A far-infrared view of the Lockman Hole from ISO 95-μm observations – I. A new data reduction method

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ABSTRACT

We report results from a new analysis of a deep 95-μm imaging survey with the photopolarimeter ISOPHOT on-board the Infrared Space Observatory, over a 40 × 40 arcmin² area within the Lockman Hole. To this end we exploit a newly developed parametric algorithm able to identify and clean spurious signals induced by cosmic rays impacts and by transient effects and non-linearities in the detectors. These results provide us with the currently deepest – to our knowledge – far-infrared (far-IR) image of the extragalactic sky. Within the survey area, we detect 36 sources with signal-to-noise ratio S/N > 3 (corresponding to a flux of 16 mJy), making up a complete flux-limited sample for $S_{95\mu m} \geq 100$ mJy. Reliable sources are detected, with decreasing but well-controlled completeness, down to $S_{95\mu m} \approx 20$ mJy. The source extraction process and the completeness, the photometric and astrometric accuracies of this catalogue have been tested by us with extensive simulations accounting for all the details of the procedure. We estimate source counts down to a flux of $\sim$30 mJy, at which limit we evaluate that 10–20 per cent of the cosmic IR background (CIRB) has been resolved into sources (contributing to the CIRB intensity $\approx 2.0 \times 10^{-9}$ W m⁻² sr⁻¹).

The 95-μm galaxy counts reveal a steep slope at $S_{95\mu m} \leq 100$ mJy ($\alpha \simeq 1.6$), in excess of that expected for a non-evolving source population. The shape of these counts agrees with those determined by ISO at 15 and 175 μm, and starts setting strong constraints on the evolution models for the far-IR galaxy populations.

Key words: methods: observational – galaxies: evolution – cosmology: observations – infrared: galaxies.

1 INTRODUCTION

The star formation in local galaxies is unequivocally found to be associated with dense dust-obscured clouds, which are optically thick in the ultraviolet (UV) and become transparent or even emissive at long infrared (IR) wavelengths. For this reason, the far-infrared domain is expected to be quite instrumental for studying not only the physics of star formation in our and closeby galaxies, but also the early phases of galaxy evolution, when stellar formation was far enhanced compared with what happens in the local universe.

The IRAS satellite mission indeed proved the potential of IR observations for detecting galaxies optically obscured by dust. Only a fraction of the 25 000 sources detected in the All-sky Survey were found to have bright optical counterparts (Soifer, Neugebauer & Houck 1987), and of these most are local late-type spirals.

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The IRAS survey was devoted to investigating the properties of the IR emission by local galaxies, at redshifts $< 0.2$ (Ashby et al. 1996). Only a few sources were detected by IRAS at higher redshifts, typically ultraluminous IR galaxies (ULIRGs) magnified by gravitational lenses, such as F10214+4724 ($z = 2.28$, Rowan-Robinson et al. 1991). IR galaxy counts based on the IRAS data (Rowan-Robinson et al. 1984; Soifer et al. 1984) showed some marginally significant excess of faint sources with respect to no-evolution models (Hacking, Houck & Condon 1987; Franceschini et al. 1988; Lonsdale et al. 1990; Gregorich et al. 1995; Bertin, Dennefeld & Moshir 1997), but did not provided enough statistics and dynamic range in flux to discriminate between evolutionary scenarios.

The cosmological significance of far-IR studies was first emphasized by the COBE detection of an isotropic far-IR/submillimetre background, of extragalactic origin (CIRB), interpreted as the integrated emission by dust present in distant and primeval galaxies (Puget et al. 1996; Hauser et al. 1998), including an energy density larger than that in the UV/optical background (Lagache et al. 1999).
With the advent of the Infrared Space Observatory (ISO, Kessler et al. 1996) the improved resolution and sensitivities of its cameras made possible deeper IR surveys, allowing us for the first time to detect faint IR galaxies at cosmological distances, both in the mid and in the far-infrared.

The deep 15-µm data determined with ISO/CAM (Cesarsky et al. 1996) have revealed a very significant departure from the Euclidean slope (Elbaz et al. 1999; Gruppioni et al. 2002), which has been interpreted as evidence for a strongly evolving population of starburst galaxies (Franceschini et al. 2001; Chary & Elbaz 2001; Xu et al. 2001; Oliver et al. 2002). ISO surveys at longer (far-IR) wavelengths with the photopolarimeter ISOPHOT (Lemke et al. 1996) found some evidence of evolution in the 175-µm channel (the FIRA BACK survey; Puget et al. 1999; Dole et al. 2001; ELAIS survey, Efstathiou et al. 2000; the Lockman Hole survey: Kawara et al. 1998; Matsushara et al. 2000; Juvela, Mattila & Lemke 2000). Unfortunately, at such long wavelengths the ISO observatory was quite limited by source confusion to moderately faint fluxes (S175µm ≥ 135 mJy).

In principle, the shorter-wavelength 95-µm C100 channel of ISOPHOT could allow a substantial improvement, by a factor of 2, in spatial resolution and a significantly lower confusion noise. Furthermore, the filter samples in an optimal way the dust emission peak in the spectral energy distribution (SED) of star-forming galaxies around 60–100 µm. For luminous infrared galaxies, emitting more than 80 per cent of the flux in the far-IR, this far-IR peak is the best measure of the bolometric luminosity of such galaxies, and the best estimator of their star formation rate.

The well-known problem with ISOPHOT C100 observations was the difficulty in the data reduction to account for all the instrumental effects, due to cosmic ray impacts and transient effects in the detectors producing spurious detections that may contaminate the final source lists.

In this paper we present a new method for the reduction of ISOPHOT C100 data, which we developed along similar lines as the code designed for ISOCAM data reduction by Lari et al. (2001, hereafter L01). We illustrate the value of this method with application to a deep ISOPHOT C100 survey in the Lockman Hole, a region particularly suited for the detection of faint infrared sources owing to its low cirrus emission. The good quality of these data and a careful reduction allow us to reach faint detection limits (∼20 mJy). We focus, in particular, on the implications for the evolutionary models as derived from galaxy counts. Our results favour a scenario dominated by a strongly evolving population, quite in agreement with the model discussed by Franceschini et al. (2001). In a forthcoming paper we will discuss the optical identifications of these Lockman 95-µm sources with radio and ISOCAM mid-IR counterparts (Rodighiero et al., in preparation) and we will explore the nature of our far-IR sources.

The present paper is organized as follows. In Section 2 we discuss our reduction technique. In Section 3 we comment on the simulations we used to compute the completeness of our sample, and the photometric corrections. Section 4 is devoted to the flux calibration. We then report in Section 5 on our application to the Lockman Hole 95-µm data and our results on source counts. Our conclusions are reported in Section 6. In the three Appendices we detail some technical aspects of our data reduction method.

Throughout this paper we assume ΩM = 0.3, ΩΛ = 0.7 and H0 = 65 km s⁻¹ Mpc⁻¹.

### 2 A NEW TOOL FOR THE REDUCTION OF ISOPHOT-C DATA

The reduction of ISO data requires a careful treatment of various external and instrumental effects affecting the detectors. The results recently obtained by L01 in developing a data reduction technique for ISOCAM data prompted us to attempt a similar approach for the analysis of ISOPHOT data.

