A multi-scale, multi-wavelength source extraction method: getsources

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ABSTRACT

We present a multi-scale, multi-wavelength source extraction algorithm called getsources. Although it has been designed primarily for use in the far-infrared surveys of Galactic star-forming regions with Herschel, the method can be applied to many other astronomical images. Instead of the traditional approach of extracting sources in the observed images, the new method analyzes fine spatial decompositions of original images across a wide range of scales and across all wavebands. It cleans those single-scale images of noise and background, and constructs wavelength-independent single-scale detection images that preserve information in both spatial and wavelength dimensions. Sources are detected in the combined detection images by following the evolution of their segmentation masks across all spatial scales. Measurements of the source properties are done in the original background-subtracted images at each wavelength; the background is estimated by interpolation under the source footprints and overlapping sources are deblended in an iterative procedure. In addition to the main catalog of sources, various catalogs and images are produced that aid scientific exploitation of the extraction results. We illustrate the performance of getsources on Herschel images by extracting sources in sub-fields of the Aquila and Rosette star-forming regions. The source extraction code and validation images with a reference extraction catalog are freely available.

Key words. stars: formation – infrared: ISM – submillimeter: ISM – methods: data analysis – techniques: image processing – techniques: photometric

1. Introduction

The Herschel Space Observatory (Pilbratt et al. 2010) provides the best opportunity to study the earliest stages of star formation. Prestellar cores and young (Class 0) protostars emit the bulk of their luminosities at wavelengths 80–400 μm, which makes the Herschel imaging instruments PACS (Poglitsch et al. 2010) and SPIRE (Griffin et al. 2010) with their 6 wavebands from 70 to 500μm perfect for performing a census of these objects down to 0.01–0.1M⊙ in the nearby (distances D < 500 pc) molecular cloud complexes. In particular, the Herschel Gould Belt survey (André et al. 2010) aims at probing the link between diffuse cirrus-like structures and compact cores with the main goal to understand the physical mechanisms of the formation of prestellar cores out of the diffuse medium, which is crucial for understanding the origin of stellar masses. Furthermore, the Herschel HOBYS survey (Motte et al. 2010) aims at performing a census of massive young stellar objects, providing accurate bolometric luminosities and envelope masses for homogeneous and complete samples of the progenitors of massive stars.

Preparing for these two Herschel surveys, we had evaluated a few popular source extraction algorithms to check whether they could be used in our surveys. The main problem was the absence of any multi-wavelength extraction technique. None of the methods was designed to handle multi-wavelength data, making it necessary to match the independent catalogs obtained at different wavelengths using an association radius as a free parameter. This posed very serious problems for detecting and measuring sources in the Herschel images with angular resolutions differing by a factor of ~7. A direct consequence of the mismatch in resolutions is that the degree to which sources in a region may be blended depends very strongly on the waveband.

With such great differences in resolution, one cannot just match independent catalogs without introducing unknown and potentially very large errors in the association of sources detected across different wavebands and in their measured properties. Studying star formation in the nearest clouds, one expects to resolve many crowded regions in the highest-resolution images at the shortest wavelengths, but at the same time, one would progressively “lose” sources within much larger beams at the longer wavelengths. In effect, the fluxes of such sources on the long-wavelength side of their spectral energy distributions (SEDs) would have large and unknown errors when matching independent extraction catalogs, greatly reducing the extraction quality (detection completeness and reliability, as well as the accuracy of the derived properties).

For large-scale projects, such as the Herschel Gould Belt and HOBYS surveys, one needs a fully automated source extraction method that can find as many sources as possible from the images in all bands, reliably distinguishing them from variable backgrounds and noise, deblending them as accurately as possible in the crowded regions by preserving and utilizing all information obtained from the higher-resolution images at shorter wavelengths. A very serious problem with some existing source extraction methods is that they do not allow sources to overlap, thus deblending of crowded regions is impossible. One cannot expect from such methods high levels of detection completeness or consistently accurate flux measurements in realistic conditions.
Note that most existing methods have been developed and oriented for use in different areas of astronomy, thus their performances for a specific project must be carefully analyzed before an appropriate method can be chosen. The SPIRE SAG3 consortium has been testing several popular source extraction algorithms using simulated skies of various degrees of complexity and those benchmarks will be published elsewhere (Men’shchikov et al., in prep.). Below we introduce the reader to the basic concepts of those techniques, to place our new method1 in a wider context.

1.1. Existing methods of source extraction

Most of the algorithms trying to solve the same (non-trivial) problem of source extraction originated from different ideas.

Stutzki & Guesten (1990)’s gaussclumps (developed for position-velocity data cubes in molecular-line studies of molecular clouds) performs least-squares fits of a Gaussian shape to the brightest peak constrained to keep the position and amplitude of the fitted shape close to the image maximum. Then it subtracts the fit from the image, producing the residuals image, and fits a new Gaussian shape to the brightest peak in the residuals. The iterations continue until the total intensity of all subtracted clumps is equal to the integrated intensity of the original image or there are no significant peaks left.

Williams et al. (1994)’s clumpfind (aimed also for molecular clouds data and position-velocity cubes) contours an image at a number of levels, starting from the brightest peak in the image. It descends down to a minimum contour level, marking as clumps along the way all connected areas of pixels that are above the contour level. This technique was “motivated by how the eye decomposes the maps into clumps” and it “mimics what an infinitely patient observer would do” (Williams et al. 1994). One should be aware that this method ignores the backgrounds in which sources are observed.

Bertin & Arnouts (1996)’s sextractor (designed for use with optical and near-IR images in extragalactic astronomy) estimates and subtracts background using sigma clipping and spline interpolation, then uses thresholding to find sources in the background-subtracted image, deblends them if they overlap, and measures their positions and sizes using intensity moments. A very useful property of this versatile algorithm is that it allows using a detection image that differs from the observed image and it can match sources with previously obtained catalogs.

CUPID2’s reinhold (oriented primarily to analyzing clumps in submillimeter data cubes) identifies “pixels within the image which mark the edges of emission clumps, producing a set of rings around the clumps. However, these structures can be badly affected by noise in the data and so need to be cleaned up. This is done using cellular automata which first dilate the rings or shells, and then erode them. After cleaning, all pixels within each ring or shell are assumed to belong to a single clump” (see the reference in the footnote).

CUPID’s fellwalker (also oriented towards clumps in submillimeter data cubes) finds image peaks by tracing the line of the steepest ascent, considering every pixel with a value above a specified threshold as a starting point for a walk to a peak along the steepest gradient. Having reached a peak, it searches for an even higher pixel intensity in a neighborhood; when found, the algorithm switches to that pixel and continues uphill. If a peak is found that is higher than all pixels in its neighborhood, a clamp has been detected and the algorithm marks all pixels visited along the way as belonging to the clamp.

Motte et al. (2003, 2007)’s mre-gcl (created for studies of star formation using ground-based submillimeter continuum imaging) combines gaussclumps with the image filtering based on a wavelet decomposition. The algorithm decomposes an image in spatial scales using an isotropic wavelet decomposition with the multi-resolution code mr_transform (Starck & Murtagh 2006), subtracts all scales larger than the largest scale of interest from the original image, and uses gaussclumps to detect and measure sources in the filtered image. Then the user defines each source’s largest extent as twice its measured size and repeats the decomposition and filtering steps for each source, runs gaussclumps again with the aim to improve the measurements of sizes and fluxes.

Molinari et al. (2011)’s cutex (developed for use with the BLAST and Herschel images) is another method that defines clumps in terms of connected pixels. A source is defined as a region of connected pixels bound by a closed isophotal contour that contains at least one pixel that is at 3σ (where σ is the standard deviation) above the bounding contour level. The algorithm starts contouring just below the peak on the image and walks down until some predefined background is reached; sources are considered finished just before they become connected to others. Sources are not allowed to overlap and no attempt is made to assign flux outside of the closed contours to any source. The technique was designed with a “purpose of replicating what a (trained) human would do with an image if extracting sources manually” (Kirk, priv. comm.).

Crowded regions that are frequently observed with Herschel; the deblending of overlapping sources is the origin of major uncertainties. Whereas clumpfind, reinhold, fellwalker, and csar merely partition the image between sources not allowing them to overlap, gaussclumps, sextractor, mre-gcl, and cutex can de-blend overlapping sources, which is quite an essential property for obtaining accurate results in crowded regions. We feel the need to stress here that the observed images are only projections of the complex three-dimensional reality onto the plane of the sky and, as such, it is a fundamental source of major uncertainties in the interpretation of observations and in the derived properties of objects. As we know from Herschel observations (e.g., Men’shchikov et al. 2010; Arzoumanian et al. 2011), the interstellar medium is highly filamentary, thus the filaments’ orientations play a very significant role in the appearance of the regions we observe.

1 For a very brief summary, see Men’shchikov et al. (2010).
2 CUPID is a source extraction software package developed by the STARLINK team for use with the SCUBA2 surveys; it is a general wrapper to which additional methods can be added. See documentation: http://docs.jach.hawaii.edu/star/sun255.htx/sun255.html
1.2. Introducing a new approach

In this paper, we present the source extraction algorithm get-sources developed with the aim to overcome the shortcomings of the existing methods and provide researchers in this Herschel era with a better extraction tool. For details on the astrophysical context of this work, we refer to Appendix A.

To clarify our terminology, we shall use the term noise to refer to the statistical instrumental noise including possible contributions from any other signals that are not astrophysical in nature, i.e. which are not related to the emission of the areas in space we are observing. In contrast, the term background will refer to the (filamentary) astrophysical backgrounds, such as cirrus or molecular clouds, containing the sources we are observing and objects we are studying (e.g., stars, protostars, cores, etc.).

In order to reduce possible confusion, we are going to clearly distinguish between the morphologically-simple (convex, not very elongated) sources of emission as determined by the source extraction algorithms and the objects of specific astrophysical nature that are selected from the entire extraction catalog on the basis of all available information (besides the images) and some additional assumptions, criteria, and techniques, depending on the specific interests of a researcher.

The problem of detecting sources in continuum images usually reduces to finding significant intensity peaks, as such images provide us with just complex intensity distributions of the sky over an observed area. At the present state of the art, source extraction procedures do not know anything about the astrophysical nature or true physical properties of the objects that produced the emission of those significant peaks. An extraction algorithm can only detect sources (that are possibly harboring our objects of interest) and determine their apparent two-dimensional intensity distributions above the variable background and noise, and measure their apparent properties at each wavelength. This is the only information contained in the images, which is available to any extraction algorithm. The purpose of source extraction is to distinguish as many real sources as possible (distinguishing them from noise and background fluctuations) and to measure their apparent properties as accurately as possible.

A catalog of such sources serves as the fundamental basis for all subsequent in-depth studies of the various objects of different nature. Only after we have detected significant sources of emission and measured all possible apparent properties (peak intensities, integrated fluxes, sizes, etc.), can we utilize those results to infer the real astrophysical nature and properties of the objects. At this step, one should combine all the information in different wavebands from the extraction catalog and also from previous or follow-up observations, as well as any other available information, and classify the objects according to their physical nature and use them to derive new astrophysical knowledge. In what follows, we only consider the sources and leave the definition of objects to the future papers exploring various astrophysical applications of this new extraction algorithm.

Unlike other source extraction algorithms (except mre-gcl, Sect. 1.1), the new method analyzes finite spatial decompositions of original images across a wide range of scales and across all wavelengths (Sect. 2.2). As part of its multi-wavelength design, get-sources removes the noise and background fluctuations from the decomposed images (Sect. 2.3) separately in each band, and constructs a set of wavelength-independent detection images (Sect. 2.4) that preserve information in both spatial and wavelength dimensions as well as possible. Sources are detected in the combined detection images by following the evolution of their segmentation masks across all spatial scales (Sect. 2.5). Measurements of the source properties are performed in the original images at each wavelength after the background has been subtracted by interpolation under the sources’ “footprints” and after overlapping sources have been deblended (Sect. 2.6). To facilitate visual analysis of the extraction results and various steps of the algorithm, a number of useful images are created for each waveband (Sect. 2.7). Based on the results of the initial extraction, detection images are “flattened” to produce much more uniform noise and background fluctuations in preparation for the second, final extraction (Sect. 2.8). The performance of get-sources for Herschel images is illustrated on small sub-fields of the Aquila and Rosette star-forming regions (Sect. 3).

