not been proven to be useful with SCUBA-2 data, particularly since line features tend to move around (i.e. a dynamic fine-detection system would have to be developed, and care would have to be taken that astronomical sources are not suppressed).

3.2.4 AST: map estimation

Map estimation is accomplished using a nearest neighbour resampling of the data on to a pre-defined map grid. For the \( i \)th map pixel, \( m(x_i, y_i) \), the brightness is estimated as the weighted average of the bolometer data samples \( b_j \), that land within that pixel (from any bolometer or point in time, provided that they are not flagged as bad or gap filled, Section 3.1.4),

\[
m(x_i, y_i) = \frac{\sum_j w_j b_j}{\sum_j w_j}.
\]

For the initial iteration, the weights \( w_j \) are set to 1, but subsequently they are set to \( 1/\sigma_j^2 \), the estimated inverse variance expected from the bolometer white noise levels, as discussed in Section 3.2.5. This weighting scheme is sensible, provided that the bolometer data have no correlated (e.g. low-frequency) noise.

In addition to the signal map, a variance map \( v(x_i, y_i) \) is estimated. The default procedure is to estimate this quantity, given the scatter in the weighted samples. This is accomplished by dividing the biased weighted sample variance by the number of samples that went into the average (akin to the formula for standard error on the mean, but accounting for weights),

\[
v(x_i, y_i) = \frac{\sum_j w_j \sum_j w_j b_j - (\sum_j w_j b_j)^2}{N \left( \sum_j w_j \right)^2}.
\]
where \( N_i \) is the total number of bolometer samples that land in the pixel. As written, this algorithm is numerically unstable if the two terms in the numerator are large, and of nearly the same value: floating point precision errors can cause the difference to be significantly incorrect. In practice, we use the superior ‘weighted incremental algorithm’ that calculates incremental differences, as described in West (1979).

We decided not to use an unbiased estimator [e.g. the extension of the common \( (1/\bar{N} - 1) \sum_j \left( \frac{1}{\bar{N}} \right) \) estimator using weights], since in practice it would require accumulating an additional array of values at every map pixel, and only results in a small difference where there are less than \( \sim 10 \) samples per pixel (a situation that is almost never encountered in a SCUBA-2 map, except in the edge pixels).

Finally, once the map estimation is complete, the map is projected into the time domain (the signal that would be produced in each bolometer by the signal represented by the map, \( a_i(t) \) in equation 2) and removed.

In addition to map estimation, the AST model can also be used to perform map-based despiking of the time series. Unlike the time-domain despiker (Section 3.1.2), this calculation utilizes the scatter in the population of samples that land in a map pixel (from different times and bolometers) to reject outliers. This method is more robust against false-positive detections of bright/compact astronomical sources since transient features in the time series are unlikely to occur by chance whenever a bolometer crosses a specific location on the sky, whereas real astronomical sources are at fixed spatial locations.

The estimated variance, \( v_p(x_i, y_j) \), of the normalized weighted samples that land in the \( i \)th map pixel is simply the biased weighted sample variance (i.e. the variance map value multiplied by the number of samples):

\[
v_p(x_i, y_j) = N_i v(x_i, y_j).
\]

In order to compare the weighted differences between the samples and the map values, \( \{ b_j - m(x_i, y_j) \} \) to \( v_p \), they must be scaled appropriately. We define a normalized difference, \( d_j \), in such a way that the variance of this new variable gives the weighted sample variance of the underlying data points:

\[
\frac{\sum_j d_j^2}{N} = \frac{\sum_j w_j \left( b_j - m(x_i, y_j) \right)^2}{\sum_j w_j},
\]

\[
\Rightarrow d_j^2 = \frac{N_i w_j \left( b_j - m(x_i, y_j) \right)^2}{\sum_j w_j}.
\]

The map-based despiker flags those \( d_j \) that are farther than some threshold number of standard deviations \( \sqrt{v_p} \) away from zero, so that they are not used in subsequent iterations.

A final option available as part of the AST model is to apply constraints to the map to improve convergence, which presently includes setting user-specified or low-S/N regions to a value of zero for all but the final iteration. See the discussion in Section 3.3 and examples in Sections 4.

3.2.5 NOI: noise estimation

The primary purpose of the noise component, NOI, is to measure the white noise levels of each bolometer, which is approximated with a single (non-time-varying) variance, \( \sigma_i^2 \). This value is then used to calculate weights for map estimation, \( w_i = 1/\sigma_i^2 \). The measurement generally occurs once all of the other models have been fitted and removed [i.e. once \( n_i^x(t) \) from equation 3 is isolated].

First, the bolometer PSDs are calculated as in equation (1). An average white noise level is then measured from 2 to 10 Hz, a clean region of the PSD that tends to lie above the 1/f knee, but below the high-frequency line features for typical bolometer data (Fig. 2). Taking this constant level for \( P(f) \), we then calculate the expected variance of the time series (in approximately 200 Hz samples) using equation (1). If the bolometer noise were produced purely by uncorrelated sources (i.e. no other low-time-scale drifts), with no high-frequency line features, and without the attenuation at even higher frequencies by the anti-aliasing filter, this is the theoretical noise limit of the detectors. These measured variances are stored, and then used in subsequent iterations to weight the data points when calculating the map estimate (Section 3.2.4). They are also used for convergence tests (Section 3.3).

Since noise estimation is usually calculated as the final step in the iteration, the data at this stage have had most of the astronomical and other large, low-frequency noise signals removed. For this reason, NOI may optionally perform some cleaning options, such as the step fixer (Section 3.1.3) and spike detection (Section 3.1.2), which may work better with these cleaner time series.

Finally, it should be noted that the default procedure is to calculate the white noise levels once within NOI, after the second iteration. The reason for fixing these values is to prevent any potential divergence in the weight estimates with iterations, and also to provide a fixed reference for the convergence tests (Section 3.3). Note that the absolute values of the noise, and therefore weights calculated by the model, are irrelevant (only their relative values matter). The reason is that the final noise in the map is measured empirically from the scatter of the weighted data points that land in each pixel (Section 3.2.4).

3.2.6 Experimental models for the removal of magnetic field pickup and the atmosphere

Additional models exist as options, although they are not generally used: DKS, the use of dark SQUIDs as a template for removing magnetic field pickup; TMP which uses the azimuth of the telescope also as a template for magnetic field pickup; SMO, which provides a time-domain smoothing alternative to the FFT-based filter model FLT; and PLN, which fits a plane to the signal distribution across the focal plane at each time slice in an attempt to remove possible coherent atmospheric sky-noise structure.