PHOT C100 is a 3 × 3 array of Ge:Ga with 0.7 × 0.7 × 1 mm³ elements. The effective size of the pixels on the sky is 43.5 × 43.5 arcsec², the distance between the pixel centres is 46.0 arcsec. There are six filters available for C100, covering the wavelength range from ~60 to ~100 µm.

As for the case of ISOCAM (long-wavelength) Si:Ga detectors, two main effects must be considered when dealing with ISOPHOT-C data, produced by cosmic ray impacts (glitches) and detector hysteresis (i.e. the slow response of the detector to flux variations).

The method discussed by L01 was based on the assumption that the incoming flux of charged particles generates transient behaviours with two different time-scales: a fast (breve) and a slow (lunga) one. The method basically consists in looking at the time history of each detector pixel and identifying the stabilization background level. Then it models the glitches, the background and the sources with all the transients over the whole pixel time history.

If the approach is similar to that for ISOCAM, some peculiarities of the far-infrared detectors need to be treated with special care. We found, in any case, that the description of transients with the equations used in the case of ISOCAM pixels also provides good fits to the PHOT-C data (after adapting the temporal and charge parameters).

Let us mention that a model such as that of Fouks & Schubert (1995) can fit, with suitable parameters, the brightest sources, both in the case of CAM (Coulais & Abergel 2000) and of PHOT (Coulais et al. 2001), indicating very similar shapes for the short-term transient. In the case of CAM the method is an alternative to this model. As far as PHOT is concerned, the glitches look very similar to those found in the time histories of the CAM pixels. Moreover, long-term transients have also been observed in the PHOT detectors. These considerations suggest that the Lari model is also applicable to PHOT data, using the appropriate parameters. We will show, that, in spite of the numerous glitches recorded, it has been possible to define a reduction strategy with reliable results, including the stability of the temporal parameters.

As already mentioned, the method by Lari et al. (2001) describes the sequence of readouts, or time history, of each pixel of CAM/PHOT detectors in terms of a mathematical model for the charge release towards the contacts. Such a model is based on the assumption of the existence, in each pixel, of two charge reservoirs, a short-lived one Qb (breve) and a long-lived one Ql (lunga), evolving independently with a different time constant and fed by both the photon flux and the cosmic rays. Such a model is fully conservative, and thus the observed signal S is related to the incident photon flux I and to the accumulated charges Qb and Ql by the relation (see also Lari et al. 2002)

\[
S = I - \frac{dQ_{\text{int}}}{dr} = I - \frac{dQ_b}{dr} - \frac{dQ_l}{dr},
\]

where the evolution of these two quantities is governed by the same differential equation, albeit with a different efficiency ϵ and time constant α.
Table 1. Model parameters for CAM and PHOT.

<table>
<thead>
<tr>
<th></th>
<th>dr (s)</th>
<th>$e_1$</th>
<th>$e_b$</th>
<th>$a_l$</th>
<th>$a_b$</th>
<th>$d t/a_l$ (s)</th>
<th>$d t/a_b$ (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAM</td>
<td>2.5</td>
<td>0.45</td>
<td>0.1</td>
<td>0.107</td>
<td>0.006</td>
<td>346 20</td>
<td>23.2323</td>
</tr>
<tr>
<td>PHOT</td>
<td>1/32</td>
<td>0.36</td>
<td>0.1</td>
<td>0.005</td>
<td>0.000</td>
<td>197 009</td>
<td>5.900 74</td>
</tr>
</tbody>
</table>

\[
\frac{dQ_i}{dt} = e_i I - a_i Q_i^2 \quad \text{where} \quad i = b, l, \quad \text{(2)}
\]

so that

\[
S = (1 - e_b - e_l) I + a_b Q_b^2 + a_l Q_l^2. \quad \text{(3)}
\]

The values of the parameters $e_i$ and $a_i$ are estimated from the data and are constant for a given detector, apart from the scaling of $a_i$ for the exposure time and the average signal level along the pixel time history, which is governed by

\[
a_i = \frac{t}{t_0} \sqrt{\frac{S}{S_0}} a_{i,0}. \quad \text{(4)}
\]

where $a_{i,0}$ is the value of $a_i$ relative to a reference exposure time $t_0$ and average signal level $S_0$. The model for the charge release, however, is exactly the same for CAM and PHOT detectors.

The values for the model parameters of CAM and PHOT, respectively, are reported in Table 1, together with the times characteristic of the long and the short transients ($dt/a_i$).

2.1 Data reduction

The Interactive Data Language (IDL) has been used to develop all the procedures needed for the reduction of PHOT-C data.

Before discussing in detail the reduction procedures, let us note the main difference between ISOCAM and PHOT. The ISOPHOT pixels can be considered as independent detectors, with entirely uncorrelated behaviours and responses. This is not the case for ISOCAM, where all pixels have a common electronics. An example is presented in Fig. 1, where we report a statistically rich data set from the ISOPHOT ELAIS surveys (Oliver et al. 2000) in the southern S1 field. For an ELAIS raster observation with ISOPHOT, we have taken all the ramps along the time history and computed the median over each ramp position (one ramp is composed of 64 readouts), excluding those readouts with a signal exceeding $3 \sigma$ (where $\sigma$ is the standard deviation of the signal over the whole pixel history). In the figure we report for each PHOT C100 detector pixel the rms of the median signal over the whole pixel history in every ramp position. This gives a quantitative idea of the intrinsic noise of each detector pixel. The values are similar, except for pixel (0, 1), which
clearly shows a noise ∼3 times higher than the others. A similar analysis is performed over all ELAIS rasters (both in northern and southern fields) and found very similar levels for each pixel. This consideration allowed us to consider the responsibilities of the pixels to be stable as a function of time and of the orbital position. The different peculiarities of the nine ISO PHOT C100 pixels imply that any kind of correction must be computed as a function of the pixel.

2.2 From raw data through the fitting algorithm

The raw data (ERD level) are converted into a raster structure containing instrumental information on the observation, and astrometric information on every pointing. The ramps (in volts) are corrected for the non-linear response of the detector using a new technique (Appendix A) and converted in ADU gain⁻¹ s⁻¹. The standard PHOT Interactive Analysis (PIA, Gabriel & Acosta-Pulido 1999) package process the data fitting the ramps (in units of volts).

In our procedure, the data are corrected for short-time cosmic rays. Readouts affected by such events are masked and their positions stored before copying the ‘deglimched’ data into a new structure (called ‘liscio’, as for ISOCAM).

We evaluate the general background as the stabilization level along the whole time history of each pixel (for clarity, in the following we will refer to this quantity as the ‘stabilization background’).

We then apply a constant positive offset signal to the data in order to take into account the contribution of the thermal dark current (which is not otherwise accounted for in the preliminary pipeline) when the latter is estimated to be important, i.e. when the depth of the deepest dipper exceeds 10 per cent of the stabilization background.

The task computing the stabilization background also performs an initial guess of the fitting parameters, storing them in the ‘liscio’ structure.

The signal as a function of time is finally processed, independently for every pixel. The fitting procedure models the transients along the time history, and the features on both short and long time-scales produced by cosmic ray impacts. At this level, the code estimates several quantities needed to build the final maps on which source extraction will be performed.