2. The get-sources extraction method

The fundamental problem in extracting sources from observed images is that all spatial scales are mixed together and the intensity of any given pixel contains an unknown contribution from the noise, background, and surrounding blended sources. The central problem in accurate source extraction is to separate those contributions from the signal of the real sources. The main idea of get-sources is to analyze decompositions of original images (at each wavelength) across a wide range of spatial scales separated by only a small amount (typically ~3–5%). Replacing originals with a set of strongly filtered images brings several significant advantages. Each of the “single scales” contains non-negligible signals from only a relatively narrow range of spatial scales, mostly only from those sources (not the noise and background fluctuations) which have sizes similar to the scale considered. In effect, this automatically filters out all contributions of the noise, background, or overlapping sources on irrelevant (much smaller and larger) spatial scales. An immediate benefit is that such a filtering allows one to manipulate entire single-scale images as a whole and use thresholding to separate sources from the background and noise in the observed images (see Sect. 2.3 for details). Furthermore, considering the same spatial scales across a wide range of wavelengths allows one to sum up single-scale images at all wavelengths in combined (wavelength-independent) single-scale detection images and thus preserve the high-resolution information across all wavebands, minimizing the effect of degrading resolutions. Besides providing a substantial “super-resolution” effect, this eliminates the need of matching multiple catalogs obtained with different beams and reduces the matching and measurement errors.

The extraction method is represented by 7 processing blocks shown in Fig. 1; they will be described below in Sects. 2.1–2.7. In order to make a clear distinction between images and various other parameters, the images are denoted throughout this paper by the capital calligraphic characters (e.g., \( \mathcal{A}, \mathcal{B}, \mathcal{C} \); see

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Appendix B for a list of all symbols and definitions). The following subsections describe the algorithm in full detail.

### 2.1. Preparing observed and detection images

The first step (Fig. 1) towards the source extraction is to convert the original images $I_\lambda$ at all wavelengths to the same grid. This means to transform them into the observed images $I_{\lambda O}$, all with the same numbers of pixels, the same pixel size, aligned across wavelengths as accurately as possible (covering the same area on the sky), the same reference pixel and its coordinates. In practice, this is done by resampling all images to the same pixel size using the astronomical utility SWarp (Bertin et al. 2002).

Note that the alignment of images must be carefully checked before extracting sources with getsources, because of its multi-wavelength design. Images in all wavebands will be combined together in wavelength-independent detection images (Sect. 2.4) that will only be good if the originals are aligned within one pixel; significant misalignments of the images can create spurious sources.

The observed images $I_{\lambda O}$ are only used to measure properties of detected sources, at the end of an extraction (Fig. 1, Sect. 2.6). Most of the processing in the algorithm is done on the detection images $I_{\lambda D}$, which in the simplest case may be the same as $I_{\lambda O}$, but in general can significantly differ from the latter. Any transformations of the observed images that have a potential to improve detection quality (such as completeness, reliability) can be used as $I_{\lambda D}$; this can be convolution, multiplication by weight images, subtraction of baseline images, etc. For example, one may want to sacrifice a little bit of the nominal angular resolution in order to reduce the unphysical pixel-to-pixel noise present in the images (on scales smaller than the observational beam size $O_\lambda$) using convolution $I_{\lambda D} = G_{\lambda j} * I_{\lambda O}$, where $G_{\lambda j}$ is the smoothing Gaussian with full width at half maximum (FWHM) chosen to slightly degrade (by $\sim$5%) the image resolution $O_\lambda$. This suppresses unphysical noise and small-scale artifacts in $I_{\lambda D}$ that otherwise may become enhanced in the smallest-scale decomposed images. Being the default way of creating detection images in getsources, such smoothing is not required and may be skipped, if not deemed beneficial. Another example of a detection image that may be useful in some applications is a column density map produced by pixel-to-pixel SED fitting of the observed images.

The last part of the preparation is creating the observational masks $M_\lambda$. Those are images with the pixel values of either 1 or 0, defining the areas in the original images that we are interested in. In practice, some areas of the observed rectangular images may not have been covered, some other areas may contain high noise or artifacts. The mask images are used by getsources to exclude from processing any area of $I_{\lambda D}$ in which the mask has zero values; in the simplest ideal case, $M_\lambda$ has values of 1 in all pixels. Very noisy areas have the potential to affect the cleaning and detection algorithms described below and every effort must be made to exclude such areas using carefully prepared observational masks.

### 2.2. Decomposing detection images in spatial scales

The spatial decomposition is done by convolving the original images with circular Gaussians and subtracting them from one another (we call this procedure successive unsharp masking):

$$I_{\lambda D j} = G_{j-1} * I_{\lambda D} - G_j * I_{\lambda D} \quad (j = 1, 2, \ldots, N_S),$$

where $I_{\lambda D}$ is the detection image (Sect. 2.1) at wavelength $\lambda$, $I_{\lambda D j}$ are its “single-scale” decompositions, $G_j$ are the smoothing Gaussian beams ($G_j$ is a two-dimensional delta-function). The latter have FWHM sizes $S_j = f_j S_{j-1}$ in the range $2 \Delta \leq S_j \leq S_{\text{max}}$, where $\Delta$ is the pixel size, $f_j > 1$ is the scale factor, $S_{\text{max}}$ is the maximum spatial scale considered, and the number of scales $N_S$ depends on the value of $f_j$ (typically $=1.05$) and $S_{\text{max}}$. We adopt $S_{\text{max}} = 3\Delta$ (MaxTel), where $A_{\text{max}}$ is the maximum FWHM sizes of sources to be extracted and an upper limit for $A_{\text{max}}$ is the image size.

Equation (1) implicitly assumes that the convolved images are properly rescaled to conserve their total flux; therefore, the original image can be recovered by summing up all scales:

$$I_{\lambda D} = \sum_{j=1}^{N_S} I_{\lambda D j} + G_{N_S} * I_{\lambda D}.$$

Before convolution, the input images $I_{\lambda D}$ are expanded from the edges of the areas covered by the observational masks $M_\lambda$ towards the image edges and the entire images are further expanded on all sides by a large enough number of pixels ($3 S_j/\Delta$) in order to avoid undesirable border effects. Both expansions are

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[^6]: In practice, the most accurate approach to alignment is to use images containing only small scales (see Sect. 2.2), up to $\sim$twice the resolution in each waveband, as they show misalignments most clearly. One should carefully choose which peaks to align, as the appearance of sources may be affected by radiative transfer effects or by fluctuating backgrounds or by the close proximity to other sources.

[^7]: The wavelength-dependent maximum sizes of sources are the only user-definable parameters in getsources. The actual maximum sizes depend on the observed images and the specific interest of a researcher. Before extracting sources, one has to obtain reasonable guesses of the maximum source sizes from the images and specify them in the configuration file (the parameter $A_{\text{max}}$ defaults to 6 $O_\lambda$).


Fig. 2. Single-scale decomposition (Sect. 2.2). The central 0.44′ × 0.44′ sub-field of the detection image $I_D$ of a 1′ × 1′ simulated star-forming region at 350 μm (upper left). Its single-scale images $I_D^j$ are shown at the scales indicated (left to right, top to bottom) for $j = 17, 30, 43, 57, 70$, $N_S = 99$, $f_S = 1.053$, $S_1 = 4''$, $S_N = 660''$ (see Eq. (1)). The image dimensions are 1800 × 1800 pixels and the pixel size $\Delta = 2''$. The scales were selected to be separated by a factor of 2 to illustrate the spatial decomposition. The scale sizes $S_j$ are visualized by the yellow-black circles and annotated at the bottom of the panels. For better visibility, the values displayed in the panels are somewhat limited in range; the color coding is a linear function of intensity in MJy/sr.

performed using the pixel values at the edges of the masks and images, respectively; after convolution, the images are reduced back to their original size.

Small values of $f_S$ ensure the best spatial resolution of the single scales, just like fine mesh sizes always better resolve structures in numerical methods. For practical reasons, the minimum value of $f_S$ is 1.03 and the maximum value of $N_S$ is 99. For large $f_S$, the single scales actually contain mixture of a wide range of scales, and faint small-scale structures become completely diluted by the contribution of irrelevant scales. Again, this is very similar to any finite-difference numerical methods, where structures smaller than a few grid zones disappear within large structures resolved by coarse grids.

To illustrate the spatial decomposition and all other processing steps of getsources, we shall use images of a simulated star-forming region that we constructed well before the launch of Herschel in order to have a reasonably realistic model for testing various aspects of our future observational program (the source extraction methods, instruments simulators, etc.); we refer to Appendix C for more details. The spatial decomposition of images using convolution has a clear interpretation in terms of the Fourier transform. Interested readers are referred to Appendix D, where we present the Fourier amplitudes for the individual components of the simulated sky and for a few selected scales of the decomposed images, as well as examples from the actual Herschel observations.

A sub-field of the simulated region at 350 μm (Fig. 2, upper left) clearly shows all ingredients: the cirrus background, protostars (bright compact peaks), and fainter starless cores of various sizes, from completely unresolved to very extended. Many sources vanish into the background and also many sources are blended with others. However, the single-scale decompositions filter out emission at all irrelevant scales and display the sources with a much higher contrast than the full image does. The decomposition of Eq. (1) thus naturally selects sources of specific sizes, which become best visible in the images with matching

8 Usually best results are obtained with $N_S$ and $f_S$ close to their limiting values. For $f_S = 2$, the decomposition of Eq. (1) is identical to that produced by the multi-resolution code mr_transform (Starck & Murtagh 2006) with its default linear wavelet transform ("à trous" algorithm).

9 Except the spatial decomposition step, where convolutions are done using a fast Fourier transform algorithm, our method has been designed to operate in the image space, which is a natural and intuitive way of source extraction.
Fig. 3. Single-scale removal of noise and background (Sect. 2.3). The field of Fig. 2 is shown as the full clean image \( I_{\lambda} \) at 350 \( \mu \)m (upper left) that accumulates clean images over all scales. The same set of spatial scales is displayed in the single-scale images \( I_{\lambda} \) (left to right, top to bottom), cleaned of noise and background with an iterative procedure described in Sect. 2.3. All intensity peaks visible in the scales belong to the sources; most of the noise and background fluctuations (visible in Fig. 2) have been removed. The scale sizes \( S_j \) are visualized by the yellow-black circles and annotated at the bottom of the panels. For better visibility, the values displayed in the panels are somewhat limited in range; the color coding is a function of the square root of intensity in MJy/sr.

The negative rings around bright sources are the direct consequence of the successive unsharp masking, the subtraction of an image convolution with a larger smoothing beam from an image convolved with a smaller beam. All peaks at the first four scales shown in Fig. 2 are identifiable with the corresponding peaks in the full image. However, the situation becomes more problematic as we proceed to larger scales, such as that displayed in the last panel of Fig. 2. For even larger scales, up to the entire image size, intensities from sources of all sizes become so heavily mixed and diluted in the large smoothing beams that one cannot disentangle the individual structures anymore.

This demonstrates the need to set a reasonable upper limit for the sources to be extracted\(^{10}\). Indeed, if huge structures were to be allowed (with sizes by orders of magnitude larger than \( O_j \)), they would also have to be used in the background subtraction and deblending, both of which become increasingly inaccurate on very large scales. For accurate removal of the background, one has to either approximate or interpolate it; both approaches become highly uncertain when large distances are involved. Deblending of overlapping structures requires a good approximation of their intensity distributions, which also becomes inaccurate on very large scales. This would also greatly reduce the quality of the detection and measurements for the majority of “normal” sources. Many of the latter would be fully contained within the much larger (sub-structured) sources and to accurately measure them, one has to consider the large sources as their background\(^{11}\).