As described in Section 2.3, wide scans can produce significant magnetic field pickup that tracks the azimuthal motion of the telescope. The DKS model uses the dark SQUID signals for each column as a template that is simply scaled (gain and offset) to each bolometer time series before removal. Unfortunately, the dark SQUIDs do not work for every column (several cases in each subarray), meaning that those columns are usually discarded when producing maps. One possible remedy is to identify dead bolometers (with otherwise working TES readouts) or intentionally disconnect working bolometers, to create replacement dark readouts in those columns. This solution has not been pursued due to the limited success at removing pickup using the presently working dark SQUIDs. Another alternative model is TMP in which the azimuth of the telescope itself is used as the template. For both DKS and TMP, there is some success at visibly decreasing the low-frequency scan-synchronous noise in certain data sets, although often it does not (and there are also examples in which the noise is increased). In the case of DKS, there may
simply be components of the signal seen by working detectors that are not apparent in the dark SQUIDs. Furthermore, in the case of TMP, the relationship between the projection of the Earth’s magnetic field on the instrument and the magnitude of the pickup may not be linearly correlated as we have assumed (verified in some cases by a comparison of the azimuthal motion with working dark SQUID signals). In no case was the use of these models able to reduce the 1/f knee substantially, necessitating the continued use of FLT to remove the remaining low-frequency noise. Neither DES nor TMP is typically used.

The SMD model uses a rolling mean or median boxcar filter to calculate the low-frequency component of the bolometer signals, which are then removed. In other words, this is an alternative to the high-pass filtering for which FLT is generally used. The primary reason for developing this model was to make it more robust against ringing near the ends of the time series, or residual spikes (for which the median filtering is particularly useful). However, the despiking and gap-filling algorithms that we have employed (Section 3.1.4) successfully mitigate these problems, and the FLT model is substantially faster.

Finally, we experimented with an alternative to CDM for removing correlated atmospheric noise. Rather than subtracting the average signal at each time slice, PLN fits a plane to the observed signal. This result is basically consistent with those from earlier instruments (e.g. the prediction for SCUBA-2 based on SCUBA data described in Chapin et al. 2002), and suggests that the angular scale of the emitting regions in the atmosphere is unresolved at the SCUBA-2 focal plane. Sayers et al. (2010), in particular, examined several different ways of modelling and removing the correlated atmospheric noise from Bolocam data at 143 and 268 GHz (also atop Mauna Kea), finding only marginal improvements by fitting a plane, or even higher order polynomials (see their fig. 10, as well as the discussion and references to earlier work in their section 4.3). In Aguirre et al. (2011) iterative PCA cleaning was used to remove the atmosphere since the simpler methods mentioned left substantial residuals in their data (similar to the SCUBA-2 data described here, although PCA cleaning is prohibitively slow in our case).

### 3.3 Convergence tests and model degeneracies

The map-maker will halt after a user-specified number of iterations, or once some convergence criterion has been achieved. Presently two numerical quantities are tracked after each iteration: the change in reduced chi-squared, $\chi^2_r$; and the change in the map. While convergence in $\chi^2_r$ is not, ultimately, a good indicator of when the solution should be stopped, we discuss its calculation and properties first as an introduction to the problem of model degeneracies.

The bolometer residual variances, $\sigma_i^2$, are measured once the modelled signal components have been removed. In the early iterations, the residuals contain both white noise, and other long-time-scale features. However, when the solution has converged, this signal should look white. Taking the component of bolometer variances due to white noise, $\sigma_i^w$ (measured from the bolometer PSDs in NOL, Section 3.2.5), $\chi^2_r$ is calculated as $(1/N) \sum_i \sigma_i^2/\sigma_i^w$, where $i$ runs over the $N$ bolometers. In other words, it is the average ratio between the measured time-series bolometer variances and their white noise levels measured between 2 and 10 Hz, and should tend to a value of 1 if the low-frequency noise (and any bright astronomical signals) has been successfully removed. However, this expression does not account for the degrees of freedom in the model. Clearly there are a large number of parameters that will ‘fit out’ some of the uncorrelated white noise, and bias this estimate of $\chi^2_r$ low. Indeed, for a converged map, values in the range ~0.85–0.95 are common, depending on the precise configuration parameters. Regardless of the normalization, once the model parametrization has been chosen, this quantity should converge to some fixed value.

Practically speaking, $\chi^2_r$ tends to converge before the map due to model degeneracies. One simple example is the degeneracy between large-scale astronomical structures (larger than the array footprint), and the common mode rejection step (CMR), which will be illustrated in Section 4.1. In this case, there is a significant space of maps with spurious large-scale structures that are anticorrelated with features in the common mode, and the solution is free to wander this space while producing flat residuals.

Instead, we typically use a map-based convergence statistic, $M_r$, the average absolute change in the value of map pixels between subsequent iterations, normalized by the map pixel uncertainties (square root of equation 5),

$$M_r = \frac{1}{N} \sum_i \frac{|m(x_i, y_i) - m(x_{i-1}, y_{i-1})|}{\sqrt{\sigma(x_i, y_i)^2}},$$

where $i$ runs over the $N$ map pixels, and $j$ enumerates the iterations. Experimentally we found that a change in this quantity <0.05 (on average, map pixels change by <5% per cent of the estimated map rms in subsequent iterations) is a good point to stop, providing correspondence with what we would choose ‘by eye’. Letting the solver run for many more iterations in several test cases yields insignificant differences.

Another major source of divergence is the correlation between CDM and FLT. Since FLT usually consists of a high-pass filter following the application of CDM, CDM is completely free to grow any large-scale structure at frequencies below the chosen filter edge. While such structure does not appear in the map (as it is removed by FLT), we found that the solution could be made to converge significantly faster by ‘re-mixing’ CDM and FLT. Immediately prior to the calculation of CDM, the values of CDM and FLT from the previous iteration are added back into the residual simultaneously. In this way, truly common mode signals, even at low frequencies, do not leak into FLT.

In order to control the degeneracy between low-frequency signal that is removed and large-scale structures in the map, we have developed a simple system for constraining regions of the map devoid of sources to a value of zero for all but the final iteration in the AST model (Section 3.2.4). Such regions are either user defined in advance or can be determined from the data using a cut on S/N. This technique is explored considerably in the examples in Sections 4.1 and 4.3.

### 3.4 Instrument and map-making performance

From a scientific perspective, the most important goal of map-making is to efficiently use all of the available data to achieve the greatest sensitivity to astronomical sources that the instrument is capable of. Generally speaking, only a small percentage of the data are flagged as unusable during map-making beyond the ~70 per cent detector yield. As an example, for the 450 μm scan of Uranus that will be presented in Section 4.1, during pre-processing: 31 per cent of the data (1587/5120 bolometers) are flagged due to data acquisition problems (dead or deactivated bolometers, or non-linear flat-fields); 0.12 per cent of the data are flagged due to steps (including a small region about the steps, Section 3.1.3); and 0.83 per cent...
of the data are flagged because the telescope was stationary (Section 3.1.6). Once the iterative solution begins: 55 spikes are detected using the map-based despiker (1.2 × 10^{-6} per cent of the data, Section 3.2.4); and 0.72 per cent of the data are flagged as outliers compared to the common mode (Section 3.2.1).