(i) The charges stored into the breve and lunga reservoirs at each readout.
(ii) The local background, i.e. the signal to be expected on the basis of the previously accumulated charges if only the stabilization background were hitting the detector.
(iii) The model signal produced by the incident flux coming from both the stabilization background and detected sources.
(iv) The ‘reconstructed’ signal, i.e. the model signal recovered not only from glitches, but also from the transients due to the pointing-to-pointing incident flux change.

Furthermore, the code recognizes sources (above a given threshold level) and recovers all the time histories ‘reconstructing’ the local background as it would appear in the absence of glitches.

With the previously defined quantities we can define two different kinds of fluxes.

(i) ‘Unreconstructed’ fluxes and maps are derived from the excess of the measured signal with respect to the ‘local background’, and represent the flux excess not recovered from transients but only from glitches.
(ii) ‘Reconstructed’ fluxes and maps are computed from the ‘reconstructed’ signal, and take into account not only the glitches, but also the transients ‘on’ the sources.

In other words, the main difference between these two flux estimates appears to be evident when a pixel ‘sees’ a source. Reconstructed fluxes describe sources taking into account the real excess of signal with respect to the local background plus the transient modelling. The latter ‘recovers’ for the flux loss due to the slow response of the pixel when it detects an intense prolonged signal, such as a source, during a pointing exposure.

Unreconstructed fluxes do not take into account the effects of this source modelling, and thus represent the effective flux collected by the detector during the raster exposure. We will see with simulations that our code is not able to properly recover faint sources, and for this reason we will use unreconstructed fluxes in order to generate our final maps.

As an example, Fig. 2 shows how the code fits and describes the background and the transients. In the top panel we plot an example of real and model data through the pixel history. The solid ‘noisy’ line represents the observed data, with the best-fitting model superimposed (continuous line), which nicely follows the transients induced by cosmic rays. The dotted line is the data corrected for transients and deglitched (reconstructed signal). The dot-dashed horizontal line is the assumed stabilization background, while the local background corresponds to the three-dots dashed line. The bottom panel shows how the code works when it sees a bright source. In this case the real data have been smoothed. The unreconstructed signal is computed as the difference of the observed data and the local background.

The fitting algorithm starts with the brightest glitches identified in the pixel time history, assumes discontinuities at these positions, and tries to find a fit to the time history that satisfies the mathematical model assumed to describe the solid-state physics of the detector. In the fit we use the same default parameter values for all the pixels (the physical parameters scaled only for the stabilization background), leaving as free parameters only the charge values at the beginning of the observations and at the ‘peaks’ of glitches.

By successive iterations, the parameters and the background for each pixel are adjusted to better fit the data, until the rms of the difference between model and real data is smaller than a given amount (e.g. 15 ADU gain⁻¹ s⁻¹).

All the features described in Fig. 2 are present in the ISOCAM LW observations as well, but sometimes (and not so rarely) we find some peculiar behaviour in our data that does not correspond to any usual transient. These drop-outs can be explained in terms of saturation of the detector: when a very strong glitch impacts on a pixel, this can reach the saturation regime (the top level of the instrument dynamical range) and then be reset. After the impact, the detector needs several readouts before losing the memory of such a shocking event. Usually these drop-outs appear as isolated features. However, we found that an intense repeated series of impacts can cause much more serious problems to the detector electronics, and many drop-outs can appear consequently in the data for a significant fraction of the pixel time history, as shown in Fig. 3. It is useful to note here that such long-duration drop-outs are not resolved in ISOCAM, where they affect only one or two readouts, because of the different temporal resolution (1/32 s for PHOT against 2 s for ISOCAM, for each readout). All the readouts affected by this problem must be masked and excluded in the fitting procedure.

2.3 The interactive analysis

After the first run of the automatic fitting procedure, the next step is the interactive mending of fitting failures. This massive work of
interactive analysis is carried out with an easy-to-use widget interface, which allows any kind of repairing that may be necessary. This stage strongly depends on the assumed level of the reduction, related to the 'goodness' of the observational data set. For this reason observations characterized by different observing parameters (exposure time, raster step, etc.) need a specific treatment during the interactive reduction procedure. In the case of PHOT we found it to be more efficient to use smoothed data as input for the fitting procedure. For the Lockman Hole we chose a smoothing factor of 32, implying that the code reads and uses only one readout out of every 32 (1 s) to which it associates the median value of the previous 32 readouts. Thus short-term features and noise are reduced, allowing a better (and faster) modelling of the general trend of the signal.

The automatic detection of sources is checked through 'eyeballing' on the time history of each pixel. If the code fails (because it finds a source where a source is not present, or when it fits a real source improperly), a local interactive fit is carried out. Furthermore, the limited number of pixels of the PHOT-C100 detector (a $3 \times 3$ array) allows one to carefully check the presence of sources scanning the time history of each pixel where the median level of the signal in a pointing position peaks with respect to nearby values.
2.4 Map generation and source detection

Once a satisfying fit is obtained for all the pixels over the whole pixel history, our pipeline proceeds with the generation of sky maps. An image for each raster position is created, by averaging the signals of all the readouts relative to that pointing for each pixel. The signal is then converted to flux units (mJy pixel\(^{-1}\), see Appendix B and Section 4.1), glitches and bad data are masked and the images are then combined to create the final raster maps (one for each raster position). These images are projected on to a sky map (raster image) using the projection algorithm available for ISOCAM data in the CIA package (Cam Interactive Analysis, Ott et al. 2001). When projecting the signal on the sky, we make use of the nominal raster astrometry.

The redundancy of Lockman ISOPHOT observations allowed us to generate high-resolution maps, rebinning the original data into a final map with a pixel size of 15 \(\times\) 15 arcsec\(^2\). The detector signal is distributed in a uniform way between the smaller pixels. This process allows a better determination of source positions.

The source detection is performed on the signal-to-noise ratio maps, given by the ratio of the ‘unreconstructed’ flux maps and the corresponding maps of the noise. For the source detection we do not need any calibrated map, a relative map is sufficient in order to find the positions of any positive brightness fluctuation (as discussed by Dole et al. 2001).

First, our task selects all pixels above a low flux threshold (0.6 mJy pixel\(^{-1}\)) using the IDL Astronomy Users Library task called FIND (based on the equivalent algorithm in DAOPHOT). This algorithm finds positive brightness perturbations in an image, returning centroids and shape parameters (roundness and sharpness). The algorithm has been carefully tuned in order to detect all sources and to miss only the spurious ones that could be found surrounding the brightest sources or close to the edges of the maps (the input parameters are, in particular, the FWHM of the instrument and the limits for the roundness and sharpness geometric acceptable galaxy values).

Then we extract from the selected list only those objects having a signal-to-noise ratio >3.

In the final stage of our reduction we use our simulation procedures to reproject the sources detected on the raster map on to the pixel time history (see Section 3). In this way we are able to check the different temporal positions assumed to contribute to the total flux of each source. This method allows one to improve the fit of the data for all the sources that appear above the interactive check threshold, and to significantly reduce the flux defect of the detected sources.