2.3. Cleaning single scales of noise and background

Before one can use the single-scale detection images \( I_{\lambda} \) for source extraction, they need to be cleaned of the contributions of noise and background to make sure that most (if not all) non-zero pixels belong to real sources. The noise and background fluctuations in the far-infrared and submillimeter images of interstellar clouds, such as those coming from the Herschel Gould Belt and HOBYS surveys, do not follow Gaussian statistics. A great advantage of the fine spatial decomposition employed by

\(^{10}\) Note that getsources has no fundamental limitation on the spatial scales or source sizes except they must be smaller than the image size.

\(^{11}\) If one is interested primarily in extracting very large structures, one could first extract all smaller sources, subtract them from the original image, and then run the extraction again, targeted specifically at those structures.
Fig. 4. Single-scale cleaning residuals (Sect. 2.3). The field of Fig. 2 is shown as the reconstructed image $I_{\lambda DR}$ of the residuals at 350 $\mu$m (upper left) that accumulates cleaning residuals from all scales. The same set of spatial scales is displayed in the single-scale images of the residuals $I_{\lambda DjR}$ (left to right, top to bottom). The cleaning procedure left no significant intensity peaks of the simulated objects in the residuals, only the noise- and background-dominated pixels (cf. Fig. 7). The scale sizes $S_j$ are visualized by the yellow-black circles and annotated at the bottom of the panels. The color coding is a linear function of intensity in MJy/sr.

getsources (Sect. 2.2) is that the emission fluctuations in the decomposed images of interstellar clouds or Galactic cirrus become approximately Gaussian. Thus, significant departures from Gaussian distribution in the single-scale images indicate the presence of sources. For more details and illustrations in terms of the power spectra of the components of the actual Herschel images, we refer to Appendix E; see also Fig. 5 below.

Cleaning can be done by global intensity thresholding of the single-scale images, as the larger-scale background has been effectively filtered out by the spatial decomposition. Unlike the original images $I_{\lambda O}$ or $I_{\lambda D}$ that often have a very strong and highly-variable background, the entire single-scale images are “flat” in the sense that all signals on considerably larger scales have been removed (see Fig. 2). Another advantage of this single-scale cleaning is that the noise contribution depends very significantly on the scale. For example, the small-scale noise gets heavily diluted at large scales, where extended sources become best visible. In effect, in a reconstructed clean image $I_{\lambda DC} = \sum_j I_{\lambda DjC}$ one can see large structures better (deeper) than in $I_{\lambda D}$.

To clean the single-scale images, we designed an iterative algorithm\footnote{A procedure similar to what is usually called “sigma clipping”.} that automatically finds at each scale a cut-off level that separates the signal of significant sources from those of the noise and background. At the first scale ($j = 1$) it computes the cut-off (threshold) $\sigma_{1j} = n_{1j} \sigma_{1M}$, where $\sigma_{1M}$ is the standard deviation over the entire image and $n_{1j}$ is a variable factor having an initial value of $n_{1j} = 6$ (this $j = 1$ value was found to be optimal in our tests). Then the procedure masks out all pixels with the values $|I_{\lambda j}| \geq \sigma_{1j}$ and repeats the calculation of $\sigma_{1j}$ over the remaining pixels, estimating a new threshold, which is generally lower than the one at the previous iteration. The procedure masks out bright pixels again and iterates further, always computing $\sigma_{1j}$ at $|I_{\lambda j}| < \sigma_{1j}$, outside the peaks and hollows, until $\sigma_{1j}$ converges ($\Delta \sigma_{1j} < 1\%$). To produce a clean single-scale image $I_{\lambda D1C}$, all pixels with $I_{\lambda j} < \sigma_{1j}$ are zeroed, which (ideally) leaves non-zero only those pixels that belong to significant peaks from sources. Several examples of clean images are displayed in the last five panels of Fig. 3.

In addition, the low-intensity pixels $|I_{\lambda j}| < \sigma_{1j}$ define the single-scale images of the residuals $I_{\lambda DjR}$, as well as the reconstructed image of the residuals $I_{\lambda DR} = \sum_j I_{\lambda DjR}$. The images are shown in Fig. 4, where one can clearly see that the single-scale residuals are much “flatter” than those accumulated over all scales. This illustrates why the single-scale cleaning can be performed on the entire images using thresholding, in contrast to the full images (for more illustrations, see Figs. 2, 5). Furthermore,
the flattening step of our method (Sect. 2.8) ensures that also the standard deviations of the single-scale residuals become as uniform as possible over the entire image.

Starting with the second scale, \( j = 2 \), the factor \( n_{ij} \) is allowed to become lower than its initial value of \( n_{ij} = 6 \) at \( j = 1 \), depending on the image and the scale. Being an important parameter for the iterations to converge to accurate cut-off levels, \( n_{ij} \) must be accurately chosen. Empirical evidence shows that if \( n_{ij} \) were smaller than an optimal value, the iterations would converge to \( \sigma_{ij} \) that is too low, resulting in noise peaks contaminating the clean images. On the other hand, if \( n_{ij} \) were larger than its optimal value, the iterations would converge to a value of \( \sigma_{ij} \) not deep enough, thus some fainter sources present in \( I_{\text{Idl}} \) would be missing in the clean images \( I_{\text{Idlc}} \).

To determine the appropriate values of \( n_{ij} \), one can use the higher-order statistical quantities, skewness and kurtosis

\[
s_{ij} = \mu_{3,ij} \sigma_{ij}^3, \quad k_{ij} = \mu_{4,ij} \sigma_{ij}^4 - 3, \tag{3}
\]

where \( \mu_{3,ij} \) and \( \mu_{4,ij} \) are the third and fourth moments about the mean (both \( s_{ij} \) and \( k_{ij} \) are zero for a standard normal distribution). The idea is that when the pixel distribution of the residuals \( I_{\text{Idl}} \) becomes too asymmetric (large \( |s_{ij}| \)) or too peaked (large \( k_{ij} \)), the optimal value of \( n_{ij} \) must actually have been lower. Thus, having iterated the cut-offs \( \sigma_{ij} \) at the first scale, getsources computes the upper limits to \( s_{ij} \) and \( k_{ij} \) given by an empirical formula

\[
s_{ij}^{\text{max}} = k_{ij}^{\text{max}} = \max \left( \frac{2.14 \ln \left( \frac{I_{\text{Idl}}^{\text{max}}}{\sigma_{ij}} \right) + 220}{11.3, 0.25} \right), \tag{4}
\]

where \( I_{\text{Idl}}^{\text{max}} \) is the maximum pixel intensity over \( I_{\text{Idl}} \).

When iterations at scale \( j \) converge to a threshold \( \sigma_{ij} \), getsources computes \( s_{ij} \) and \( k_{ij} \) in the image of the residuals \( I_{\text{Idl}}^{\text{R}} \). If \( |s_{ij}| > s_{ij}^{\text{max}} \) or \( k_{ij} > k_{ij}^{\text{max}} \), the algorithm slightly (by a few percent) reduces \( n_{ij} \), whose initial value is \( n_{ij-1} \) from the previous scale, and re-iterates \( \sigma_{ij} \). This procedure ensures that \( s_{ij} \) and \( k_{ij} \) always stay within the empirical bounds in the process of obtaining the thresholds and cleaning the single-scale images. Extensive experimentation has shown that the limits of Eq. (4) work very well for all images that we have tested\(^{13}\).

The pixel distributions shown in Fig. 5 illustrate the cleaning algorithm. The histogram for the original image \( I_{\text{D}} \) shown

\(^{13}\) We have applied getsources to the multi-wavelength images of a dozen of simulated fields, the ground-based (sub-mm) images of NGC 2068, NGC 2071, NGC 2264, W 43, and the Herschel images of Aquila, Cepheus, Cygnus X, IC 5146, Lupus, M 16, NGC 4559, NGC 7538, Orion B, Perseus, Pipe, Polaris, RCW 79, RCW 82, RCW 120, Rosette, Taurus, Vela W 3, W 48.
in the upper-left panel contains all spatial scales and is therefore very wide and asymmetric; it cannot be used to separate sources from noise and background using global thresholding. All scales are blended together in such images and any threshold would enable one to either find only the brightest peaks losing most fainter sources or create many spurious peaks from the pixels belonging to the variable background or noise. In contrast, the highly-filtered single-scale images $I_{\lambda j}$ contain only narrow ranges of spatial scales and thus the histograms of the residuals $I_{\lambda j R}$ (representing the background and noise fluctuations) are much narrower and symmetric, resembling a Gaussian distribution (Fig. 5). Having no signals from all irrelevant larger scales, the images are much “flatter” and therefore well suited for the cleaning algorithm. The single-scale histograms show that using the upper limits of Eq. (4) for skewness and kurtosis helps in correcting the variable factor $n_{ij}$ and thus in getting deeper thresholds $\sigma_{ij}$ and much better detection of fainter sources while avoiding creation of spurious sources.

2.4. Combining clean single scales over all wavelengths

The cleaning algorithm outlined in Sect. 2.3 is applied to the single-scale detection images $I_{\lambda j}$ independently in each waveband. Clearly, getsources also works the same way for just one image at a single wavelength. It is necessary to fully complete “monochromatic” extractions as they provide the footprints of all sources and also the estimates of the sizes $A_{\lambda j}^{\text{max}}$ of the largest sources, the information used by our flattening procedure (Sect. 2.8). Combining wavelengths means utilizing all information across all bands and this should be used to improve the detection and measurement qualities over the simple approach of matching separate catalogs obtained in each waveband independently. Whereas combining independent catalogs on the basis of the association radius is possible for a few images obtained with similar angular resolutions, this usual approach of associating sources between wavelengths would introduce large and unknown errors when applied to Herschel images whose resolutions differ by as much as a factor of ~7.

In general, it is impossible to combine images at different wavelengths in a meaningful way using full images containing signals on all spatial scales. The fine spatial decomposition employed by getsources (Sect. 2.2) that filters out signals from all irrelevant scales, together with the single-scale cleaning (Sect. 2.3) enable us to create wavelength-independent clean images that accumulate only significant intensity peaks from all wavelengths, representing potential sources. The combined images must be normalized because of highly varying intensities in different bands; there is no need to preserve the spectral behavior of sources in the images used only for detection (Sect. 2.5). Indeed, the wavelength-dependent properties of all sources will be measured in the observed images $I_{\lambda 0}$ (Sect. 2.6) after all sources have been detected.

The cleaning procedure described in Sect. 2.3 works well when the small-scale noise and background fluctuations are relatively uniform across the image and there are no strong artifacts. It is not unusual, however, for the observed images to contain quite variable noise and various types of artifacts, including those from the map-making process. In order to reduce possible contamination of the clean images with the pixels belonging to the noise peaks or artifacts, getsources additionally employs a lower limit on the number of pixels $N_{3 \lambda}$ in a cluster of connected pixels that may remain in single-scale images:

$$N_{3 \lambda}^{\min} = \max \left( \frac{1}{3} \pi \left( \frac{O_4}{2\Delta} \right)^2, N_{3 \lambda}^{\min} \right),$$

where $O_4$ is the observational beam size, $\Delta$ is the pixel size, and the default value of the parameter $N_{3 \lambda}^{\min}$ is 4. Small clusters with $N_{3 \lambda} < N_{3 \lambda}^{\min}$ are removed from the single-scale images $I_{\lambda j R}$ before the latter are combined.

When combining single scales from different wavebands, getsources only sums up limited ranges of spatial scales, depending on the angular resolution and the sizes of sources that can be found in the images. The range of scales is limited from below because the smallest scales may contain decreasing (and progressively noisier) contribution for the images obtained at longer wavelengths with poorer resolutions. Single scales within a factor of 3 below the nominal resolution
Fig. 7. Combination of single-scale images (Sect. 2.4). The field of Fig. 2 is shown as source masks $M_{DC}$ accumulated over all scales and wavebands (upper left) that give a summary view of how the sources, made visible by the cleaning (cf. Fig. 3), change their shapes and sizes. The same set of spatial scales is displayed in the combined clean single-scale images $I_{DC}$ (left to right, top to bottom) that accumulate information at those scales from all wavelengths. For better visibility, the values displayed in the masks image are limited to 300 and in the normalized images $I_{DC}$ they are limited to 0.07, 0.3, 0.3, 0.6, and 0.6. The scale sizes $S_j$ are visualized by yellow-black circles and annotated at the bottom of the panels. The color coding is a logarithmic function of intensity.