The white noise levels of SCUBA-2 bolometers are measured between 2 and 10 Hz in the PSDs (as described in Section 3.2.5), leading to noise equivalent powers (NEPs, with units W s^{1/2}) – the rms time-series noise in a 1 s integration (see section 3.5.2 in Holland et al. 2013). The NEPs are then converted into more useful NEFDs (with units Jy s^{1/2}) through multiplication by the extinction correction and the FCF. For an ideal scan pattern in which every bolometer spends an equal amount of time observing each point on the sky, the expected noise in a map pixel is NEFD_{eff} / t^{1/2}, where t is the integration time, and the effective NEFD, NEFD_{eff} = (1/\sum i \times NEFD_i^{1/2})^{1/2}, is the sensitivity of the entire array including all bolometers i. Experimentally it has been found that the map noise based on the weighted scatter of the data (equation 5) and the scatter of map pixels in small apertures both correlate well with this expected limiting noise performance for maps that are larger than the array footprint (for smaller maps, the assumption of uniform coverage is incorrect). As an example of observing under favourable conditions with line-of-sight opacities of 0.87 and 0.34 at 450 and 850 µm (zenith sky opacities at 225 GHz of 0.04 and 0.065 at 450 and 850 µm, respectively, at an average airmass of 1.2, from table 3 in Holland et al. 2013), the mapping speed is approximately 6 × 10^{-3} and 3 × 10^{-3} deg² h^{-1} m²^{-2}, at 450 and 850 µm, for the default pixel sizes of 2 and 4 arcsec, respectively. If maps are filtered and cross-correlated with the PSF for the optimal extraction of point sources (see Section 4.2), the mapping speeds increase to approximately 5 × 10^{-4} and 1.5 × 10^{-2} deg² h^{-1} m²^{-2} in this example, independently of the chosen map pixel sizes. See the online SCUBA-2 integration time calculator for mapping speeds under arbitrary observing conditions and scan modes.⁵

4 EXAMPLES

While most of the steps described in Section 3 for reducing data with SMURF are applicable to all data sets, there is no ‘default’ reduction that provides good results for a wide range of source S/N and angular scales. However, SMURF does have a small number of configurations with variations on these baseline parameters that are applicable to most common types of data. In this section, we illustrate the differences between these configurations with the following examples: a bright point source, Uranus (Section 4.1); a blind survey of high-redshift galaxies in the Lockman Hole (Section 4.2); and a map of a bright extended star-forming region in our Galaxy, M17 (Section 4.3).

4.1 Known point source

The accurate measurement of positions and brightnesses of known point sources is necessary in real time to establish telescope pointing offsets and foci. They are also necessary to measure the FCF (absolute calibration), and hence the noise performance of the instrument in astronomically-useful units. In this example, we reduce a 450 µm map of Uranus (observation 26 on 2011 October 17), which is a nearly point like source for SCUBA-2 that is commonly used as a primary flux calibrator. The CV daisy pattern was used, with a scan speed of 155 arcsec s^{-1}. We perform several different reductions of the data to illustrate the purpose of various model components and the convergence properties of the solution (Fig. 11). In all cases, the maps are produced on a grid of azimuth (horizontal) and elevation (vertical) offsets from the position of Uranus (the origin), using 2 arcsec pixels.

The first, simplest reduction of the data uses only the COM model to estimate and remove the common mode signal in order to suppress low-frequency noise in the data. After COM, the extinction correction is applied (EXT), and an initial map is estimated using equal weighting for all of the detectors. This estimate of AST is then removed from the data, and the noise is measured in the residuals to estimate weights for the subsequent and final iterations. The resulting map after these 2 iterations is shown in Fig. 11(a). While the peak S/N of Uranus is clearly large (~160), enabling us to see the faint sidelobes (circle and cross pattern), the map also has obvious circular streaks and other large-scale ripples. The circular streaks are due to the fact that COM does not account for all of the low-frequency (i.e. uncorrelated) noise (see Fig. 2), and therefore each bolometer leaves a trace of the circular scan pattern in the map, as their baselines slowly drift independently. A significant contribution to the larger scale ripples in the map, however, can be made by degeneracies in the map solution, as we discuss below.

To illustrate how large-scale ripples can form (and grow), the same map solution is run for 100 iterations and shown in Fig. 11(b), now exhibiting a strong vertical gradient. The degeneracy is easy to understand if the time-domain behaviour of each model component is considered. The top panel of Fig. 12 shows the residual signals for a single bolometer after 2 (black) and 100 (grey) iterations, which are nearly identical, yet the change in the estimated COM (green) and AST (red) signals between 2 and 100 iterations is large. However, it is also clear that the estimated COM and AST signals are complementary. In other words, the large change in the AST signal is cancelled by the freedom in the COM signal to grow with opposite sign. For comparison, the bottom panel of Fig. 12 shows the telescope pointing for this section of data, and the shapes of the AST and COM signals match the elevation component, which is aligned with the gradient in Fig. 11(b). Generically, the calculation of COM will remove any information on angular scales that are larger than the array footprint (outline shown in Fig. 11b for reference), meaning that the map solution is unconstrained on such large scales.

Attacking the problem of streaks, a simple method of removing residual (uncorrelated) sources of low-frequency noise is to apply a high-pass filter after the common mode removal. A third reduction of the data uses the baseline map-making parameters, as described in Section 3, which adds the FLT model to accomplish this task immediately prior to map estimation. We set the filter edge based on an angular scale of 200 arcsec, which, given the scan speed of 155 arcsec s^{-1}, corresponds to a frequency of 0.78 Hz (note in Fig. 2 that this frequency is slightly above the 1/f knee at 450 µm after common mode removal). Now using the automatic map-based convergence test (Section 3.3), the solution converges after 10 iterations (Fig. 11c). Both the circular streaks and the large-scale gradient are now removed, but they have been replaced by an obvious, circularly-symmetric ringing pattern about Uranus. The reason for this ringing is that the hard-edged high-pass filter in frequency space is equivalent to a sinc function like response in map space. Since the scan pattern is fairly isotropic (scans at all position

⁵ http://www.jach.hawaii.edu/jac-bin/propscuba2itc.pl
Figure 11. Multiple reductions of a 450 µm CV daisy scan of Uranus, all scaled between −0.002 (white) and +0.002 pW (black). In all cases, extinction correction has been applied immediately after common mode removal. (a) Reduction in which only common mode subtraction is used to suppress low-frequency noise, and the reduction is forced to use 2 iterations (after the first iteration an estimate of the source flux is removed, and the noise is measured in the residuals to obtain appropriate weighting for the second and final iteration). The circular streaks are caused by independent low-frequency noise that is not removed by the common mode (Uranus peak 0.358 pW). (b) Same as (a) but using 100 iterations, illustrating the degeneracy between large-scale structure and the common mode (the footprint of the working bolometers is also shown for reference; Uranus peak 0.358 pW). (c) Reduction in which high-pass filtering above 0.775 Hz (corresponding to a spatial scale of 200 arcsec, as indicated) is applied after common mode removal, but before the map estimate. The map-based convergence test is activated and the solution halts after 10 iterations, but leaving large-scale ringing due to the filter (Uranus peak 0.353 pW). (d) Same as (c), but now the region of the map beyond the white dot–dashed circle is constrained to a value of zero until all but the final iteration. The map is now extremely flat, there is no attenuation of the source flux compared with the first two reductions, and the diffraction pattern is clearly seen (Uranus peak 0.358 pW).
angles), and there is a bright point-like source at the centre, the result is an azimuthally-symmetric sinc function like pattern in the map. The peak flux has also been attenuated to 0.353 pW in this reduction, compared with 0.358 pW in the first two reductions. The gradient resulting from the degeneracy between the common mode and map has been removed because the filter scale of 200 arcsec (3.3 arcmin) is smaller than the array field of view (∼5 arcmin). If it were greater, degeneracies would again begin to appear on those larger scales.