3 SIMULATIONS

The only way to assess the capability of our data reduction method for source detection and flux estimate is through simulations. We use the ISOPHOT C100 point spread function (PSF) (stored in the PIA file PC1FOOTP.FITS), rebinned in order to have the same pixel size (15 \(\times\) 15 arcsec\(^2\)) of the final maps in which the source extraction has been performed. Through the projection task used to produce maps, we project the PSF scaled to any given input flux on the raster maps. This corresponds to generating a synthetic source in the real map. Furthermore, our code is able to modify the time histories in those raster positions (of every pixel) contributing to the total flux of a given source. This is done by converting the given input flux excess (with respect to the local background) from mJy to ADU gain\(^{-1}\) s\(^{-1}\), and adding it to the real pixel histories (containing glitches and noise). When this excess is added to the underlying signal, it is modelled by the algorithm that takes into account the transient response of the detector pixels (see Appendix C for details) and finally reproduces a real source, as it usually appears along any original pixel time history.

In our approach we make use of this powerful instrument at two different but complementary levels.

(i) Simulation of detected sources in the same positions as they are detected on raster maps. As already anticipated in Section 2.4, with this procedure we can improve the data reduction and the reliability of our final sample. Simulating all detected sources with signal-to-noise ratio >3, we can check all the pieces of pixel histories supposed to contribute to them. In this way we can reject all spurious detections, and perform a better fit when needed.

(ii) Simulation of a sample of randomly located sources, in order to study the completeness and reliability of our detections at different flux levels and estimate the internal calibration of the source photometry. The strategy we have adopted for the Lockman Hole is described here. We added 40 randomly distributed point sources at five different total fluxes (37, 75, 150, 300, 600 mJy). To avoid confusion, we imposed a minimum distance of 135 arcsec (~3 pixel) between the simulated and real sources on the maps. For the same reason, at each flux level we have distributed the 40 sources between the four rasters (each covering an area of ~0.13 deg\(^2\)): 10 sources per raster, divided into two simulation runs, with each containing five sources.

We reduced the simulated data cubes exactly in the same way as we did for the original data, performing the same checks and repairs. We produced the simulated maps on which we extracted the simulated sources, following the procedures used for real rasters. For each detected simulated source we have measured positions and peak fluxes. As in L01, the peak fluxes measured on the maps will be referred to as \(f_1\) and \(f_2\) (both for real and synthetic sources), respectively, for ‘unreconstructed’ and ‘reconstructed’ maps. The corresponding theoretical peak fluxes associated with the excess
flux maps, not reduced and containing neither glitches or noise, will be named \( f_0 \) and \( f_\alpha \). The theoretical quantities are produced only by the Lockman Hole observational strategy and the ISOPHOT instrument, while the measured quantities are also affected by our reduction method. These simulated data cubes contain both real sources and simulated ones. They also have the same noise, ‘glitches’ and background transients as the original data.

In Fig. 4 (top) we compare the output peak fluxes obtained for the simulated sources affected only by the mapping effects \( f_\alpha \) with the output fluxes of the reduced simulated sources \( f_i \). There is a linear correlation, and we observe that the reduced fluxes are always slightly lower than the unreduced ones. We find a similar correlation in the corresponding ‘reconstructed’ peak fluxes \( f_0 \) and \( f_\alpha \), although for faint sources our algorithm is not able to reconstruct the fluxes correctly (see Fig. 4, bottom). In order to have a correct flux determination at each level (both bright and faint), we will always use the ‘unreconstructed’ fluxes.

Fig. 5 shows the distribution of the ratio between \( f_i \) and \( f_0 \), for the simulated sources detected above \( 3 \sigma \), compared with the same ratio for the detections above \( 3 \sigma \). The peak of the distribution at \( 0.88 \) indicates a general underestimation of the total fluxes (derived from \( f_i \)). Two combined effects can explain this failure of the code to correctly compute total fluxes: one is the fact that \( f_0 \)

3.1 Completeness

As mentioned in the previous section, with simulations in the Lockman Hole we have derived the distribution of the measured \( f_i \) to theoretical \( f_0 \) peak flux ratio. This distribution is crucial in deriving the completeness of the catalogue and the internal flux calibration, as it allows one to predict the number of detected sources at a given flux level (the \( g \)-function described in detail in Gruppioni et al. 2002).

Our data reduction method can introduce some additional incompleteness if a source is interpreted as a background transient, and lost from the final source catalogue. We can estimate the incompleteness of our method from simulations, by computing the ratio between the number of detections and the number of expected sources in different peak flux intervals.

The results of the simulations are reported in Table 2 and shown in Fig. 6, where the resulting function describing the incompleteness of our survey is plotted as a function of the simulated input flux. The loss of bright sources happens only when they are located at the extreme edges of the raster maps. We need to also consider the areal coverage of our survey (i.e. the fraction of the survey area where a source of peak flux \( f_i \) can be detected with \( S/N/3\sigma \)), which is reported in Fig. 7.

<table>
<thead>
<tr>
<th>Input flux (mJy)</th>
<th>Number of simulated sources</th>
<th>Number of detected sources</th>
<th>Detection rate in the simulations (per cent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>37</td>
<td>40</td>
<td>12</td>
<td>30.0</td>
</tr>
<tr>
<td>75</td>
<td>40</td>
<td>31</td>
<td>77.5</td>
</tr>
<tr>
<td>150</td>
<td>40</td>
<td>35</td>
<td>87.5</td>
</tr>
<tr>
<td>300</td>
<td>40</td>
<td>35</td>
<td>87.5</td>
</tr>
<tr>
<td>600</td>
<td>40</td>
<td>37</td>
<td>92.5</td>
</tr>
</tbody>
</table>
4 FLUX DETERMINATION

The simulations performed in the Lockman field provided not only the completeness of our detections at different flux levels, but also the internal calibration of the source photometry and the distribution of the ratio between the measured and the theoretical peak fluxes.

Here we summarize some relevant definitions and the relations used to derive the final total fluxes of real detected sources, as in L01 and Gruppioni et al. (2002).

(i) $f_s$ is the peak flux measured on maps for both real and simulated sources. Its value depends both on the data reduction method, on the Lockman observing strategy and the ISOPHOT instrumental effects;

(ii) $f_0$ is the ‘theoretical’ peak flux measured on simulated maps containing neither glitches or noise. Its value depends only on the Lockman observing strategy and the ISOPHOT instrumental effects.

(iii) $q = f_s/f_0$.

(iv) $q_{\text{med}}$ is the peak of the $f_s/f_0$ distribution (also called the systematic flux bias) and is 0.88. This value is used to correct the measured flux densities.

(v) The flux density $s$ of a source is computed by applying a correction factor to the measured peak flux $f_s$ in order to have a measure of its ‘total’ flux. This can be done using the output information stored after the simulation process of real sources in the positions where they have been detected (see Section 3). This gives the ratio between the injected simulated total flux $s_0$ and the corresponding theoretical peak flux $f_0$ measured on the simulated maps. This ratio represents the correction needed to derive total fluxes from peak fluxes. In this way the flux density is

$$s = \left( \frac{f_s}{f_0} \right) / q_{\text{med}}.$$  \hspace{1cm} (5)

For simulations $s_0$ is the injected total flux, while for real data $s_0$ is derived through successive iterations starting from a rough estimated value:

$$s_0 = f_s / \langle f_s/s_0 \rangle_{\text{aim}},$$  \hspace{1cm} (6)

where $\langle f_s/s_0 \rangle_{\text{aim}} = 0.23$ is the average value resulting from simulating a point source of unitary flux. We can consider $s$ as the measured flux density and $s_0$ as the ‘true’ flux density of a source.