Fig. 8. Evolution of sources in the clean single-scale images (Sect. 2.5). The full image of the source at 350 $\mu$m with a size of 3.7 $\times$ 3.7 (left) has been cut out of the corresponding panel in Fig. 2 (the source is located south-east of the image center, it is resolved in all wavebands). The other panels show the source in single-scale images $I_{DC}$ at the scales of 18, 36, 138, and 199 $''$, maximum intensities in the panels being 0.31, 0.89, 3.09, and 1.84 MJy/sr, respectively. The scale sizes $S_j$ are visualized by the blue circles and annotated at the bottom of the panels. The color coding is a linear function of intensity.

in each band may still contain considerable signal from the sources. Accordingly, the lower limit of scales $S_j$ being combined defaults to max($S_1$, 0.33 $O_j$), allowing for a substantial “super-resolution” in getsources. On large scales, the range of scales is also limited by the (wavelength-dependent) maximum sizes $A_{max}^\lambda$ of sources (see Sect. 2.2). Initial guesses for $A_{max}^\lambda$ are given as input to getsources, however, they are accurately determined during the initial extraction and used in the final extraction (Sect. 2.8).

It is necessary to define two sets of wavelength-combined single-scale images (illustrated in Fig. 6) for different purposes. The images $I_{DC}$ are used to detect sources and track the
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Fig. 9. Single-scale source detection (Sect. 2.5). The field of Fig. 2 is shown as the initial footprint image $F_D$ after the source detection (upper left). The same set of spatial scales is displayed in the single-scale segmentation images $I_{Dj}$ (left to right, top to bottom) showing the source segmentation masks determined from $I_{Dj}$ (Fig. 7). The masks were obtained and analyzed by the detection procedure described in Sect. 2.5. The scale sizes $S_j$ are visualized by the yellow-black circles and annotated at the bottom of the panels. The color coding is a function of the square root of the source number (which makes up the actual pixel values in these segmentation images).

Evolution of their shapes across all spatial scales (see Sect. 2.5) and the images $I'_{Dj}$ are used to follow the dependence of the peak intensities of detected sources on scales. The first set of combined detection images is normalized such that all cleaning thresholds become equal to 1 in each band:

\[ I_{DjC} = \frac{1}{N} \sum_{\lambda} f_{\lambda j} \max \{ I_{D\lambda jC}, T_{\lambda j} \} , \tag{6} \]

where $T_{\lambda j}$ is the threshold image (all pixels of which are equal to $\sigma_{\lambda j}$), $N$ is the number of wavelengths, and $f_{\lambda j}$ gradually “turns on” the scales smaller than the observational beam $O_\lambda$ (for larger scales, $f_{\lambda j} = 1$):

\[ f_{\lambda j} = \left( \frac{S_j}{O_\lambda} \right)^3, \quad \max \{ S_1, 0.33 O_\lambda \} \leq S_j \leq O_\lambda. \tag{7} \]

The renormalization of images, the threshold $\sigma_{\lambda j}$ in the curly brackets, and the turn-on factor $f_{\lambda j}$ ensure that the images from different wavebands become smoothly combined in $I_{DjC}$ (Eq. (6)) with no discontinuities and that there are no large changes in the combined images between any two adjacent scales (Fig. 6, left).

The normalization of $I_{DjC}$ to a common threshold before summing them up is the most natural way of combining wavelengths to maximize sensitivity. It removes, however, the natural dependence of the source brightness on scales, which is used by our detection algorithm to determine the characteristic scale and initial footprint for each source (Sect. 2.5). Our second set of combined images allows that, as they are normalized only at the smallest scale (there is no reason to use the factor $1/N$ here):

\[ I'_{DjC} = \sum_{\lambda} w_{\lambda j} I_{\lambda jC}, \tag{8} \]

where $I_{\lambda jC}$ is the maximum intensity over $I_{DjC}$ and the weight $w_{\lambda j}$ enhances contributions of the images with higher angular resolutions:

\[ w_{\lambda j} = \left( \frac{\bar{O}}{O_\lambda} \right)^{\gamma}, \tag{9} \]

where $\bar{O} = N^{-1} \sum O_\lambda$ is the average observational beam size and $\gamma > 1$ is a weighting exponent with a default value of 6. The aim of such weighting is to effectively separate the contributions of different wavebands over the intensities when computing $I'_{DjC}$ (Eq. (8)). After the weighting, the summation of
$I_{\Delta j C}$ practically does not alter their individual intensity profiles (Fig. 6, right). If a source exists in some high-resolution single-scale images at a certain wavelength, the dependence of its peak intensity across scales is fully preserved in $I_{\Delta j C}$. In the detection process, the source position, characteristic size, and footprint are largely determined by the high-resolution images and the spatial scale where it becomes the brightest (Sect. 2.5). The initial size and footprint obtained in the detection step are recomputed during the measurement iterations (Sect. 2.6).

Figure 7 illustrates our method of combining wavelengths. The upper-left panel shows an image of single-scale masks accumulated over scales and all $Herschel$ wavebands, obtained from the clean single-scale images:

$$M_{\Delta j C} = \sum_j \sum_{\lambda} \frac{1}{\sigma} \min \{I_{\Delta j C}, \sigma_{\lambda j}\} = \sum_j \sum_{\lambda} \frac{I_{\Delta j C}}{\sigma_{\lambda j}},$$

where $T_{\lambda j}$ is the threshold image and, of course, the division of the image by itself can only be done in non-zero pixels. The accumulated mask image presents a cumulative view of how the sources made visible by cleaning change their shape and size across all scales and wavelengths. All sources that can possibly be found in the clean images have left their mark in $M_{\Delta j C}$. The other panels of Fig. 7 display the combined detection images $I_{\Delta j C}$ for several single scales, which accumulate information from all wavebands. Comparing them with the corresponding panels of Fig. 3, one can verify that each combined scale is indeed populated by more sources than any of the clean single scales at individual wavelengths.

2.5. Detecting sources in combined single-scale images

As can be seen in Figs. 3 and 7, sources “evolve” from small to large scales in single-scale images. In the clean images $I_{\Delta j C}$, the sources appear at some relatively small scales (smaller than their actual size), become the brightest at a scale roughly equal to their size, and eventually vanish at significantly larger scales (see Fig. 8 for an illustration). The idea of our source detection scheme is to analyze all $I_{\Delta j C}$ ($j = 1, \ldots, N_j$), identifying the sources and tracking the “evolution” of their shapes from small to large scales. For that purpose, get sources employs the $Tint Fill$ algorithm (Smith 1979)\(^{14}\), developed for coloring arbitrary shapes in digital images. The algorithm assumes that the sets of pixels belonging to any shape are 4-connected, i.e. that for any pair of pixels $\Pi_l$ and $\Pi_n$ in the shape, there is a path from $\Pi_l$ to $\Pi_n$ through pixels in that shape, such that neighboring pixels in the path are connected to each other only by their sides (Fig. 10). Given a set of 4-connected (side-connected) pixels, each one having the same property (e.g., color), the algorithm fills all (and only) pixels of that shape with a new value.\(^{15}\)

The algorithm has been slightly generalized to be suitable for the source detection in single-scale images by replacing color with another pixel property of having a non-zero intensity.

The modified version of the $Tint Fill$ algorithm looks, at each scale ($j = 1, 2, \ldots, N_j$), for 4-connected areas of non-zero pixels in $I_{\Delta j C}$. and assigns the value of the running source number $i$ to each of those connected pixels, producing a segmentation image $I_{\Delta j S}$. The latter consists of the segmentation masks of the sources found at scale $j$ and previous smaller scales (get sources always analyzes single-scale images from small to large scales). A source mask is the area of 4-connected pixels (with values $i$) in $I_{\Delta j S}$. all those pixels having non-zero intensity in $I_{\Delta j C}$ at $j$ or at smaller scales. The masks uniquely identify the sources and allow tracking them across all single scales (Fig. 9).

In order to better disentangle and follow the evolution of blended sources in $I_{\Delta j C}$, the algorithm splits the images between their maximum and $\sigma_l$ by a number of intensity levels $\omega_j$ with a spacing $\delta \ln \omega_j = 0.1$ or smaller. At each scale $j$, our source detection procedure works on a sequence of “partial” images $I_{\Delta j C \lambda} = \max \{I_{\Delta j C \lambda}, \omega_j\}$, from top to bottom, where the last partial image is the entire single-scale image $I_{\Delta j C}$. For better efficiency, we only consider those levels $\omega_j$ that increase the number of pixels in $I_{\Delta j C \lambda}$ with respect to $I_{\Delta j C \lambda+1}$ by at least

$$\delta N_{\lambda j \Omega}^{\min} = \max \left\{ \frac{1}{3} \pi \left( \frac{S_j}{2 \Delta} \right)^2, \delta N_{\lambda j \Omega}^{\min} \right\},$$

where $\Delta$ is the pixel size and $\delta N_{\lambda j \Omega}^{\min} = 9$. The levels $\omega_j$ with $\delta N_{\lambda j \Omega} < \delta N_{\lambda j \Omega}^{\min}$ are skipped by the detection algorithm. Processing a partial image $I_{\Delta j C \lambda}$ within scale $j$, get sources first gives the coordinates of the sources already found at previous scales and levels to the modified $Tint Fill$ algorithm and the latter fills the evolved shapes of the “old” sources with their numbers $i$. Then it checks all remaining pixels of $I_{\Delta j C \lambda}$ to find new 4-connected areas of non-zero pixels that first appear at the current scale $j$; when found, the segmentation mask of each “new” source is filled with its new number $i$.

When an isolated source vanishes at a certain scale, its pixels are freed and may eventually become occupied by its neighbor or another (significantly larger) source that may appear there at a larger scale. One of two touching sources can also disappear from larger scales, when it becomes fainter at progressively larger scales and finally merges with the brighter neighbor (i.e., when the saddle point between the peaks disappears). When two or more isolated sources become connected in a single-scale image, their segmentation masks are not allowed to overlap. A boundary between two sources is maintained along the normal to the straight line connecting their centers (the normal being defined at a position along the line where intensity is at minimum); the sources can still grow at larger scales in the perpendicular direction. This boundary exists, however, only within a limited range of scales, until one of the touching sources vanishes or merges with another. The algorithm is perfectly able to handle hierarchical structures, as the segmentation masks can overlap at different scales for sources of significantly dissimilar dimensions. Whether a larger source containing smaller sources is detected as such or considered as the background, depends on the relative difference in the characteristic scales between the large and small sources, on the location of the small sources within the larger structure, and on the relative brightness of the peaks. If the source sizes are significantly different, the hierarchical structures are detected; a number of examples can easily be found in Fig. 9 (upper-left), Fig. 17 (right), and Fig. 18 (bottom).

One can show that a resolved isolated circular source $i$ with the FWHM sizes $A_i = B_i$ would have its maximum peak intensity $I_i$ in a single-scale image with a smoothing beam $S_i \approx A_i$. Recall that the spatial decomposition (Eq. (1)) is based on convolution; the latter acts as a natural selector of scales in the decomposed images (cf. Sect. 2.2). Indeed, convolving with small beams ($S_i \ll A_i$) would have almost no effect on the source, whereas using extended beams ($S_i \gg A_i$) would greatly dilute the source. In both these extremes, excessive unsharp masking

\(^{14}\) Available at http://portal.acm.org/citation.cfm?id=809249.807456

\(^{15}\) Identification of distinct connected regions in similar algorithms is also known as connected-component labeling.
produces decreasing peak intensities (Fig. 8) while creating the strongest signal for the sources with sizes \( A_i \approx S_j \); completely unresolved sources are the brightest at spatial scales \( S_j \lesssim O_i \).