This example illustrates the need for constraints in the map solution in many situations. For calibrators (and other previously known bright, compact sources), a good, simple prior is to constrain the map to a value of zero away from the known locations of emission (part of the AST model calculation, Section 3.2.4). In Fig. 11(d), a solution is produced in an identical manner to Fig. 11(c), but now setting the map explicitly to zero beyond a radius of 60 arcsec from the location of Uranus (much larger than the FWHM of the main lobe), for all but the final iteration. In this case, the map converges after 6 iterations, and the ringing has been effectively removed. The attenuation from the previous reduction is now removed, and Uranus again has a peak value of 0.358 pW. For reference, the Uranus model distributed with Starlink predicts a peak brightness of 176 Jy on this date, yielding an FCF of 491 Jy pW⁻¹, which is well within the typical range for SCUBA-2 of (492 ± 67) Jy pW⁻¹ (see Dempsey et al. 2013, for details). Since the map is now flat away from the source, and constrained to a value of zero, it is appropriate for performing aperture photometry directly, with no need for an additional reference annulus.

The way this prior works can be understood from the point of view of differential measurements. Bolometer data contain information up to scales corresponding to the filter edge (or the scale of the array footprint, whichever is smallest). In this example, the relevant scale is 200 arcsec. Since the map is constrained to zero within 60 arcsec of the peak of Uranus (well within 200 arcsec), the solution is able to accurately reconstruct the differential peak intensity of Uranus with respect to this constrained background. This approach to mapping is similar to that employed for poorly cross-linked scans of compact (though resolved) sources by Wiebe et al. (2009) using BLAST data.

4.2 Deep point source survey

SCUBA-2 surveys designed to detect extremely-faint point sources (e.g. high-redshift star-forming galaxies, and features in debris discs) are ideally limited by the white noise performance of the instrument. The approach described here for maximizing the S/N of point sources involves three major steps: (i) generating a map that removes most large-scale noise sources with approximately linear response, without prior knowledge of the location of sources; (ii) applying a Fourier-space ‘whitening filter’ to suppress residual large-scale noise; and (iii) detecting point sources using a ‘matched filter’. Note that variations on this general procedure have been used extensively in the submillimetre cosmology community using previous instruments (e.g. Scott et al. 2002; Borys et al. 2003; Laurent et al. 2005; Coppin et al. 2006; Scott et al. 2008; Perera et al. 2008; Devlin et al. 2009). In this section, we reduce scans of the Lockman Hole taken during S2SRO as a pilot project for the SCUBA-2 Cosmology Legacy Survey. It consists of ~8.5 h of data taken in 36 separate scans (average 15 min each) spread over 2010 February and March. Each scan is a 360 arcsec rotating PONG pattern, with a scan speed of 240 arcsec s⁻¹, covering an area of about 50 arcmin². The full list of dates and observation numbers includes: 2010 February 18, 63, 64, 65, 70, 71, 72, 90, 91, 92, 97, 98, 99; 2010 February 20, 111, 112, 113, 118, 128, 129, 130; 2010 March 3, 61, 62, 64, 69, 70, 72, 73, 74, 75; 2010 March 9, 87, 88, 90, 91; and 2010 March 11, 59, 64, 65, 72. These observations represent about 80 per cent of the total data taken as part of the project; the remaining observations were dropped due to problems in keeping the arrays properly tuned during S2SRO, and were easily identified by their highly variable and erratic bolometer time series (which resulted in maps full of large streaks).

The first step, map generation, is different from that described in Section 4.1 in two key ways. Since the locations of sources are unknown a priori, a map constraint is not employed. Large-scale diverging structures in the map must be mitigated, and the method used in this example (the baseline processing in SMURF) is to apply a high-pass filter to the data once, as a pre-processing step. The iterative solution is then run using only COM, EXT, AST and NOI. In other words, there is no information in the bolometer signals below some cut-off frequency, and residual correlated high-frequency noise above the cut-off is only removed through iterative common mode subtraction. In this case, the filter edge has been chosen to remove scales larger than 200 arcsec, or a high-pass filter above 1.2 Hz, given the scan speed. Since the data are high-pass filtered prior to the iterative solution, GAUSS (fitting an independent amplitude of COM to each bolometer) has been de-activated, since there is very little structure in the common mode with which to fit an accurate gain. The map is shown in Fig. 13(a). The map-maker has been tested in two ways: (i) large numbers of iterations are used to verify that the maps converge without the growth of large structure; and (ii) adding synthetic sources to the real time series data (a built-in feature of SMURF) at a range of brightnesses verifies that the map-maker response to them is linear (i.e. the relative...
shape and amplitude compared to the input source are independent of brightness). The response to a synthetic point source (solid line) after map-making (dotted line) is shown in Fig. 14. Clearly the use of a high-pass filter as a pre-processing step, and having no other map constraints, has the downside of introducing sidelobes around the main peak. Furthermore, the details of this shape depend on the high-pass filter edge that has been chosen (the higher the frequency, the greater the attenuation of the central peak, and the larger the negative sidelobes). However, the way this filter affects point sources is measurable (using the synthetic source injection facility of \textit{SMURF}), and linear.

Even though the map looks quite flat, there is a mixture of faint astronomical sources and what is probably residual low-frequency noise, causing faint patchiness visible to the naked eye. Since the mixture of the two components is unknown, the first step is to suppress the low-frequency noise, under the assumption that such contaminants occur randomly in time, while astronomical sources are (usually) constant.