(vi) Finally, we need to increase the derived flux density by a factor of 1.2. This correction is needed because the PSF we use to simulate sources is undersampled and it misses the flux present in the external wings of an ISOPHOT source profile.

4.1 Calibration

We have computed a new estimate of the detector responsivities, which converts digital units (ADU gain $^{-1}$ s$^{-1}$) to physical flux units (mJy). The detailed description is reported in Appendix B. In order to check the general consistency of our calibration, we have reduced a set of external calibrators with our procedures, by following the same steps described in the previous sections.

It is very difficult to find good ‘standards’ for far-infrared observations. An absolute calibration is hampered by the intrinsic uncertainties and by the low sensitivities of previous measurements (IRAS, COBE-DIRBE), especially at faint fluxes. Our set of ‘calibrators’ includes four stars and two IRAS sources, as reported in Table 3. For IRAS sources we have a direct measure of the far-infrared flux (from the IRAS Point Source Catalogue). To obtain the 95-μm flux we made an interpolation between the fluxes at 60 and 100 μm. For stars we compare our fluxes with predictions from spectral energy distribution (SED) models. In particular, we select stars from the ISO Ground-Based Preparatory Programme (GBPP, Jourdain de Muizon & Habing 1992). Synthetic SEDs for these stars are available in the ISO calibration Web page (http://www.iso.vilspa.esa.es/users/expl.lib/ISO/wwwcal/). The optical and near-infrared photometry observed in the GBPP have been fitted with a Kurucz model to provide the flux densities at longer wavelengths, thus extending the SED out to 300 μm (Cohen et al. 1996). We have chosen to adopt these SEDs model fluxes for use in our calibration at 95 μm, after convolution with the PHOT C$_{95}$ filter. A summary of the fluxes obtained with our reduction and the expected fluxes are reported in Table 3. Quite good agreement with the comparison fluxes is found over a wide range of fluxes. Only for source F10507+5723, the only IRAS galaxy in the Lockman Hole, is our value a factor of 2 lower than
the interpolated IRAS flux. Given the uncertainties of the IRAS 100-µm flux (~10–20 per cent), we have chosen to assume our calibration as a final estimate of the flux, without applying any other scaling factor. Excluding this IRAS source, Table 3 shows that, over a wide range of fluxes, the error on the photometry is within 20 per cent. A more secure constraint on the calibration will be available after the reduction of ELAIS 95-µm fields (~15 deg²), which will provide a wider sample of IRAS galaxies (few tens).

### 4.2 Flux errors

To compute the errors associated with our flux estimates, we have taken into account the two major contributions to the uncertainties. The first one depends on the data reduction method, given by the distribution of the ratio between fluxes measured after the reduction \( f_s \) and those measured taking into account only mapping effects \( f_0 \). If \( f_0 \) is the real flux and if we measure after the data reduction \( f_s \), it means that the reduction has introduced an error in the measurement (by modifying the real flux). We can estimate this error as the width of the distribution of \( f_s / f_0 \). The second error term is due to the noise of the map.

Combining these two quantities, we obtain the final errors on the photometry (as reported in Table 5 in Section 5.2). The median of the error distribution is ~20 per cent.

### 4.3 Positional accuracy

With the set of simulations used to derive the completeness and the photometric corrections, we can also estimate the uncertainties on the astrometric positions. For each simulated source we have the injected and the measured coordinates. The local background noise can affect the estimate of the position of each galaxy centroid. The resulting effect is that a source, simulated in a given position, will be detected by the extraction algorithm in a slightly different location.

Fig. 8 shows the distribution of the differences in RA (top) and Dec. (bottom) between the injected and the found positions for the simulated sources. The median of the error distribution is ~20 per cent.

### 5 OBSERVATIONS OF AN AREA IN THE LOCKMAN HOLE

The 95-µm observations of the Lockman Hole field (P.I.Y. Taniguchi–Kawara et al. 1998) by the photopolarimeter ISOPHOT represent one of the best data sets available in the ISO archive to test the performance of our reduction technique. The long elementary integration times (~16 s for each raster position) and the observing...
Table 4. Lockman Hole ISOPHOT 95-\(\mu\)m observational parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Integration time per sample</td>
<td>1732 s</td>
</tr>
<tr>
<td>Integration time per pointing</td>
<td>16 s</td>
</tr>
<tr>
<td>Total integration time per pixel</td>
<td>1.44 h</td>
</tr>
<tr>
<td>Number of horizontal and vertical steps</td>
<td>18, 18</td>
</tr>
<tr>
<td>Step sizes</td>
<td>69, 69 arcsec</td>
</tr>
<tr>
<td>Grid size</td>
<td>(42 \times 42) arcmin(^2)</td>
</tr>
<tr>
<td>Redundancy</td>
<td>4</td>
</tr>
<tr>
<td>Total area covered</td>
<td>0.5 deg(^2)</td>
</tr>
<tr>
<td>Equatorial coords of the field centre RA = 10(^h) 52(^m) 00(^s) Dec. = +57(^\circ) 20(^\prime) 00(^\prime)</td>
<td></td>
</tr>
<tr>
<td>Galactic coords of the field centre Long. = 149.5(^\circ) Lat. = +53.17(^\circ)</td>
<td></td>
</tr>
</tbody>
</table>

redundancy allow us an accurate evaluation and modelling of any transient effects, for both long and short time-scales.

5.1 The ISOPHOT observation strategy

The Lockman Hole (Lockman, Jahoda & McCammon 1986) was selected for its high ecliptic latitude (|\(\beta\)| > 50), to keep the zodiacal dust emission at a minimum, and for the low cirrus emission. This region presents the lowest H\,I column density in the sky, and hence is particularly suited for the detection of faint infrared extragalactic sources. This consideration triggered a number of multifrequency observing campaigns over the past several years. The spectral coverage includes the X-rays (e.g. Hasinger et al. 2001), the optical (e.g. Fadda et al., in preparation), the mid-infrared (Fadda et al. 2002), the far-infrared (Kawara et al. 1998, and this work), the submillimetre (Scott et al. 2002) and the radio bands (De Ruiter et al. 1997, Ciliegi et al. in preparation). In contrast, the published spectroscopic information is still sparse.

Two different regions in the Lockman Hole have been observed by ISOPHOT. Each one of the two fields, called LHEX and LHNW, covers an area of \(\sim 44 \times 44\) arcmin\(^2\) and has been surveyed at two far-infrared wavelengths with the C100 and C200 detector (respectively, at 95 and 175 \(\mu\)m, with the C\(_{90}\) and C\(_{160}\) filters), in the P22 survey raster mode (see Kawara et al. 1998). We focused our analysis on the LHEX field, which consists in a mosaic of four rasters, each one covering an area of \(\sim 22 \times 22\) arcmin\(^2\). The ISOPHOT detector was moved across the sky describing a grid pattern, with about half the detector steps (corresponding to 1.5 detector pixels or 67 arcsec) in both directions. This strategy improves the reliability of source detections and the image quality, as each sky position is observed twice in successive pointings. Table 4 summarizes the observational parameters for the C\(_{90}\) filter. These data have been retrieved from the ISO data archive through the web interface http://isowww.estec.esa.nl/.