The scale \( j_f \), where a source is the brightest, provides the best initial estimate for its actual FWHM size \( A_i (=B_i) = S_{j_f} \). This footprinting scale defines a source footprint, i.e. the entire area of the image pixels making non-negligible contribution to the total flux of the source. For unresolved sources, the footprints cover circular areas \( \approx \pi O_i^2 \), whereas for well-resolved sources with intrinsically Gaussian intensity distributions, they cover elliptical areas \( \approx \pi A_i B_i \). During the detection process, \textit{get sources} creates initial footprints (cf. Fig. 9, upper-left) with full sizes of \( A_{j_f} (=B_{j_f}) = 1.15 (2 S_{j_f}) = 2.3 S_{j_f} \), where the empirical factor 1.15 was found to improve results in our tests. The footprints generally become elliptically-shaped in the measurement iterations (Fig. 15), reflecting the source shapes obtained from intensity moments (Sect. 2.6).

In a multi-wavelength extraction, the combined images are sums of rescaled images over all individual wavebands (Eq. (8)) using the weighting (Eq. (9)) that effectively separates \( I_{DJ/C} \) in the combined detection images \( I'_{DJ/C} \). Although the weighting biases \( S_{j_f} \) towards higher-resolution images (makes the initial footprints smaller), this does not affect the results, as the sizes found in the detection process are replaced with the values obtained from the monochromatic images \( I_{DJ/C} \) during the measurement iterations (Sect. 2.6).

Coordinates of a source are computed from the moments of intensities (Appendix F) in a limited range of scales, only up to a scale 4 times larger than the one it first appeared at or up to the footprinting scale \( j_f \), whichever is smaller. This gives more accurate positions than if recomputed at even larger scales, since the latter tend to mix in more and more of the signals from the surroundings and thus distort the single-scale intensity distribution of sources. To improve the positional accuracy even further, \textit{get sources} uses only the pixels with values greater than \( I_{ij}/1.4 \), where \( I_{ij} \) is the peak intensity of a source \( i \) and the number in the denominator has been found empirically.

In general, observed images contain structures at all scales and there is a real danger of creating spurious sources by mistakenly detecting noise peaks or background fluctuations that happen to lie on top of larger structures. Although the latter may be relatively faint, they tend to “amplify” the small-scale noise and background and make the small structures appear as significant sources. This can be especially problematic if the local uncertainties of the peak intensities (Sect. 2.6) are not possible to estimate due to crowding, as the fluctuations outside the large structures may be noticeably smaller and thus the signal-to-noise ratio \( (S/N) \) may easily be overestimated.

There is a mechanism in \textit{get sources} to greatly reduce this possibility. The idea is that small-scale peaks on top of larger structures tend to survive up to larger scales than they would do otherwise, without the “support” of the underlying structures. The latter tend to make the peaks eventually touch each other or merge at some spatial scale and this is used by the algorithm to identify and discard insignificant intensity peaks. Noise peaks on top of larger structures become diluted if considered relative to the intensity level contributed by the larger structure.

When \textit{get sources} analyzes the intensity levels \( \omega_{ij} \) of the partial images \( I_{DJ/C} \), it finds the level where two or more sources first touch each other and computes the contrast \( C_i = I_{ij}/\omega_{ij} \), where \( I_{ij} \) is the source maximum intensity in the image. The contrast of touching sources is checked to decide whether the sources should be treated as significant ones. The basis for this decision is the fact that when an insignificant source touches another source (either real or spurious), its contrast becomes quite low due to the underlying intensity of a larger structure. In practice, \textit{get sources} requires that any real source must have its contrast \( C_i \) above the minimum value

\[
C_i^{\text{min}} = \eta \max \{ C_{iA}, C_{iE}, 1 \},
\]

where \( \eta > 1 \) is a parameter that depends on the noise level.
Where \( \eta \) is the configuration parameter of guessed sources (with the default value of 1.35), \( C_i \alpha \) is the amplification factor, and \( C_i \) is the elongation factor:

\[
C_i = \max \left\{ \frac{1}{2} \left( \frac{F_i}{F_{F}} \right), 1 \right\}, \quad C_i = \max \left\{ \frac{1}{2.5} \left( \frac{a_i}{b_i} \right), 1 \right\},
\]

where \( F_{F} \) is the flux integrated over the source segmentation mask below the current intensity level \( \omega_j \) (at which the source first touches another source) and \( F_{F} \) is the flux integrated above that level; \( a_i \) and \( b_i \) are the major and minor lengths of the source segmentation mask. These factors describe two aspects of the behavior of noise peaks on top of larger structures: the amplification factor increases with a stronger contribution of the underlying structure, whereas the elongation factor becomes large when the structure has filamentary shape. For \( C_i \alpha C_i \leq 1 \), the source is considered real if its contrast \( C_i \geq \eta \) (Fig. 12); larger values of the product \( C_i \alpha C_i \) raise the “barrier” higher. For \( C_i < C_i \) the current source is flagged as spurious and its segmentation pixels are freed to be used by more prominent sources. If some or all of the touching peaks have contrasts above \( C_i \), they survive the test and their evolution is followed further to larger scales.

Having detected all sources in the combined images \( \lambda D_{i,j} \) over all spatial scales of interest and collected the information in a detection catalog, guessed sources now returns to the actual observed images \( \lambda D_{i} \) in each waveband for measurements of the basic properties of the sources, such as their peak intensity, total, integrated flux, and size.

### 2.6. Measuring and cataloging properties of sources

All measurements are performed in the observed images \( \lambda D_{i} \) for known positions \((x_i, y_i)\) of all sources, obtained in the detection process (Sect. 2.5) and not recomputed anymore\(^{16}\). The measurements must be done together with the background subtraction, deblending, and improvements of the footprints; these are non-trivial interconnected problems that require iterations (Fig. 11).

To properly measure parameters of a source, one has first to determine and subtract the background. As discussed in Sect. 1, we define sources as significant intensity peaks detected by the algorithm and whose entire contribution to the image is bound by their footprints. Based on this definition, guessed sources determines the background by linearly interpolating pixel intensities in \( \lambda D_{i} \) under the source footprints (Figs. 12, 15). The interpolation is done in the four main directions (two image axes and two diagonals), based on the pixels just outside the footprints, which do not belong to any source. For each pixel, values from the 4 directions are averaged to produce the background intensity at the pixel. This procedure results in the image of clean background \( \lambda D_{i} \) and the background-subtracted image \( \lambda D_{i} \) (Figs. 14, 17). In very crowded areas of images with many overlapping sources it is not possible to probe the background around each of the sources. In this case, the interpolation gives the best possible background estimate based on the nearest background pixels available around the blended areas\(^{17}\).

Having created the background-subtracted images \( \lambda D_{i} \), the algorithm deblends values of pixels in overlapping sources and computes peak intensities \( \lambda D_{i} \), and total fluxes \( \lambda D_{i} \) for each source \( i \). At the first measurement iteration, it uses the initial size estimate \( \lambda D_{i} \) obtained during the detection (Sect. 2.5), whereas in the subsequent iterations, the size and orientation from a previous iteration are used. Our iterative algorithm employs deblending shapes, the two-dimensional analogs of the function (Moffat 1969)

\[
\lambda D_{i} = \lambda D_{i} \left( 1 + \left( \frac{r}{R_{0}} \right)^{2} \right)^{-\zeta},
\]

where \( r \) is the radial distance from the peak and \( R_{0} \) is a function of the FWHM shape \((A_{i}, B_{i}, \Theta_{i})\) of a source \( i \). The power-law exponent is fixed at \( \zeta = 10 \) to have stronger, more realistic wings compared to the exponential wings of a Gaussian (\( \zeta \to \infty \))\(^{18}\). The deblending shapes (Eq. 14) are used to split the intensity \( \lambda D_{i} \) of a pixel between the source \( i \) and all overlapping sources according to a fraction of the profile’s intensities at that pixel:

\[
\lambda D_{i} = \frac{\lambda D_{i} \lambda D_{i}}{\sum_k |\lambda D_{i}|} \lambda D_{i} \lambda D_{i},
\]

where the summation is done over all sources whose footprints contain the pixel (Figs. 13, 14). The deblending iterations start with the original (blended) intensities \( \lambda D_{i} \) at the positions of each source and perform the splitting of the pixel values until the intensity \( \lambda D_{i} \) at the center of each source converges to its deblended peak intensity \( \lambda D_{i} \). The deblended intensities \( \lambda D_{i} \) within the footprint ellipses (Fig. 15) are then used to integrate the total fluxes \( \lambda D_{i} \), as well as their FWHM shapes \((A_{i}, B_{i}, \Theta_{i})\) from the intensity moments (Appendix F).

Local uncertainties of the peak intensities \( \lambda D_{i} \) are given by the standard deviations \( \sigma_{i} \) estimated in the observed images

\(^{16}\) Positions were derived using filtered detection images and recomputing them from the observed images contaminated by irrelevant spatial scales would not make them more accurate.

\(^{17}\) This simple method works well (as long as one determines accurate footprints) and it is sufficient, as the background under sources is fundamentally unknown. Estimates of the background based on more complicated approaches, such as its approximation by some two-dimensional functions, always involve assumptions and free parameters, and our simulations show that they may well be less accurate than the simple linear interpolation.

\(^{18}\) As an example, the intensity of a circular \( \lambda D_{i} \) at the footprint edge is by a factor of 1.565 higher than that of the corresponding Gaussian.
This is equivalent to the standard approach of measuring flux errors for an isolated source. Heavily crowded fields present, however, a serious problem, as no source-free annulus exist around many of the sources situated within the regions. No relevant local values of the uncertainties can be found in that case, as more distant source-free areas of images are likely to have different properties in case of highly-variable background or noise.

\[ \sigma_{\text{flux}} = \left( A_{\text{FWHM}} B_{\text{FWHM}} \right)^{1/2} \times 1.15 \left( \sum O_i \right) \]

where \( A_{\text{FWHM}} \) and \( B_{\text{FWHM}} \) are the major and minor axes of the footprint ellipse (cf. Eq. (20)). \( O_i \) is assumed to be a circular

\( I_{\text{FOV}} \) in an elliptical annulus defined around each source \( i \) just outside its footprint\(^{19}\). To ensure that the uncertainties are statistically meaningful, the images of annuli \( A_i \) (Fig. 16) are constructed by requiring that the area of any annulus must contain 50 areas of the observational beam \( O_i \). In the crowded fields, such as the one used for the illustrations in this paper, the footprints and annuli may overlap quite heavily (Figs. 15, 16) and therefore not all pixels can be used, as many of them belong to other sources. In such cases, \( \text{get sources} \) obtains an estimate

\( \sigma_{\text{flux}} \) as local as possible by expanding the outer edge of the annulus outwards, until its usable area of non-zero pixels becomes \( 50 \, O_i \) (Fig. 16, middle).

Uncertainties \( \sigma_{\text{flux}} \) of the total fluxes \( F_{\text{flux}} \) are estimated under the following assumptions. If a source footprint contains \( N_{\text{B}} \) observational beams \( O_i \), then the error of the sum of intensities over the footprint area will be the square root of the quadratic sum of the individual errors, since the beam measurements are statistically independent. Assuming the individual errors to be identical and equal to \( \sigma_{\text{flux}} \), the total flux uncertainty is

\[ \sigma_{\text{flux}} = \sigma_{\text{flux}} \left( A_{\text{FWHM}} B_{\text{FWHM}} \right)^{1/2} \times 1.15 \left( \sum O_i \right) \]

\(^{19}\) This is equivalent to the standard approach of measuring flux errors for an isolated source. Heavily crowded fields present, however, a serious problem, as no source-free annulus exist around many of the sources situated within the regions. No relevant local values of the uncertainties can be found in that case, as more distant source-free areas of images are likely to have different properties in case of highly-variable background or noise.
Fig. 15. Converged footprints of the measured sources (Sect. 2.6). The field of Fig. 2 is shown at 70, 100, 160, 250, 350, 500 μm (left to right, top to bottom) as the footprints of all detected sources after the measurement iterations. The pixel values are the standard deviations $\sigma_{i\lambda}$, due to the local noise and background variations, estimated for each source in an elliptical annulus around its footprint (Fig. 16). Strongly elliptical or too large footprints may appear at those wavelengths where some sources are too faint to be measurable. For such sources, the information is essentially lost and the intensity moments cannot provide meaningful estimates of their sizes and orientation. The color coding is a function of the square root of intensity in MJy/sr.