First, the angular power spectrum of noise is estimated from a ‘jackknife map’: maps are produced from two independent halves of the total data set, and the jackknife signal in a map pixel, \( S_{JK} \), and its variance, \( \sigma_{JK}^2 \), are estimated from the two input map fluxes, \( S_1 \) and \( S_2 \), and the corresponding variances, \( \sigma_1^2 \) and \( \sigma_2^2 \), as

\[
S_{JK} = \frac{S_1 - S_2}{2}, \quad (10)
\]

\[
\sigma_{JK}^2 = \frac{\sigma_1^2 + \sigma_2^2}{4}. \quad (11)
\]

Provided that the noise in one-half of the data is uncorrelated with that from the other half, the signal in the jackknife map should resemble noise drawn from the same parent distribution as that of the real map. The astronomical signal, however, should be cleanly removed (provided that there are no strong time-varying signals, and also assuming that errors due to calibration between the two halves are insignificant). The approach we have taken to minimize systematics is to produce the two maps using odd and even scan numbers (i.e. each map will contain a nearly uniformly spaced sampling of data across the full data set).
Slice through the angular response to an ideal Gaussian point source (solid line) along the RA axis following map-making using the blank-field processing configuration with SMURF (dotted line), and upon application of the whitening filter (dashed line). The 'map-filtered' response is produced by adding the ideal Gaussian to the real data near the centre of the Lockman Hole map, and re-reducing the data. The resulting dotted line gives the expected shape of a source in panel (a) from Fig. 13. Applying the whitening filter to the dotted line (dividing the Fourier Transform of the map-filtered response by the square root of the solid orange line in Fig. 15, and then transforming back to real space) gives the whitened line (dashed), which is the expected shape of a source in panel (b) from Fig. 13. Finally, cross-correlating the whitened map with this whitened PSF is an effective 'matched filter' for identifying point-like sources, and this smoothed map is shown in panel (c) of Fig. 13.

Since the SCUBA-2 scan strategy is usually isotropic (all position angles scanned with roughly equal weights), we make the simplifying assumption that the angular noise power spectrum is azimuthally symmetric. For these data, there are no obvious anisotropic structures in the two-dimensional FFT. The radial (azimuthally averaged) angular power spectrum therefore encodes all of the useful information about the noise properties. These power spectra for the raw output of SMURF and the jackknife map (transforming only the approximately uniform region indicated by the square in Fig. 13d in each case), are shown by the dashed black and solid orange lines in Fig. 15, respectively. Both power spectra are approximately flat at spatial frequencies $\lesssim 0.06$ arcsec$^{-1}$, with the exception of a spike at $\sim 0.175$ arcsec$^{-1}$ (a scale of $\sim 5.7$ arcsec). One possibility for this feature is that it is related to the inter-bolometer spacing in the focal plane (which happens to be this size); small relative drifts in the baselines of adjacent bolometers may produce faint parallel stripes in the map along the scan direction. It is not likely that this signal is due to astronomical sources because it appears with a nearly equal amplitude in both the real map and the jackknife. At lower spatial frequencies, both the real map and the jackknife power spectra grow significantly, as a result of the more obvious large-scale patchiness in Figs 13(a) and (d).

To suppress noise in the map, we construct a whitening filter whereby the Fourier transform of the map is divided by the square root of the jackknife power spectrum (orange line in Fig. 15), normalized by the white noise level estimated from the rms power at angular frequencies $>0.1$ arcsec$^{-1}$, and transforming back into real space. The whitened map is shown in Fig. 13(b), and for comparison the jackknife map has also been whitened in Fig. 15(e).

In both cases, the maps are visibly flatter than the non-whitened cases.

The angular power spectrum of the whitened signal map is shown with a solid line in Fig. 15. At low angular frequencies ($\lesssim 0.5$ arcsec$^{-1}$), there is significantly less power than for the raw map. However, it also clearly has some power in excess of the white noise level. In theory, this residual signal is produced by astronomical signals, although its origin cannot be determined from this plot alone, nor are astronomical signals readily visible in the maps. To identify sources, we next apply a 'matched filter' to the whitened maps.

For blind, high-redshift surveys, individual sources are expected to be unresolved by the SCUBA-2 7.5–14.5 arcsec FWHM beams. Under this assumption, and also assuming that the map noise is white, cross-correlation between the map and the known PSF, or matched filtering, yields the maximum-likelihood flux density of supposed point sources centred over every location in the resulting map (an extremely well known result throughout astronomy, see Stetson 1987). Peak identification in such smoothed maps has been used extensively in the submillimetre community, as both an efficient source detection and photometric measurement strategy. For the case at hand, we may use this cross-correlation technique since the map has been whitened. However, we must first establish the effective shape of point sources in this map due both to map-making itself and to the whitening filter. We determine the effect of map-making by adding a synthetic (and high-S/N) point source to the real data, and measure its resulting shape in the map (solid

![Figure 14](https://example.com/figure14.png)

**Figure 14.** Slice through the angular response to an ideal Gaussian point source (solid line) along the RA axis following map-making using the blank-field processing configuration with SMURF (dotted line), and upon application of the whitening filter (dashed line). The 'map-filtered' response is produced by adding the ideal Gaussian to the real data near the centre of the Lockman Hole map, and re-reducing the data. The resulting dotted line gives the expected shape of a source in panel (a) from Fig. 13. Applying the whitening filter to the dotted line (dividing the Fourier Transform of the map-filtered response by the square root of the solid orange line in Fig. 15, and then transforming back to real space) gives the whitened line (dashed), which is the expected shape of a source in panel (b) from Fig. 13. Finally, cross-correlating the whitened map with this whitened PSF is an effective 'matched filter' for identifying point-like sources, and this smoothed map is shown in panel (c) of Fig. 13.

![Figure 15](https://example.com/figure15.png)

**Figure 15.** Radial (azimuthally averaged) angular PSDs for the raw map output by SMURF (dashed black line), the jackknife (solid orange line) and whitened (solid black line) maps [panels (a), (d) and (b) from Fig. 13, respectively], considering only the square region indicated in Fig. 13(d). Since the raw map contains spatially correlated signals on large scales, both due to noise and astronomical signals (low spatial frequencies), the jackknife map (difference of two approximately equal length subsets of the data) is used to generate a plausible realization of pure noise. Assuming that the noise properties are isotropic, a whitening filter is estimated from the reciprocal of the jackknife power spectrum with only a radial dependence. The power spectrum of the resulting signal map still has residual power on large scales, which is presumably due to astronomical sources.

In both cases, the maps are visibly flatter than the non-whitened cases.

The angular power spectrum of the whitened signal map is shown with a solid line in Fig. 15. At low angular frequencies ($\lesssim 0.5$ arcsec$^{-1}$), there is significantly less power than for the raw map. However, it also clearly has some power in excess of the white noise level. In theory, this residual signal is produced by astronomical signals, although its origin cannot be determined from this plot alone, nor are astronomical signals readily visible in the map. To identify sources, we next apply a 'matched filter' to the whitened maps.

For blind, high-redshift surveys, individual sources are expected to be unresolved by the SCUBA-2 7.5–14.5 arcsec FWHM beams. Under this assumption, and also assuming that the map noise is white, cross-correlation between the map and the known PSF, or matched filtering, yields the maximum-likelihood flux density of supposed point sources centred over every location in the resulting map (an extremely well known result throughout astronomy, see Stetson 1987). Peak identification in such smoothed maps has been used extensively in the submillimetre community, as both an efficient source detection and photometric measurement strategy. For the case at hand, we may use this cross-correlation technique since the map has been whitened. However, we must first establish the effective shape of point sources in this map due both to map-making itself and to the whitening filter. We determine the effect of map-making by adding a synthetic (and high-S/N) point source to the real data, and measure its resulting shape in the map (solid
and dotted lines in Fig. 14, respectively). Next, the Fourier transform of the map filtered PSF is divided by the square root of the jackknife noise power spectrum to calculate the final whitened PSF (dashed line in Fig. 14). Both the whitened signal and jackknife maps are smoothed by this shape and shown in Figs 13(c) and (f), respectively. Note that these images are plotted in $S/N$ units, where the smoothed noise maps have been calculated by propagating the original noise map output by SMURF through both the whitening and matched filters (each of which is a linear operation). In terms of the angular power spectra, this complete process can be thought of as an optimal band-pass filter that has both suppressed low-frequency noise and information on scales that are smaller (higher frequencies) than the beam.