5.2 The 95-\(\mu\)m source catalogue in the Lockman Hole

The final catalogue obtained with our method contains 36 sources detected at 95 \(\mu\)m in the Lockman Hole LHEX, over an area of 0.5 deg\(^2\). All sources have a signal-to-noise ratio greater than 3 and a flux greater than 16 mJy.

In Fig. 9 we show the final mosaicked map obtained by combining together the four rasters. The open circles, the sizes of...
which are roughly proportional to the source fluxes, indicate our detected sources. IAU-conformal names, sky coordinates (right ascension and declination at Equinox J2000), the detection significance (signal-to-noise ratio), the 95-\(\mu\)m fluxes (in mJy) and their uncertainties are reported in Table 5. As previously discussed, all sources have been extracted from the map and confirmed by visual inspection on the pixel history (by two independent people). This approach produces a highly reliable source catalogue.

In a forthcoming paper we will discuss the optical, radio and mid-IR identifications of the Lockman 95-\(\mu\)m sources with radio and ISOCAM counterparts (Rodighiero et al., in preparation; Fadda et al., in preparation; Aussel et al., in preparation) and we will analyse the nature of our far-IR sources and their redshift distribution where the spectroscopic information is available.

5.3 Source counts from the Lockman Hole LHEX 95-\(\mu\)m survey

In the present paper we concentrate on discussing the statistical properties of the sample, such as the source counts, confusion and the contribution of the detected sources to the cosmic far-IR background (CIRB).

In the small area covered by the present study (~0.5 deg\(^2\)), we have computed the 95-\(\mu\)m source counts down to a flux level of 30 mJy (in total 32 sources have been taken into account for this analysis). The integral counts have been obtained by weighting each single source for the effective area \(A_{\text{eff}}\) corresponding to that source flux (as derived in Section 3.1). The errors associated with the counts in each level have been computed as \(\sqrt{\sum_i [1/A_{\text{eff}}(S_i)]}\) (Gruppioni et al. 2002), where the sum is for all the sources with flux density \(S_i\) and \(A_{\text{eff}}(S_i)\) is the effective area. So the contributions of each source to both the counts and the associated errors are weighted for the area within which the source is detectable. In any case these errors represent the Poissonian term of the uncertainties, and have to be considered as lower limits to the total errors.

Our estimated values of the integral counts at different flux levels are plotted in Fig. 10(a) as starred symbols. Our results are compared here with those from other surveys: the preliminary analysis of the ISOPHOT ELAIS survey (Efstathiou et al. 2000, open circles), and the counts derived from the IRAS 100-\(\mu\)m survey (open squares). Our data are in excellent agreement with these results in the flux range in common. The slope of the counts is \(\alpha \sim 1.6\).

A comparison of these integral counts with those published by Linden-Vornl et al. (2000), Kawara et al. (1998) and Juvela et al. (2000) is reported in Fig. 10(b). We see quite a substantial scatter in these data. We believe that our improved analysis and careful check of all systematic and noise terms have produced a most reliable outcome. Obviously, our results are limited by the small survey area of about 0.5 deg\(^2\) and source statistics. However, we find encouraging our excellent agreement with the source counts by Efstathiou et al. (2000), which are based on a far larger survey area. We take this to indicate that our deeper survey should not be biased too much by pathological clustering effects.

In Fig. 11 we report the differential 95-\(\mu\)m counts d\(N/dS\) normalized to the Euclidean law \(N \propto S^{-3/2}\), providing a statistically independent data set to be compared with model predictions (the data are reported in Table 6). A comparison is performed with modelled differential counts by Franceschini et al. (2001), Xu et al. (2001) and Lagache, Dole & Puget (2002).

The spatial distribution of the sources in our map of Fig. 9 is clearly non-random. We see, in particular, significant clustering in the eastern sector of the map. The number of sources in the four quadrants are 7, 7, 13 and 9 going in a clockwise order from the upper right-hand corner. In this situation, the evaluation of the source confusion noise requires some care. Using the beam of the ISOPHOT C100 (see Section 3) detector that has a FWHM of 45 arcsec, we have estimated that at the flux limit of 20 mJy for each source in the map there are ~90 independent cells. This value is above the formal confusion limit, which is classically reached for a source area density of \(1/(30 \text{ independent beams})\) assuming Euclidean number counts (see Franceschini 1982, 2000, Section 8.3). Around 20 mJy the Lockman 95-\(\mu\)m counts are still close to the Euclidean regime (see Fig. 11). In the quadrant of the map with the highest number of sources, the area density is \(1/(45 \text{ independent beams})\), still above the confusion limit. We conclude that our 95-\(\mu\)m map achieves a sensitivity close to the confusion limit in its most crowded parts, but still should not be much affected by the confusion noise. This is partly due to the significant incompleteness that our survey suffers at the faintest flux limits. For an ideal complete survey, our best-fitting model implies a (3\(\sigma\)) confusion limit of ~20 mJy occurring at an areal density of 30 beam sources\(^{-1}\). Kiss et al. (2001) have computed the 3\(\sigma\) confusion noise for ISOPHOT C100 90-\(\mu\)m around 21 \pm 2 mJy, while Matsuura et al. (2000)
Figure 10. Left-hand panel: integral counts at different flux levels. Our estimated values (starred symbols) are compared with data from other surveys: the preliminary analysis of ELAIS (open circles, Efstathiou et al. 2000), IRAS (open squares). A comparison is made with predicted counts by Franceschini et al. (2001, solid line), Lagache et al. (2002, dot-dashed line), Xu et al. (2001, dashed line) and Rowan-Robinson et al. (2001, dotted line). Right-hand panel: comparison of our estimated integral counts with those published by Linden-Vornle et al. (2000, open triangles), Kawara et al. (1998, open diamonds) and Juvela et al. (2000, cross). The solid line is the model prediction by Franceschini et al. (2001). We report as a dashed line the contribution of quiescent non-evolving spirals.

Figure 11. Differential 95-µm counts $dN/dS$ normalized to the Euclidean law ($N \propto S^{-5/2}$). Symbols are the same as in Fig. 10. For comparison we report as a long-dashed line the contribution of non-evolving spirals in the model of Franceschini et al. (2001). Our observed counts reveal a significant excess above this curve at the faintest fluxes, supporting the existence of an evolving population of IR galaxies.

report a value of $\sim 30$ mJy. All of these estimates confirm that our survey should not be confusion limited.

It may be instructive to compare these figures for the ISO 90-µm selection with the confusion noise at longer wavelengths for observations with ISOPHOT C200 170 µm. From the analysis of the FIRBACK fields Kiss et al. (2001) report a 3σ value of 45 ± 4 mJy, while Dole et al. (2001) estimate a 3σ confusion noise of 135 mJy. This discrepancy is partly reconciled by considering that, in the computation of the confusion limit, Kiss et al. have used the default ISOPHOT PSF, while Dole et al. have modelled the ISOPHOT 170-µm beam, thus recovering the flux fraction stored in the external wings of an ideal source (which indeed is lost by using the standard PSF). This confirms that the C100 imager is much less affected by confusion noise with respect to the C200 results (≈20 versus $\sim 135$ mJy respective limits). For this reason, in spite of the more severe problems related to the C100 data, the
90-µm ISOPHOT observations provide in principle a deeper view and smaller error boxes compared with longer-wavelength observations.