Fig. 16. Annuli around measured sources (Sect. 2.6). The field of Fig. 2 is shown as the true intensities of the model sources at 350 μm convolved to a 17′′ resolution (left), the image of annuli $A_{\lambda}$ of all detected sources (middle) slightly modified to highlight the annulus area around the source 244 from Fig. 14, and the product $A_{\lambda}I_{\lambda}$ (right) to visualize the actual observed intensities used to compute the flux uncertainties $\sigma_{i\lambda}$ shown in Fig. 15. The corresponding footprint images $F_{\lambda}$ are presented in Fig. 15 and the observed image $I_{\lambda}$ is displayed in Fig. 18. The color coding in the left panel is a function of the square root of intensity, in the other panels it is a linear function of intensity in MJy/sr.
Simulations show that \( \Xi_i \) gives a notably more accurate representation of the true model S/N and with a much lower dispersion than the conventional estimates do using the full images containing all spatial scales.

Gaussian, and the empirical factor 1.15 has been introduced in Sect. 2.5.

With the peak intensities and their uncertainties estimated for each source, one can define the standard S/N ratio \( \Omega_{i,j} = F_{i,j}/\sigma_{i,j} \), to quantify how prominent the sources are against the noise and background fluctuations in their immediate environments. Conventional practice is to use the quantity for defining reliability criteria to avoid contamination of the extraction catalogs with spurious detections; at the same time, \( \sigma_{i,j} \) determines the errors of the measured fluxes. However, in contrast to the traditional source extraction methods, \textit{getsources} performs detection on highly-filtered images \( I_{D,i,j} \) that are quite different from the measurement images \( I_{io} \), and it is important to make a clear distinction between the detection and measurement qualities.

In the wavelength-dependent detection images \( I_{D,j} \), we define the contrasts \( C_{i,j} = I_{i,j}/\sigma_{i,j} \), similar to those introduced in Sect. 2.5. At the footprinting scale \( j_k \) the contrast is, within a factor of \( n_{i,j} \) (Sect. 2.3), the monochromatic detection significance

\[
\Xi_{i,j} = \frac{I_{i,j}}{\sigma_{i,j}} = n_{i,j} C_{i,j}.
\]

Although \( \Xi_{i,j} \) is the single-scale analog of \( \Omega_{i,j} \), the quantity \( \sigma_{i,j} \) evaluates the level of uncertainties at the footprinting scale in the single-scale detection images, whereas \( \sigma_{i,j} \) quantifies the level of fluctuations during measurements in the full observed images.

Extraction of an isolated source situated in approximately uniform background and noise results in \( \Xi_{i,j} \approx \Omega_{i,j} \). For sources in more complicated environments, however, \( \Xi_{i,j} \) gives a cleaner and more accurate estimate of the detection quality and a better criterion for selecting real sources. The measured value of \( \Omega_{i,j} \) inversely depends on the fluctuation level of highly-variable backgrounds, such as those observed by Herschel in Galactic regions. The single-scale cleaning of \( I_{D,j} \) (Sect. 2.3) filters out all irrelevant spatial scales and thus substantially reduces the fluctuations outside sources. Therefore, the significance of detections by \textit{getsources} may well be considerably higher than the conventional \( \Omega_{i,j} \) would indicate.\(^20\)

Since \textit{getsources} is a multi-wavelength extraction method and the detection is generally performed in the combined images \( I_{D,j} \), it would be useful to define another quantity to measure the significance of source detection more globally, across all wavebands. To obtain a meaningful quantity, one cannot use the combined images, because they contain renormalized and summed up monochromatic images (Eq. (6)). Assuming that we have a set of independent images \( I_{D,j} \), it makes sense to define the global significance as

\[
\Xi_j = \left( \sum_i \Xi_{i,j}^2 \right)^{1/2}.
\]

We consider two levels of the robustness of source detection: the reliable level \( \Xi_{rel} \) and tentative level \( \Xi_{tent} \) (default values of 7 and 5, respectively). Reliable sources, i.e. those with \( \Xi_{i,j} \geq \Xi_{rel} \) in at least one waveband used for detection, are cataloged without checking whether they are detected at any other wavelength. Tentative sources, i.e. those with \( \Xi_{i,j} < \Xi_{rel} \) in all wavebands used for detection, are kept in the final catalog only if \( \Xi_{i,j} \geq \Xi_{rel} \) and \( F_{i,j} \geq 1/2 \) in at least \( n_{det} \) wavebands (\( n_{det} \) defaults to 1 and 2 for the monochromatic and multi-wavelength extractions, respectively). For any cataloged source, \( \Xi_{i} \geq \Xi_{rel} \), and for reliable sources, \( \Xi_{i} \geq \Xi_{rel} \).

Having measured the properties of all detected sources at each wavelength, \textit{getsources} completely removes those that are likely to be spurious. The algorithm treats removal of such sources with great care, dividing the measurement iterations into three phases. During the first phase, only non-detections are removed from the catalog, i.e. those sources that do not fulfill the above requirement of the simultaneous detection in at least \( n_{det} \) wavebands, all other detected sources are given a chance to converge. During the second phase, the algorithm removes sources with extremely low goodness \( G_j \leq 0.01 \) which we define as

\[
G_j = \min \left\{ \frac{1}{2} \left( \frac{R_i}{\Xi_{rel}} - 1 \right), 1 \right\},
\]

where \( R_i = \Xi_i \Omega_i C_{i,j}^{-1} \) is the source reliability, \( \Omega_i \) is the global signal-to-noise ratio defined analogously to the global significance \( \Xi \) (cf. Eq. (18)), and \( C_{i,j} \) is the elongation factor (Eq. (13)) at the footprinting scale \( j_k \). Finally, during the third phase, all remaining sources with \( G_j \) are removed.
phase, sources are also removed when their position is too close to another source (within max \{1.5, (O_{min}/\Delta)\}/3 pixels, where $O_{\text{min}} = \min(O_i)$ of almost the same size (within a factor of 2) and they have a lower value of $\Xi_\Omega$ than the other source.

Since getsources is a multi-wavelength extraction method, globally good sources may well be detectable ($\Xi_\lambda \geq \Xi_{\text{det}}^{i-1/2}$) or measurable ($\Omega_\lambda \geq 1$) in only a limited number of wavebands. Indeed, it is quite usual that sources are either insignificant or non-measurable at some wavelengths and this generally leads to their footprints being very unreliable. In order to produce most accurate measurements, the footprints of such sources are removed from the corresponding footprint images $F_\lambda$ in that waveband. This becomes very important in crowded regions with many overlapping sources. Since the quality of both the background subtraction and deblending depends directly on the accuracy of the accumulated footprints, $F_\lambda$ must always remain as clean as possible, free of the footprints of insignificant or non-measurable sources. This wavelength-dependent removal is done starting from the second phase; however, the measurements of such sources are still kept in the catalog from the first phase of iterations.

After the removal of bad sources, getsources analyzes the spatial distribution of all sources at each wavelength and flags them to provide some useful information on global properties of a source. The single-digit flag $f_i$ is assigned to sources according to the following definitions. A source is called **isolated** ($f_i = 0$) if it is not blended with any other source at any wavelength. Two sources are called **blended** ($f_i = 1$) if the intersection area of their footprints is greater than 20% of either of the footprints in at least one waveband. A source is called **sub-structured** ($f_i = 2$) if a footprint of at least one smaller source is fully contained within the inner 56% of the footprint area (or within 0.75 $A_{\lambda i}$ and 0.75 $B_{\lambda i}$). A source is called **sub-structuring** ($f_i = 3$) if it causes another source to be flagged as sub-structured. In addition to the global flag $f_i$, we also define the monochromatic flag $f_{\lambda i}$ that carries information on the wavelength-dependent properties for each source. Among other details, the flag identifies sources that are insignificant or non-measurable in a waveband.

Further, getsources updates the extraction catalog, where each line contains the source number, coordinates, world coordinates (using the $xy2sky$ utility, Mink 2002), global significance, flag, and goodness, followed by the measured properties at each wavelength:

$$i, x_i, y_i, \alpha_i, \delta_i, \Xi_\lambda, f_i, G_i, (\Xi_\lambda, f_{\lambda i}, F_{\lambda i} \sigma_{\lambda i}^P, F_{\lambda i} \sigma_{\lambda i}^T, A_{\lambda i}, B_{\lambda i}, \Theta_{\lambda i}, \lambda_i).$$

The standard signal-to-noise ratio $\Omega_{\lambda i}$ is not cataloged, because it can easily be derived from the catalog entries. The last
processing block of each measurement iteration updates the accumulated footprints $F_\lambda$ of all sources, based on the latest values of the source sizes and position angles. Full sizes and orientation of the footprint ellipses are computed from

$$
A_{iF\lambda} = 2.3 \max \left\{ O_i, S_{\lambda i} \right\}, \quad B_{iF\lambda} = \frac{B_i}{A_{iF\lambda}}, \quad \Theta_{iF\lambda} = \Theta_{i\lambda}. \quad (20)
$$

Having obtained the improved footprints, getsources checks whether the total number of non-zero pixels in $F_\lambda$ has noticeably changed with respect to the previous iteration. If so, the measurement iterations continue until the total area of all footprints changes by less than 0.1%. Convergence properties of the measurement iterations vary for different fields; somewhere between 5 and 30 iterations may be required to obtain a stable pattern of all footprints for each waveband (Fig. 15) and to produce the final catalog. In the last iteration, getsources creates an additional catalog of colors from all possible combinations of total fluxes $I_{\lambda T}$ over all $\lambda$, a catalog of peak and background intensities, as well as three versions of the azimuthally-averaged intensity profiles (beamed images, $I_{\lambda 0}$, $I_{\lambda OBS}$, $I_{\lambda OBSD}$) computed from the original, background-subtracted, and deblended images, respectively.

### 2.7. Visualizing extractions

In order to facilitate visual analysis of the extraction results, getsources produces a number of useful images for each waveband. These include (but are not limited to) the background-subtracted images $I_{\lambda DBS}$, $I_{\lambda OBS}$ (Fig. 17), observed images $I_{\lambda 0}$ with the extraction ellipses overlaid on top (Fig. 18), and detection images $I_{\lambda D}$ (Fig. 19). Other images show just the central positions of the detected sources on top of the images $I_{\lambda DBS}$ and $I_{\lambda OBS}$; these are useful for visualizing crowded regions, where very little can actually be seen under the ellipses. Furthermore, the source images $I_{\lambda OBSD}$ display the background-subtracted, deblended intensity distribution for each individual source at each wavelength (Fig. 14).

For an easy visualization of the various steps of the algorithm, getsources produces also a number of useful additional images. These include (but not limited to) the interpolated backgrounds $I_{\lambda DCB}$, $I_{\lambda OCB}$, the images of $\sigma_{\lambda 1F}$ (Fig. 15), the annuli $A_1$ (Fig. 16), the deblending shapes $I_{\lambda M}$ (Fig. 17). The clean single-scale images $I_{\lambda DC}$ (Fig. 3), $I_{\lambda DC}$ (Fig. 7), the accumulated footprints $F_\lambda$ (Fig. 9), and segmentation images $I_{\lambda DS}$.
The three parameters automatically lowered in the initial extraction
may differ by orders of magnitude between various areas of a
large image \( I_{\text{ID}} \). Any simple thresholding method would have
a difficulty in handling such images, as the global thresholds
would not be good for all areas. Although the single-scale decom-
position used in our method makes the images \( I_{\text{ID}} \) much
"flatter" and more suitable for use with global thresholding, it
cannot overcome the problem completely, as the backgrounds
fluctuate on all spatial scales, from the smallest to the largest
ones. If the background or noise fluctuations strongly vary be-
tween some areas of the image \( I_{\text{ID}} \), they will still influence the
intensity distributions of the single-scale images \( I_{\text{IDf}} \), although
to a much lesser degree.

Our method adopts a special two-step approach (Fig. 20)
to overcome the problem; essentially, two complete extractions are
performed instead of a single one. The initial deeper extrac-
tion\(^{21}\) aims at finding all possible candidate sources, in or-
der to remove them and create the cleanest background im-
gages, free of any sources. The background images are then used
to create the standard-deviation images \( I_{\text{DF}} \), which reflect
the differences between some areas of the image \( I_{\text{IDf}} \), they will still influence the
intensity distributions of the single-scale images \( I_{\text{IDf}} \), although
to a much lesser degree.