Have real astronomical sources been detected using the matched filter? For both the smoothed signal and the jackknife maps, the blue circles denote $3.8\sigma$ peaks. While not justified here, this threshold is fairly typical for other ground-based submillimetre surveys in recent years (e.g. Coppen et al. 2006; Perera et al. 2008; Weiβ et al. 2009) leading to estimated false-identification rates of the order of $\sim 5\%$ per cent, and is chosen as a convenient reference. In the former, 10 peaks are found, whereas there is only one in the latter. However, this test does not preclude the possibility that some correlated noise made it into the jackknife map, in which case the estimated $S/N$ is misleading.

One simple test of the calculated noise properties is to compare the signal and jackknife $S/N$ distributions with ideal Gaussians. The top panel of Fig. 16 shows the whitened (but not match-filtered) signal (blue) and jackknife (histograms), along with a Gaussian (mean 0, standard deviation 1, and area normalized to the number of map pixels) as a dashed line. In this case, it is clear that the $S/N$ distributions for both maps are nearly indistinguishable from the theoretical distribution of white noise. This result shows us that: (i) the whitening filter appears to have removed correlated large-scale noise, since the jackknife map histogram is consistent with white noise; and (ii) any potential astronomical signals are small compared to the typical white noise in most map pixels (unsurprising, given the appearance of Fig. 13b). Next, we examine the $S/N$ histograms for maps processed with the matched filter in the bottom panel of Fig. 16. Again, the histogram of the jackknife $S/N$ data appears consistent with pure noise. However, the signal map now deviates significantly from a Gaussian distribution, with a clear positive tail (as one would expect for emitting sources). In fact, integrating the positive tails beyond our $3.8\sigma$ source-detection threshold (vertical solid line) yields 229 map pixels in the signal map, compared to 3 in the jackknife map (out of 80 603 pixels in the entire region). Recall that, given the small pixel size of the map, several pixels generally contribute to each peak. This procedure gives only a flavour of the analysis that is usually required to produce a robust source list. Additional tests, along with a careful consideration of completeness and false-positive rates, usually require a series of Monte Carlo simulations that are beyond the scope of this work. We direct the interested reader to a selection of papers on the subject: Scott et al. (2002), Coppen et al. (2006), Perera et al. (2008), Weiβ et al. (2009) and Chapin et al. (2011).

As an additional external check, we have overplotted orange `+’ signs at the locations of 1.4 GHz radio sources from Owen & Morrisson (2008) with $S \gtrsim 15\mu Jy$. Such radio catalogues have historically proven invaluable for the precise identifications of high-redshift SMGs due to their low surface densities (compared with optical catalogues, for example) and a strong correlation between the radio and submillimetre emission mechanisms (e.g. Smail et al. 2000; Pope et al. 2006; Ivison et al. 2007; Chapin et al. 2009). Taking a representative search radius of 8 arcsec from these studies with similar $S/N$ sources and source sizes (the same size as the blue circles), 9 out of 10 peaks in the smoothed signal map have potential radio counterparts, whereas the single peak in the smoothed jackknife map does not lie near any radio source. Again, a proper cross-identification analysis must inevitably include simulations to establish completeness, false-positive rates, as well as the effects of point source clustering and confusion. See the aforementioned papers and references therein for examples.

Figure 16. Histograms of $S/N$ using pixels from the central region of the Lockman Hole (second contour in Fig. 13a). The top panel shows the histograms for pixels from the whitened signal and jackknife maps (Figs 13b and e), compared to a Gaussian distribution with mean zero, standard deviation 1, and an area normalized to the total number of pixels – the expected distribution for a map of spatially uncorrelated Gaussian noise. The good agreement indicates that these maps are indeed dominated by white noise. The lower panel shows the results for matched filtered signal and jackknife maps (Figs 13c and f). The filtered jackknife map distribution is still close to the expectation (Gaussian), but now the matched filter has picked out significant signal, leading to the large positive tail. The vertical solid line shows the chosen $3.8\sigma$ source detection threshold.

4.3 Bright extended emission

In this final example, we analyse a map of M17 which contains bright, extended emission. The data are from observation 11 on 2011 May 31 using the 850 $\mu$m array. It is a rotating PONG scan covering a diameter of 0.375, with a scan speed of 300 arcssec $^{-1}$, and a transverse spacing of 180 arcsec, taking 37.5 min to complete.

The baseline reduction of these data is shown in the top panels of Fig. 17, after 2 iterations (the first map estimated after the noise weights have been measured) and 17 iterations (when the map has converged), which uses iterative common
Figure 17. An 850 µm rotating PONG map of M17. Intensity is logarithmically scaled between −0.0003 (white) and +0.01 pW (black). Iteration numbers are given in the corner of each panel. Panels (a) and (b) show the results for a reduction using the baseline parameters (the solution halted after reaching the map-based convergence criterion in 17 iterations). Panel (a) also depicts the array footprint (position angle indicative of the start of the observation), and a 300 arcsec line shows the spatial scale corresponding to the FLT high-pass filter. Similar to Fig. 11(c), the high-pass filtering introduces ringing around bright sources. Panels (c) and (d) show the ‘bright extended’ reduction, in which a zero mask is created iteratively from all of the pixels that lie below a S/N of 5. While this region (outside the red contour) only avoids the brightest peaks early in the solution, in the final iteration, it skirts most of the bright, extended emission, and significantly helps with negative ringing.

mode subtraction and high-pass filtering. The first panel also depicts the array footprint, and the angular scale (300 arcsec) corresponding to the high-pass filter edge (0.6 Hz). Much like the reduction of a point source without any prior constraints (Fig. 11c), there are ripples around bright sources due to the filtering.

Unlike the case of a known point source (Section 4.1), it may not be possible for the observer to define, in advance, a mask of regions containing blank sky. Indeed, for this map, much of the field clearly contains extended structure. Furthermore, the goal of such maps may be to detect previously unknown cool, dense regions of the interstellar medium that may not have appeared at other wavelengths (e.g. the first optically-thick cloud-collapse stages of star formation). While the option does exist for the user to supply their own mask, a facility has been added to SMURF to generate one automatically by flagging pixels below some S/N threshold to be set to zero after each iteration as part of the ‘bright extended’ configuration.
The results of this automatic masking are shown in the bottom panels of Fig. 17. After the second iteration, everything but the brightest peaks are set to zero (outside the red contours). However, as the solution progresses, the negative bowls around the bright sources are slowly reduced and the mask ‘grows’ out from the brightest areas. By the final iteration, most of the obvious structures in the data are excluded in the mask, negative bowling is significantly reduced, and the brightest regions are more extended.