5.4 Source counts interpretation

In Figs 10 and 11 we have compared our determined source counts with various modelled estimates. The long dashed lines in Figs 10(b) and 11, in particular, show a comparison with the predictions for a non-evolving source population: our observed counts reveal a significant excess above these curves at the faintest fluxes, the significance of which is better appreciated in Fig. 11 in terms of the independent flux bins of the differential counts. These results then confirm and substantiate earlier claims for the existence of an evolving population of IR galaxies, as previously identified in deep ISOCAM mid-IR and ISOPHOT 175-µm counts.

A comparison is made in Figs 10(a) and 11 with predicted counts by Lagache et al. (2002) (dot-dashed lines), Xu et al. (2001) (dashed line) and by Rowan-Robinson (2001) (dotted line in Fig. 10a). These models typically assume that the whole local galaxy population evolves back in cosmic time in source luminosity or number density (with the exception of the Lagache model, which accounts for both luminosity and density evolution). All of these curves fit the bright IRAS counts well, but tend to more or less exceed those at fainter fluxes.

A better fit is provided by the multiwavelength evolution model of Franceschini et al. (2001, hereafter F01) (solid lines). This model was designed to reproduce in particular the observed statistics (counts, z distributions, luminosity functions) of the ISOCAM mid-IR selected sources, but it also accounts for data at other IR and submillimetric wavelengths. This model assumes the existence of three basic populations of cosmic sources characterized by different physical and evolutionary properties (their separate contributions are detailed in Figs 11 and 12). The main contributions come from non-evolving quiescent spirals (long dashed line in Figs 11 and 12) and from a population of fast evolving sources (dotted line in Fig. 12), including starburst galaxies and type-II AGNs (a third component considered are type-I AGNs (dot-dashed line). The solid line represents the total contribution.

<table>
<thead>
<tr>
<th>$S$ (mJy)</th>
<th>$dN(&gt;S)$ (deg$^{-2}$)</th>
<th>Flux bin (mJy)</th>
<th>Bin centre (mJy)</th>
<th>Differential Number of sources detected in the bin</th>
<th>$dN/dS \times S^{3/2}$ (deg$^{-2}$ mJy$^{3/2}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>80.1</td>
<td>30–100</td>
<td>54</td>
<td>23</td>
<td>$3.20 \times 10^4 \pm 1.3 \times 10^4$</td>
</tr>
<tr>
<td>60</td>
<td>47.2</td>
<td>60–150</td>
<td>94</td>
<td>16</td>
<td>$3.56 \times 10^4 \pm 1.4 \times 10^4$</td>
</tr>
<tr>
<td>100</td>
<td>15.5</td>
<td>100–300</td>
<td>173</td>
<td>6</td>
<td>$2.96 \times 10^4 \pm 1.5 \times 10^4$</td>
</tr>
<tr>
<td>150</td>
<td>9.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>300</td>
<td>3.6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 12. 95-µm integral counts compared with the different predicted IR populations in the model of Franceschini et al. (2001). The main contributions come from non-evolving quiescent spirals (dashed line) and from a population of fast evolving sources (dotted line) including starburst galaxies and type-II AGNs. A third component considered are type-I AGNs (dot-dashed line). The solid line represents the total contribution.

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and Xu et al. (2001) we derive a contribution of \( I \sim 2.8 \) and 5 nW m\(^{-2}\) sr\(^{-1}\), respectively, to the CIRB at the limit of \( S_{\text{lim}} = 20 \) mJy. These values are consistent with the spread observed in the counts predictions for the different models at 20 mJy (a factor of 3 between the models of Franceschini and Xu).

Deep confusion-limited maps with MIPS on SIRTF at 70 \( \mu \)m could not be compared with the CIRB intensity (not directly measurable at this wavelength), while at 160 \( \mu \)m they are expected to be limited by confusion at \( S_{160} \sim 80 \) mJy (Franceschini et al. 2001). A significant improvement will require the substantially better spatial resolution of the Herschel Space Observatory in 2007.

6 CONCLUSIONS

We have developed a new procedure to clean and reduce deep survey data obtained with the photopolarimeter ISOPHOT C100 on-board the Infrared Space Observatory. These deep imaging data would, in principle, have the advantage over longer-wavelength ISOPHOT 175-\( \mu \)m observations of a better spatial resolution and a lower confusion noise, but their use was limited by highly unstable detector background and responsivity.

Our procedure consists of a parametric algorithm fitting the signal time history of each detector, and able to extract from it the fusion noise, but their use was limited by highly unstable detector background and responsivity.

The source extraction process, completeness, the photometric and astrometric accuracies of the final catalogues have been tested by us with extensive sets of simulations, by inserting into the real image sources with known flux and position, and accounting for all the details of the procedure. The flux calibration was also verified by reducing C100 observations of calibrated stars using the same technique.

We have tested our procedure by re-analysing data from a deep imaging survey performed at 95 \( \mu \)m with ISOPHOT C100 over a 40 \times 40 arcmin\(^2\) area within the Lockman Hole. Within this area we detect 36 sources with S/N > 3, making up a complete flux-limited sample for \( S_{95} \geq 100 \) mJy. Reliable sources are detected, with decreasing but well-controlled completeness, down to \( S_{95} \simeq 20 \) mJy.

These results provide us with the currently deepest far-IR image of the extragalactic sky. We estimate from it source counts down to a flux of \( \sim 30 \) mJy, at which limit we evaluate that of the order of 10–20 per cent of the cosmic IR background has been resolved into sources.

The 95-\( \mu \)m galaxy counts reveal a slope at \( S_{95} \lesssim 100 \) mJy quite steeper than that expected for a non-evolving source population. These observed counts are consistent with those determined from ISO surveys at 15 and 175 \( \mu \)m (Elbaz et al. 1999; Puget et al. 1999; Dole et al. 2001; Gruppioni et al. 2002). The detailed shape of these counts constrains the evolving population to dominate only below \( \sim 100 \) mJy, whereas at brighter fluxes the majority of the sources are expected to be massive spirals at moderate to low redshift. We will report on the identifications and physical analyses of the 95-\( \mu \)m sources in separate papers (Aussel et al., in preparation; Efstathiou et al., in preparation; Rodighiero et al., in preparation).

ACKNOWLEDGMENTS

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APPENDIX A: THE LINEARITY CORRECTION

One of the main aspects of the PHOT-C detector is its non-linear response to the incoming flux, which requires a suitable correction that has to be carefully derived. We have tried to follow a different approach from that of the standard PIA pipeline. An accurate analysis of the good stability of the detectors with time, enables us to construct a linearity correction starting from the data set available for the S1 ELAIS field (for a total area of ~4.5 deg²) and to compare the result with the PIA internal calibration.

In order to obtain such a correction, we have divided the data into 121 voltage intervals (from −1.2 to 1.2, covering the full dynamical range of the detector). With each voltage step we have computed the median of the differences in ADU gain $^{-1}$ s$^{-1}$ and normalized to the median over the whole dynamical range. This means that the zero point of our correction is referred to the voltage range where the vast majority of the observed data in the ELAIS S1 field is located ($−0.8 < V < −0.4$). We have taken into account for the computation only data around the background (to neglect the influence of deep transients in the final correction), discarding every readout corresponding to destructive readings, to the first two points of each ramp, to the sources and to the saturated readings.