The flattening procedure is illustrated in Fig. 19. For refer-
ence, the upper-left panel shows the original detection image \( I_{\text{ID}} \)
at 350\( \mu \)m of the simulated star-forming region used in this pa-
per for illustrations of the method; the entire image \( \times 1 \) is shown
here in order to clearly see the flattening effect. The simulated
background in this field has a temperature gradient along one
diagonal of the image, clearly visible in the images. The dust
temperature \( T_D \) linearly varies from 20 K in the upper-left corner
down to 15 K in the lower-right corner, where the background
appears much brighter at 350\( \mu \)m. The footprint image \( F_0^* \) shown
in the upper-middle panel is the image \( I_{\text{DF}} \) (Fig. 15) somewhat expanded by convolution, to make sure that the resulting clean
background has no residual artifacts that would influence the
quality of the final flattening image. The image \( F_0^* \) is used to re-
move all sources from the detection image with our background
interpolation scheme (Sect. 2.6).

The interpolated background in Fig. 19 is smooth and clean,
except for a couple of artifacts at its lower edge. The images
that are bright and variable at their edges may lead to such edge
artifacts, because \( \text{getSources} \) uses convolution and interpolation.
Although the images are sufficiently expanded (extrapolated) by
the algorithm before convolution, they remain essentially un-
known beyond their edges. This type of artifacts never happens
with the entire images from real-world observations that produce
very low intensities at their edges, due to the baseline subtrac-
tion. Such problems may only exist in simulated images or in
sub-fields that have been cut out of full larger images\(^{22}\).

From the background image \( \text{getSources} \) creates the image of
standard deviations \( D_0 \), computed in a very small \((3 \times 3\) pix-
elts) sliding window. The aim here is not to produce statistically-
meaningful values, but to ensure that the features of \( D_0 \) remain
as local as possible; much larger windows would smooth out
the values, which may not be suitable for the original highest-
resolution images. The image \( D_0 \) is further median-filtered using
a 21 \( \times \) 21 pixels sliding window to reduce the effects of possi-
ble residuals or artifacts. The same image \( F_0^* \) is used again to
interpolate the median-filtered pixel values under the footprints,
resulting in the image shown in the lower-left panel of Fig. 19.
The scaling (flattening) image \( I_{\text{F}} \) is obtained by convolving the
filtered \( D_0 \) image with a circular Gaussian beam \( G_{3\lambda} \) of a size
3 times the maximum size of sources \( A_{\text{max}} \) measured in the
initial extraction; the smoothing ensures that the flattening does not
distort the intensity distribution of even the largest sources.
The scaling image \( I_{\text{F}} \) resembles fairly well the original tempera-
ture gradient that was introduced in the simulated images along
their diagonal. The resulting flattened image \( I_{\text{IDF}} \) is the origi-
nal image \( I_{\text{ID}} \) divided by \( I_{\text{IF}} \). The large-scale background var-
iations clearly visible in the original detection image \( I_{\text{ID}} \) have
been mostly removed from the flattened image \( I_{\text{IDF}} \), making the
latter suitable for the global single-scale thresholding applied by
\( \text{getSources} \) in the final extraction.

\(^{21}\) The depth is automatically adjusted by lowering 4 configuration pa-

\(^{22}\) The three parameters automatically lowered in the initial extraction

\(^{23}\) A natural remedy is to define the sub-fields that are larger than the
area one is interested in studying and make sure that the intensities at
the edges of the extraction area are relatively low.
3. Applications to Herschel images

In Sect. 2, our multi-wavelength source extraction method was described and illustrated using the images of a simulated star-forming region. The simulation is one of our suite of benchmarks designed to aid in the development of getsources and in accurate tests of its performance in various conditions against the model images with fully known properties of the sources, background, and noise (the benchmarks will be described elsewhere; Men’shchikov et al., in prep.). In addition to the purely synthetic skies, getsources has been successfully tested on the ground-based millimeter continuum survey of the Aquila Rift complex (Maury et al. 2011), where all extracted sources have been carefully verified by eye inspection and their parameters evaluated manually.

We present here two real-life examples of getsources extractions for our Gould Belt and HOBYS surveys of the nearby and more distant star-forming regions with Herschel. For this purpose, we defined sub-fields of the observed images of Aquila and Rosette, small enough to enable readers to verify the extraction results with their own eyes. We emphasize that the only goal of this presentation is to help the readers clarify various aspects of this new source extraction method; any astrophysical analysis of the fields is beyond the scope of this paper.

3.1. A cluster of resolved prestellar cores in Aquila

The observations, data reduction, and first results for the Aquila star-forming region (part of the Herschel Gould Belt survey, adopted distance $D = 260$ pc) have been described by André et al. (2010); Men’shchikov et al. (2010); Könyves et al. (2010); Bontemps et al. (2010). The Aquila sub-field (365 × 365 3.′0 pixels), shows a cluster of cold prestellar cores, clearly visible in all SPIRE wavebands south-east of the bright W40 region in the Aquila field. The “cold cluster” was chosen to illustrate the performance of our new method for studying the earliest phases of low-mass star formation in the nearby regions (Figs. 21, 22).

The lower-right panel of Fig. 21 shows a 3-color composite image of the extracted sources in the Aquila sub-field, represented by their elliptical deblending shapes $S_j$ (Eq. (14)) with the measured peak intensities, sizes, and orientations. The image gives an overview of the source properties combining the information from the 500, 250, and 160 μm bands in a single image. With just a few exceptions, all sources are red, yellow-red, and green, indicating that the radiation is emitted by cold starless objects, without any significant central energy source. Only 8 protostars (blue, white-red, and white-pink sources) are visible in the composite and PACS images, while as many as 39 cold prestellar cores become detectable and measurable in the SPIRE wavebands, as can be seen in the lower panels of Fig. 21.

The dense cold prestellar cores are clearly situated within a complex web of filamentary structures at significant intensity peaks; due to their nature, the cores must also coincide with significant column density peaks. The left panel of Fig. 22 displays a column density image of the cold cluster, demonstrating that most extracted sources are indeed centered on the column density peaks. A couple of compact sources appear to be offset from the column density peaks and intensity peaks at SPIRE wavelengths. These are the protostars prominent in the PACS bands that happened to either coincide (in projection) with those locations or form off-center in the dense clumps. We show in Fig. 22 the ellipses of all 46 detected sources; there are 7 additional sources that are not measurable at some wavelengths and therefore not visualized by ellipses in Fig. 21. The middle panel of Fig. 22 shows the same set of extraction ellipses on top of the combined detection image (at scales $S_j ≤ 80′′$) that clarifies why getsources found the sources at all those locations. In addition, the right panel shows the clean background image $I_{\lambda0CB}$ at 500 μm that demonstrates that no significant sources in the Aquila sub-field were left undetected by getsources.

These results (visualized in Figs. 21, 22) demonstrate that getsources handles very well the multi-wavelength Herschel observations of resolved starless cores, the main ingredient of the Aquila sub-field. Although all unresolved protostars were also extracted, it is the next example that focuses on protostellar population.

3.2. Clustered unresolved protostars in Rosette

The observations, data reduction, and first results for the Rosette star-forming region (part of the HOBYS survey, adopted distance $D = 1.6$ kpc) have been described by Motte et al. (2010); Schneider et al. (2010); Hennemann et al. (2010); di Francesco et al. (2010). The Rosette sub-field (395 × 395 1′/4 pixels), shows a central part of the Rosette field with an extended bright area at 70 μm and a number of unresolved isolated and clustered protostars in the PACS wavebands. This sub-field of Rosette was chosen to illustrate the performance of getsources for studying faint unresolved protostars in distant star-forming regions (Figs. 23, 24).

Similarly to Fig. 21, the lower-right panel of Fig. 23 shows a 3-color composite image of the extracted sources in the Rosette sub-field, represented by their elliptical deblending shapes with the measured peak intensities, sizes, and orientations. Note, however, that the color image is strongly affected by the difference in spatial resolutions in the wavebands (by factors of ∼3 and 2) than the color image shown in Fig. 3a, as most of the sources in the distant Rosette sub-field are unresolved even at 70 μm. Most of the sources remain in all of the Herschel images displayed in the other panels of Fig. 23; they are deblended and remain measurable all the way to the lowest resolution of the 500 μm band. Figures 23, 24 also highlight severe problems encountered by the usual “monochromatic” algorithms when they extract sources independently at individual wavelengths and then associate sources based on their positions in the images with such greatly varying resolutions.

The redder (colder) sources are mostly found in the lower half of the image, whereas the bluer sources are scattered over the Rosette sub-field. Here we will focus on the compact unresolved sources visible quite clearly in the 70 μm waveband in relatively low-background conditions, which can be used to judge whether getsources is able to separate faint peaks that are close to each other. One can count 35 such sources that are mostly clustered in groups of two, three, or four; we will limit our discussion to the six groups labeled A–F in Fig. 23. Aiming to clarify why getsources found the sources at those locations, the left panel of Fig. 24 shows the extraction ellipses of all sources on top of the combined detection image (at scales $S_j ≤ 12′′$). The middle panel of Fig. 24 displays the background-subtracted image giving the clearest view of the sources and its right panel shows the clean background image $I_{\lambda0CB}$ at 70 μm demonstrating, that no significant sources in the Rosette sub-field were left undetected by getsources.

Group A consists of 4 protostars of different brightness but very similar separations between the neighbors, clearly distinct

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24 The respective sub-fields are similar to the areas displayed in Fig. 5 of Könyves et al. (2010) and in Fig. 1 of Hennemann et al. (2010).
Fig. 21. The Aquila sub-field (18′ × 18′) is shown as the observed images $I_{\lambda,O}$ at 70, 160, 250, 350, 500 $\mu$m (left to right, top to bottom) with the extraction ellipses (FWHM) of only measurable sources ($F_{\lambda,P} > \sigma_{\lambda,P}$ and $F_{\lambda,T} > \sigma_{\lambda,T}$) overlaid, as well as the composite 3-color RGB image (500, 250, 160 $\mu$m) created using the images $I_{\lambda,M}$ of the deblending shapes of each extracted source (lower-right). The default condition, that a tentative source must be detected in at least two bands, was used. Only the protostars are visible at 70 $\mu$m, whereas at 160 $\mu$m one starless core appears, the other cold sources becoming clearly visible in the SPIRE bands. For better visibility, the values displayed in the panels are somewhat limited in range; the color coding in the lower-right panel is linear, in all other panels it is a function of the square root of intensity in MJy/sr.

Fig. 22. The Aquila sub-field is shown as a column density image with a 37″ resolution (left, Könyves et al. 2010), an accumulated clean combined detection image containing spatial scales of up to 80″ (middle), obtained by summing up the single scales $I_{\lambda,C}$ in that range, with the 500 $\mu$m ellipses of all detected sources overplotted. Also shown is the clean background $I_{\lambda,OCB}$ (right) at 500 $\mu$m. For better visibility, the values displayed in the panels are somewhat limited in range; the color coding in all panels is a function of the square root of column density and of intensity in MJy/sr.
Fig. 23. The Rosette sub-field (9’ × 9’) is shown as the observed images $I_{\lambda}$ at 70, 160, 250, 350, 500 $\mu$m (left to right, top to bottom) with the extraction ellipses (FWHM) of only measurable sources ($F_{\lambda 1} > \sigma_{\lambda 1}$ and $F_{\lambda 2} > \sigma_{\lambda 2}$) overlaid, as well as the composite 3-color RGB image (500, 250, 70 $\mu$m) created using the images $I_{\lambda 3}$ of the deblending shapes of each extracted source (lower-right). The default condition, that a tentative source must be detected in at least two bands, was used. Most of the compact sources visible at 70 $\mu$m are unresolved protostars; several groups of them, discussed in Sect. 3.2, are labeled A–F. For better visibility, the values displayed in the panels are somewhat limited in range; the color coding in the lower-right panel is linear, in the other panels it is a function of the square root of intensity in MJy/sr.