While the reduction in the bottom panels of Fig. 17 is (in a cosmetic sense) superior to those in the top panels, it is important to quantify both the noise properties of the maps and the response to real structures (the transfer function). We would also like to know how each is affected by our choice of filter scale. Similar to the previous section, we will use a jackknife test to estimate the noise, as well as injecting known sources into the data to observe how they are attenuated.

Maps are produced using the first and second continuous halves of the data in Fig. 18. This is not an ideal situation, since the noise properties may evolve with time (e.g. due to changing sky conditions), leading to a biased estimate of the parent noise distribution in the complete map from the jackknife. Also, since the zero masking depends on the S/N of the map, it will be restricted to regions approximately \( \sqrt{2} \) times shallower in these maps than for the full data set. Finally, the cross-linking (position angles sampled) is similar, though not identical in the two halves. Ideally, one would have many full maps, as in the case of the Lockman Hole data in the previous section, from which alternating maps could be combined.

Since our goal in this section is to measure the response of the map-maker to extended structures, we inject a simulated signal with power at a range of scales into a relatively empty region of the map. It is created by drawing a realization of noise from an angular power spectrum \( P(k) \propto k^{-3} \), which is appropriate for Galactic cirrus clouds (e.g. Gautier et al. 1992), within an 800 arcsec on a side box. It is then filtered again with a 14.5 arcsec Gaussian to model the effect of the SCUBA-2 optical response. The rms of these fluctuations is then normalized to 0.002 pW so that they are comparable to the dynamic range of M17 itself. The minimum is then subtracted so that the signal is positive. Finally, multiplication by half a period of a \((1+\cosine)/2\) function is used to roll off the signal to zero between radii of 300 and 400 arcsec.

The first row of Fig. 18 shows the total signal image averaging the maps made of each independent half of the data, for the baseline configuration (inverse-variance weighting has been used). The columns show reductions using 150, 300, 600 and 900 arcsec filter edges. The synthetic data are clearly seen as the circular region south of M17. As the filter scale is increased, the size of the ripples increases accordingly. While larger astronomical structures do seem to appear, negative bowls are a major problem without any other map constraints. Since the largest scale that is completely inscribed by the array footprint is about 400 arcsec, and the diagonal of the array is about 600 arcsec, scales ranging from \(~400\) to \(600\) arcsec up to the scale of the filter will be unconstrained due to the degeneracy between the common mode and map (see discussion in Section 4.1). This degeneracy therefore causes some of the large-scale patchiness in the 600 and 900 arcsec filtered maps that lie away from the central bright sources. The second row of Fig. 18 shows the jackknife maps. The astronomical emission is almost perfectly removed, except for a slight impression of M17 near the centre of the map, which is probably due to some combination of detector gain and pointing drifts. Otherwise, the jackknife appears to be a plausible realization of noise from the same parent distribution as for the averaged maps.

The third and fourth rows in Fig. 18 repeat this exercise using the bright extended configuration, in which the S/N threshold of 5 is again used to identify low-significance pixels that are set to zero after each iteration. As the filter scale is increased, more of the extended structure in M17 is reproduced in the map, as evidenced by the blue and red contours (masks generated from the first and second halves of the data, respectively). The masking does a generally good job of suppressing the largest scale ripples that are produced by the baseline reduction. However, the noise away from regions of bright emission does increase noticeably (mottled appearance) – due to residual \(1/f\) noise following common mode removal that has a knee at a frequency above the filter edge. With filter scales \(\gtrsim600\) arcsec, virtually the entire region of synthetic emission is correctly identified by the S/N mask and allowed to vary freely in the solution.

Next, we analyse the angular PSDs of the maps to understand the signal and noise properties of the map-maker in the region of synthetic sources, as a function of filter scale. In Fig. 19(a), we show the raw PSDs for the input synthetic signal (thick black line), the output map signals (thin solid lines) and the jackknife maps (dashed lines). Colours encode the filter scales used: 150 arcsec (red); 300 arcsec (orange); 600 arcsec (green); and 900 arcsec (blue). Note that, with the exception of the synthetic data, we only plot the PSDs down to the second-lowest spatial frequency bin of \(1.875 \times 10^{-3}\) arcsec\(^{-1}\), or 533 arcsec, since the lowest is very poorly sampled, and therefore noisy. At small scales (\(\lesssim20\) arcsec) the map and jackknife PSDs flatten. However, unlike Fig. 15, these white noise levels are slightly larger in the jackknife maps, suggesting that the differences have not completely removed the astronomical signals. A strong possibility is that the two half-maps that go into the differences have not converged equally, probably due to the lack of prior constraints.

As the filter edge is increased, more power is measured in the map PSDs at larger scales. However, much of this power is clearly produced by noise which appears in the jackknife PSDs. We estimate the map-maker transfer function as the ratio of the portion of the signal PSDs not produced by noise to the input PSD, or

\[
G(k) = \frac{P_S(k) - P_R(k)}{P_S(k)},
\]

where \(k\) is the spatial frequency, and the subscripts ‘M’, ‘JK’ and ‘S’ refer to the signal map, jackknife map and synthetic map, respectively.

The transfer functions \(G(k)\) are plotted as the thin solid lines in Fig. 19(b). This formula produces extremely noisy values at large frequencies (small scales), and we therefore set it to a value of 1 above 0.015 arcsec\(^{-1}\), as well as any point in the curve where \(P_S(k)\) exceeds \(P_R(k)\) [i.e. \(G(k)\) is assumed to be \(\lesssim1\)]. As expected, the larger the scale of the filter, the lower the spatial frequency at which the map transfer function falls. We then correct the map and jackknife PSDs by dividing by \(G(k)\) to produce the thick solid and dashed lines in Fig. 19(b). This shows us that, even though the raw noise in Fig. 19(a) is lower at small scales when a smaller scale filter is used (e.g. the red dashed line), once we correct for the transfer function, we actually win in a S/N sense at large scales using the larger scale filter (the corrected noise is lower), as would be expected.

These tests are then repeated using the bright extended reduction, in Fig. 20. The most obvious improvement with this reduction over the baseline reduction is that the transfer functions fall more slowly at large angular scales, accompanied by a slower increase in noise; in other words, there is greatly improved S/N at large angular scales (an obvious conclusion, given the appearance of the maps in Fig. 18). In
Maps of M17 used to characterize the noise properties and transfer function of SMURF (same intensity scale as Fig. 17). For each column, a different high-pass filter edge scale was adopted (indicated in the top panels). First (top) row: average of two halves of the data analysed independently, using the baseline configuration. The data have had added to them synthetic signal within a 600-arcsec-diameter circle (south of M17) created as a realization of noise from a $P(k) \propto k^{-3}$ angular power spectrum multiplied by the PSF, subtracting the minimum to make it positive, scaling it to a similar signal range to M17 itself, and rolling off the edges smoothly using half a period of a radial $(1+\cos) / 2$ function across 100 arcsec beyond the edge of the 600 arcsec region. Second row: jackknife maps produced from the differences of the maps of each half of the data that went into the first row. Third row: average of the two halves of the data using the bright extended reduction. The regions outside the blue and red contours are constrained to zero for each half of the data (note for the 300 arcsec case that these regions about M17 closely match the mask in Fig. 17(d) using a full reduction). Clearly as the filter scale is increased, due to the high S/N of the data, larger emission regions are (correctly) detected and reproduced in the map. Fourth (bottom) row: jackknife maps for the bright extended reductions.