The result for an example pixel is shown in Fig. A1, where the PIA standard correction (dashed line) is compared with ours, as a function of voltage. The corrections reported are percentage. There is quite a good agreement at $V < 0$ (the deviation is of the order of 10 per cent), considering the larger quantity of data used in the computation of the PIA correction.

To check the consistency and the quantitative effects of the two corrections, we have estimated the residual correction we obtain after the data have been processed with PIA. In other words, we have derived with the same prescriptions our correction from data already PIA corrected. Such a ‘residual’ correction is shown in Fig. A2 (continuous line) and compared with the usual PIA percentage correction (dashed line, as in Fig. A1). It is clear that at $V > 0$ the PIA calibration is underestimated, and that we need to apply a further second-order correction for better linearity at higher voltages (which we took into account).

We have considered the possibility of a further dependence of the linearity on the ramp position. In a similar way to that of the voltage dependence, we have thus constructed a second-order ‘geometrical’ correction from the data, normalized to the central region of the ramp, which allows one to correct any residual non-linearity (a mean correction for the dependence of the ramp index completely erases the effects on the background, but can leave residuals on the stronger sources).

APPENDIX B: FLUX CALIBRATION

In order to obtain a good flux calibration, we have tried to compute a new estimate of the detector pixel responsivities. By responsivities we mean those factors that convert digital units (ADU gain $^{-1}$ s$^{-1}$) to physical flux units (mJy). We made use of a wide set of internal lamps, the so-called fine calibration sources (FCS, ISOPHOT Handbook, Laureijs et al. 2002). In particular, we have taken into account all FCS measurements associated with raster observations in the ELAIS fields, in the Lockman Hole and with other minor mini-rasters of point sources, in order to cover an extended range of voltage levels. For every raster considered here, observed in the P22 mode, there are two FCS measurements available: the first (FCS$_1$) taken before the science observation and a second (FCS$_2$) at the end of the observation. As discussed in Section 2.1, we are confident
about the stability of the detectors as a function of time. This justifies our attempt to compute the responsivities from a set of observed data.

We have reduced the FCS data following the same procedures described in this paper for raster science observations. However, we have previously applied the dark-current correction and the reset-interval correction, both parts of the standard PIA package (Gabriel & Acosta-Pulido 1999; Schulz et al. 2002). Our good statistics of internal calibrators enable us to reject all bad observations (mostly due to the massive presence of cosmic rays), and take into account only those for which the fitting algorithm has not failed. The main problem when dealing with FCS data is their short total exposure time (usually 1024 readouts), which prevents one from determining a correct value for the stabilization level and may translate into an underestimation of the flux.

Once the lamps have been reduced, we proceed to the statistical analysis for the calculation of responsivities. Fig. B1 shows that with our reduction FCS1 and FCS2 are well correlated over the whole range of voltages considered, and for all pixels. The values reported are in units of V s⁻¹ and represent the median values of every pointing (each FCS is composed of a single pointing). Different symbols refer to different pixels. The solid line represent the one-to-one relation. There seems to be a slight tendency for different symbols refer to different pixels. The solid line represent the one-to-one relation.

Figure B1. The figure shows the correlation between FCS1 and FCS2 reduced with our pipeline. They are well correlated over the whole range of voltages considered, and for all pixels. The values reported are in units of volt s⁻¹ and represent the median values of every FCS observation. Different symbols refer to different pixels. The solid line represent the one-to-one relation.

In order to compute the responsivities, we chose to use the average value between each pair of FCS1 and FCS2. In the following we will call these values $V_{\text{FCS}}$ (V s⁻¹). $V_{\text{FCS}}$ are related to the responsivities via the equation

$$\text{RESP}(i) = V_{\text{FCS}}(i)K(i)/P_{\text{FCS}}(i),$$

where $\text{RESP}{}$ are the responsivities, $K$ is a constant, which depends only on the pixel and accounts for the illumination matrix and other instrumental effects of the detector, $P_{\text{FCS}}$ are the inband fluxes (which represent the expected fraction of energy filtered through the system detector+filter, and collected as an output signal on the detector), expressed in units of watt. The $i$ index indicates the dependence of each variable on the nine different pixels. The previous equation is a syntax simplification of the formula reported by Schulz et al. (2002) and in the ISOPHOT Handbook.

In order to compute the inband fluxes we have used the standard PIA power curve (Schulz et al. 2002), derived from a careful and complete analysis of external calibrators (stars, planets and asteroids). This calibration curve allows one to correct the given heating powers (the total energy emitted from the FCS), to inband fluxes.

We can rewrite equation (B1) as

$$V_{\text{FCS}}(i) = \text{RESP}(i)P_{\text{FCS}}(i)/K(i)$$

and compute for every pixel the best linear fit between the two independent variables $V_{\text{FCS}}(i)$ and $P_{\text{FCS}}(i)/K(i)$ (each observation of our selected calibration data set gives a point in this linear relation). The slope of this relation [$\text{RESP}(i)$ represents the responsivities. It is clear that the responsivities we obtain with this procedure are only a function of the pixel, and are assumed to be constant through the temporal history of the satellite. The values we derived are consistent with that of the standard PIA values.

The responsivities function of the pixels represent our best flat field.

Finally, we can use our responsivities to calibrate our maps (to convert the signal from ADU gain⁻¹ s⁻¹ to flux units of mJy pixel⁻¹).

In order to check our calibration and look for any further physical scalefactor (the absolute calibration) we have studied and reduced a few external calibrators (see the discussion in Section 4.1). The good agreement we found at different flux levels and the intrinsic uncertainties on previous 95-µm measurements, made us confident in using the responsivities without applying any offset correction. We have estimated the photometric errors of our calibration throughout simulations and found they are of the order of 20–30 per cent.

APPENDIX B: DETAILS ON THE SIMULATION PROCESS

To correctly simulate a source on a raster map and to determine its profile along the pixel time history, we make use of the ISOPHOT C100 PSF and of the projection algorithm. The PHOT readout frequency is higher with respect to ISOCAM (1/32 s versus 2 s), the pixel size is greater (45 × 45 arcsec²) and the distance between adjacent raster pointings is quite large (of the order of half the detector array, 69 arcsec, in the case of the Lockman Hole, and greater for other surveys such as ELAIS). The combination of these effects requires the simulation of a high-resolution source profile. In the ISOCAM procedure, the predicted flux level of a source was projected on every raster pointing and assumed to be constant there. For PHOT we have created a second raster structure with astrometric information on each readout along the time history, including those where the satellite moves from a raster position to the other (not on target readouts). The projection of the PSF on these more gridded series of pointings and the lecture of these levels projected on every readout, is able to reproduce the exact profile of how the detector should see a source (if its response were linear to the incoming flux). The detailed description of this profile is mainly important between two raster pointings, when the detector moves on the sky. Given the size of the PHOT pixels, the detector starts to see a source when it is still moving and not yet positioned in a raster pointing. If we do not take into account this flux recorded by the detector (when the source
enters and leaves a pixel) we could underestimate the total flux of the source. This correction is crucial when simulations are used to compute the corrections to the fluxes of the detected sources. In the following step, the projection algorithm we use takes into account the transient behaviour of the detector, and ‘models’ the simulated source profile along the time history in order to introduce the instrumental effects and to obtain sources very similar to the real ones.

Our ‘simulator’ is very efficient, as it can describe sources independent of their position inside the pixel.

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