Fact, using the 900 arcsec filter edge, the map response is still above 80 per cent right out to the largest scale accurately measured in the PSDs, 533 arcsec, which is about the largest scale that should be recoverable, given the size of the array footprint and the fact that we use common mode rejection. Another interesting feature of these reductions is that the increase in small-scale noise as the filter edge is increased is not as drastic as in the baseline reduction. Finally, note that both the map and the jackknife white noise levels (at scales $\lesssim 20$ arcsec) are in excellent agreement, unlike the previous example.

One case in which the S/N is worse using the bright extended reduction is when using a 150 arcsec filter. Here the noise is
Figure 19. Angular PSDs for the region of the M17 map in Fig. 18 containing synthetic data, using the baseline configuration. (a) Raw PSDs for the input (noiseless) simulated data (thick black line), the signal (average of each half) PSDs (thin solid lines), and noise PSDs estimated from the jackknives (dashed lines). The vertical dotted lines indicate the high-pass filter scales: 150 arcsec (red); 300 arcsec (orange); 600 arcsec (green); and 900 arcsec (blue). PSDs are also colour-coded by filter scale. (b) Since the input PSD is known, it is possible to measure the transfer function of the map-maker as the ratio between the difference of the output map signal PSDs and jackknife PSDs, and the input PSDs, giving the thin coloured lines (linear vertical axis shown in the right-hand side of the plot). The remaining lines are as in (a), but now corrected by the transfer function. This plot shows that increasing the filter scale improves the S/N at intermediate scales (≈ 200–600 arcsec), although the S/N worsens at smaller scales (<200 arcsec).

Figure 20. Lines have the same meaning as in Fig. 19, except now using the bright extended configuration. This configuration has resulted in an improved transfer function and S/N at large angular scales. Also note that increasing the filter scale does not have as large an impact on the small-scale noise as in the baseline configuration.

considerably larger in the bright extended reduction, as evidenced by the ‘kink’ near 150 arcsec. Referring to the mask contours in the left-hand panel of the third row in Fig. 18, it is clear that the map-maker has failed to identify much of the bright, extended emission in the region of the synthetic source. Each area that is not within the contours is constrained to zero throughout the solution, therefore suppressing power (and lowering the transfer function), and subsequently reducing the S/N of the final result. This measurement...
serves as a warning: the map-maker response is non-linear when using S/N masking. Harsh filtering can provide misleading results, as in this example. Maps of faint extended emission will also suffer considerably, as the structures of interest may lie below the S/N threshold for the mask.

Note that alternatives to the zero-masking approach do exist for other iterative map-makers. For example, Kovács (2008a) typically restricts the solution to a small fixed number of iterations (≤10), so that there is probably little opportunity for degeneracies between the map and common mode to appear in the map. Experimentation with the model order is also advocated to gain an impression of the convergence properties. This approach is perhaps more relevant to their SHARC-II data for which a more complicated model is developed; the degeneracies we have observed for SCUBA-2 maps using our more brute force approach with a high-pass filter tend to look similar regardless of the order (only the convergence time is affected). For Bolocam data of the Galactic plane, Aguirre et al. (2011) used a maximum-entropy filtering step to suppress large scales. Regardless of the method used, simulations are always required to establish the transfer function and noise properties as a function of angular scale.

5 CONCLUSIONS

This paper has described SMURF, which was designed to produce maps from the rapidly sampled ~10^4 bolometers of the SCUBA-2 instrument. While similar to other algorithms in the literature that iteratively model and remove correlated noise components from the data, successively improving the map (e.g. Kovács 2008a; Aguirre et al. 2011; Schuller 2012), we have shown that a fairly simple approach provides good results for SCUBA-2 data, with reasonable computational requirements. This conclusion is encouraging for the development of future large-format bolometer arrays, for which our specific approach should be useful when even larger volumes of data are involved.

A major obstacle to making maps of SCUBA-2 data is low-frequency correlated noise (probably a mixture of atmospheric signals and magnetic field pickup), which occurs at predominantly ≤2 Hz. Much of this signal can be removed using common mode rejection, although PCA identifies a number of other less-significant correlated noise patterns at low frequencies. Unfortunately, these patterns are difficult to model, and their character varies from observation to observation. One could use the PCA directly to remove them, but this technique is prohibitively slow for existing high-end desktop computers, given the volume of SCUBA-2 data. However, we have demonstrated that high-pass filtering can remove the bulk of these residual correlated noise components using significantly more efficient FFTs. The basic algorithm therefore consists of iterative common mode rejection and high-pass filtering along with estimates of the map, which allows us to approach the white noise limit of the instrument.

We have found that the iterative solution tends to diverge on large angular scales due to the degeneracy between the map and the low-frequency signal components that are removed (namely the common mode). In addition, the high-pass filtering produces significant ringing around bright sources. A simple strategy of constraining empty regions of the map to zero (using either a user-supplied mask for known sources or an iterative determination of signal below some S/N threshold) provides good constraints for both compact objects and bright/extended structures. Particularly in the latter case, using a combination of synthetic sources and an empirical measurement of the map noise from jackknife tests (differences of independent portions of the data), we have demonstrated that we can effectively recover angular scales up to the order of the array footprint (approximately 5 arcmin).

For maps of faint point sources, a single (non-iterative) high-pass filter at the start of the reduction produces maps that are nearly white noise limited and linear (i.e. the response does not depend on S/N). Residual large-scale noise can be removed with a whitening filter (also established from jackknife estimates of the noise) based on the Fourier transform of the maps, and sources detected using a matched filter (smoothing with the effective filtered PSF).

The iterative solution is stopped once convergence in the map itself is achieved. This enables SMURF to run in a pipeline setting without user interaction for a wide variety of observations. Furthermore, the execution times are typically shorter than the observation lengths, and memory requirements for even the longest SCUBA-2 observations are within the capabilities of single, high-end desktop computers. SMURF can therefore provide real-time feedback at the telescope to observers.

One regime in which SMURF does not presently perform well is in maps of faint extended structures, since the zero-masking technique we have adopted cannot be used. Since SMURF is both highly configurable and extensible, it may be possible to develop an improved data model and/or map constraint to assist in these situations, as more experience with the instrument is gained. However, provided sufficient computing power is available, the best solution in the long term will be a maximum-likelihood algorithm, such as SANEPIC (Patanchon et al. 2008). Even in this case, the existing iterative solution from SMURF will probably be used as an initial step, since it can quickly clean the bolometer time series, as well as perform map-based despiking (a necessarily iterative procedure).

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