Fig. 24. The Rosette sub-field is shown as the accumulated clean combined detection image containing spatial scales of up to 12” (left), obtained by summing up the single scales $I_{D\lambda j}$ in that range, with the 160 $\mu$m ellipses of all detected sources overplotted. Also shown are the background-subtracted image $I_{D\lambda BS}$ (middle) and clean background $I_{D\lambda CB}$ (right) at 70 $\mu$m; when added together, they make up the original 70 $\mu$m image in Fig. 23. For better visibility, the values displayed in the panels are somewhat limited in range; the color coding is a function of the square root of intensity in MJy/sr.
at 70 μm and extracted by getsources across all wavelengths. Group B presents a more difficult case of 4 sources with decreasing brightness and distance between the members; the faintest protostar on top of group B is almost merged with its neighbor, but still has been detected and measured in 4 bands. A similar case is displayed by group C, where one faint source is situated between two other brighter sources; the faintest source is measurable only in the highest-resolution image at 70 μm. In group D we have another similar cluster of 4 sources with an extremely faint source surrounded by the brighter ones; most members of group D are measurable across all wavelengths. Group E is correctly extracted as two close companions, with only the brighter source being measurable in all wavebands. Group F is two relatively bright protostars at a very small separation. Although they are practically merged together, with a saddle point just a few percent below the peaks, the binary is detected as such and both components are measurable up to 250 μm.

The results presented in Figs. 23, 24 show that getsources handles very well the multi-wavelength Herschel observations of unresolved protostars, the main ingredient of the sub-field. It fully preserves the highest-resolution information from the 70 μm waveband and uses it to correctly identify and measure close companions in all groups of protostars at all wavelengths.

4. Conclusions

The multi-scale, multi-wavelength source extraction method getsources presented in this paper, was designed primarily for use in large far-infrared and submillimeter surveys of star-forming regions with Herschel. Instead of following the traditional approaches of extracting sources directly in the observed images (Sect. 1.1), the method analyzes highly-filtered decompositions of original images over a wide range of spatial scales (Sect. 2.2). The algorithm separates the peaks of real sources from those produced by the noise and background fluctuations (Sect. 2.3) and constructs wavelength-independent sets of combined single-scale detection images (Sect. 2.4) preserving spatial information from all wavebands. Sources are detected in the combined detection images by tracking the evolution of their segmentation masks across all spatial scales (Sect. 2.5). Source properties are measured in the original background-subtracted and deblended images at each wavelength in iterations (Sect. 2.6). Additional catalogs and images are produced to aid in the analysis of the extraction results (Sect. 2.7), complementing the main catalog of sources. Based on the results of the initial extraction, detection images are flattened to produce much more uniform noise and background fluctuations in preparation for the second, final extraction (Sect. 2.8). The performance of the new method on Herschel images was illustrated by extracting sources in small sub-fields of the Aquila and Rosette regions (Sect. 3).

There are several significant advantages of getsources over other existing methods of source extraction. (1) The fine spatial decomposition filters out irrelevant spatial scales and improves detectability, especially in the crowded regions and for extended sources. (2) The multi-wavelength design enables combining data over all wavebands, eliminating the need to match independent extraction catalogs and enabling substantial super-resolution in the images with lower spatial resolution. (3) The single-scale detection algorithm identifies sources and determines their characteristic sizes, avoiding spurious peaks on top of large structures and filaments. (4) The background subtraction and deblending, based on the wavelength-dependent footprint of each source, disentangle crowded regions with overlapping sources. (5) The extraction process is fully automatic and there are no free parameters involved: the default configuration works best in all cases that have been tested.

A disadvantage of the algorithm is that it may not be very fast and it may require considerable storage space, depending on the numbers of pixels, spatial scales, wavelengths, iterations, and potential sources detected (Appendix G); most of the space can be freed, however, after the extraction has been completed.

The method has been thoroughly tested using many simulated benchmark images and real-life observations. In particular, the overall benchmarking results (Men’shchikov et al., in prep.) have shown that getsources comes on top of the other source extraction methods that we have tested (Sect. 1.1) in both the completeness and reliability of source detection and the accuracy of measurements. The source extraction code is automated, very flexible, and easy-to-use; the code and validation images with a reference extraction catalog are freely available (see Appendix G).

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Appendix A: Astrophysical objects: dense cores

The primary goal of this work is to develop a source extraction method suitable for the systematic detection and measurement of dense cores in molecular clouds with Herschel: one of the main observational objectives of the Gould Belt survey (Andrè et al. 2010) is to obtain a complete census of such prestellar cores in nearby molecular clouds.

The structure of molecular clouds is often filamentary (e.g., Schneider & Elmegreen 1979); it is also known to be highly hierarchical and self-similar over a wide range of scales (e.g., Falgarone et al. 1991). This structure can be attributed to the role of supersonic interstellar turbulence (e.g., Larson 1981) and is reasonably well described by fractal models (e.g., Elmegreen & Falgarone 1996). However, interstellar turbulence dissipates on small scales; coupled to the effects of gravity in gravitationally-bound clouds, this breaks the self-similarity of cloud structure on scales below ~0.1 pc (e.g., Williams et al. 2000). The latter is the typical scale below which prestellar cores, the self-gravitating condensations of gas and dust giving birth to individual stars or systems, are observed in molecular clouds (e.g., Motte et al. 1998, 2001; Andrè et al. 2000). Prestellar cores are observed at the bottom of the hierarchy of interstellar cloud structures and depart from Larson (1981)’s self-similar scaling relations. They correspond to “coherent” regions of nearly constant and thermal velocity dispersion which do not obey Larson’s power-law linewidth vs. size relation (e.g., Myers 1983; Goodman et al. 1998). The 18” angular resolution of Herschel at 250 μm, equivalent to 0.03 pc at a distance of 350 pc, is sufficient to resolve the typical Jeans length in the nearby clouds; this is also the characteristic diameter expected for Bonnor-Ebert-like cores.
To first order, known prestellar cores have simple, convex, not very elongated shapes, and their density structure approaches that of the Bonnor-Ebert isothermal spheroids bound by the external pressure exerted by the parent cloud (e.g., Johnstone et al. 2000; Alves et al. 2001). Conceptually, a dense core may be defined as the immediate vicinity of a local minimum in the gravitational potential of a molecular cloud, corresponding to the part of the cloud under a given local gravitational influence. While, in general, the gravitational potential cannot be inferred from observations, it turns out to be directly related to the observable column density distribution (e.g., Elia et al. 2004, Padoan et al. 2004). The supercritical layers produced by supersonic turbulence in numerical simulations of cloud evolution (Gong & Ostriker 2011). In practical terms, this means that one can define a dense core (more precisely, its projection onto the plane of the sky) as the immediate vicinity of a local maximum in observed column density maps, such as those derived from Herschel imaging, where dust continuum emission is largely optically thin and directly traces column densities. The source extraction method presented in this paper offers a new approach to the detection and measurements of sources, making full use of the multi-scale, multi-wavelength nature of the source extraction problem in the case of Herschel data. Analyzing a wide range of spatial scales, our method is able to detect the hierarchical structures of molecular clouds (cf. Sect. 2.5). Unlike such techniques as the dendrogram analysis (Rosolowsky et al. 2008), however, getsources is not explicitly designed to characterize the hierarchy of structures; our main focus is on the “compact” sources, at the end of the hierarchy.

### Appendix B: List of symbols

For convenience of the readers, we list and define all symbols introduced in Sect. 2 of this paper:

- \( A_i \) images of the annuli around all detected sources
- \( D_i \) images of local standard deviations for flattening
- \( J_i \) image of the initial footprints after source detection
- \( F_i \) images of source footprints in measurement iterations
- \( F_i^* \) images of source footprints expanded by convolution
- \( G_i \) smoothing Gaussians in successive unsharp masking
- \( G_i^A \) smoothing Gaussians used to create detection images
- \( I_{Dj,C} \) clean detection images combined over wavelengths
- \( I_{Dj,C1} \) partial detection images above the sub-level \( \omega_{j1} \)
- \( I_{Dj,C} \) clean detection images combined over wavelengths
- \( I_{Dj,S} \) single-scale segmentation images of source masks
- \( I_{OBS} \) background-subtracted, deblended images of sources
- \( I_j \) original observed images produced by a map-maker
- \( I_{DF} \) flattened detection images for the final extraction
- \( I_{Dj} \) detection images: either \( I_{Oj} \) or transformed \( I_{Oj} \)
- \( I_{Dj,C} \) single-scale decompositions of the images \( I_{Dj} \)
- \( I_{Dj,C} \) single-scale images cleaned of noise and background
- \( I_{Dj,C1} \) full clean images reconstructed from \( I_{Dj,C1} \)
- \( I_{Dj,R} \) single-scale images of the cleaning residuals
- \( I_{DR} \) full residuals images reconstructed from \( I_{Dj,R} \)
- \( I_{DF} \) scaling images smoothed by convolution
- \( I_{DM} \) images of the deblending shapes of all sources
- \( I_{QO} \) measurement images: \( I_1 \) resampled to pixel \( \Delta \)
- \( I_{OBS} \) background-subtracted images of all detected sources
- \( M_{BC} \) clean-background images with all sources removed
- \( N_{BC} \) source mask images accumulated over scales and \( \lambda \)
- \( M_i \) observational mask images defining areas of interest
- \( T_{j1} \) threshold images with all pixels set to \( \sigma_{j1} \)
- \( a_i \) major length of a source segmentation mask at \( \omega_{j1} \)
- \( A_i \) major FHWM size of a source \( i \)
- \( A_i \) major axis of the footprint ellipse of a source \( i \)
- \( A_i \) major axis of the footprint ellipse of a source \( i \) at scale \( \lambda \)
- \( A_{max} \) maximum FHWM sizes of sources to be extracted
- \( B_i \) minor length of a source segmentation mask at \( \omega_{j1} \)
- \( B_i \) minor FHWM size of a source \( i \)
- \( B_i \) minor axis of the footprint ellipse of a source \( i \)
- \( B_i \) minor axis of the footprint ellipse of a source \( i \) at scale \( \lambda \)
- \( C_i \) contrast of a source \( i \) above the sub-level \( \omega_{j1} \)
- \( C_i \) minimum contrast \( C_i \) for real sources
- \( \lambda \) required minimum contrast \( C_i \) for real sources
- \( \eta \) amplification factor in the detection of noise peaks
- \( \eta \) elongation factor in the detection of noise peaks
- \( \sigma_{j1} \) elongation factor at the footprinting scale \( j \)
- \( \omega_{M} \) contrast of a source
- \( \Delta \) peak intensity of a source
- \( j \) running number of a source in the extraction catalog
- \( j \) peak intensity of a source \( i \) at scale \( j \)
- \( j \) peak intensity of a source \( i \) in the image \( I_{Dj,C} \)
- \( j \) peak intensity of a source \( i \) in \( I_{Dj,C} \) at scale \( jF \)
- \( j \) pixel intensity in a single-scale detection image
- \( j \) maximum intensity over the clean image \( I_{Dj,C} \)
- \( j \) running number of a decomposed spatial scale
- \( j \) number of the footprinting scale of a source
- \( j \) contrast of a source
- \( j \) maximum allowed value of \( k_{j1} \) during cleaning
- \( j \) running number of the intensity sub-level \( \omega_{j1} \)
- \( j \) minimum number of \( \lambda \)'s a source must be detected at
- \( j \) number of pixel in a partial detection image
- \( j \) contrast of a source
- \( j \) smallest pixel in a cluster of connected pixels
- \( j \) minimum value of \( N_{Lj} \) for detecting sources in \( I_{Dj,C} \)
- \( j \) number of pixels in a cluster of connected pixels
- \( j \) minimum value of \( N_{Lj} \) for \( I_{Dj,C} \) for making \( I_{Dj,C} \)
- \( j \) observational angular resolution: FHWM beam size
- \( j \) observational beam size averaged over wavelengths
- \( j \) reliability of an extracted source
- \( j \) maximum allowed value of \( s_{j1} \) during cleaning
- \( j \) spatial scale: FHWM of a smoothing Gaussian beam
- \( j \) characteristic footprinting scale of a source in \( I_{Dj,C} \)
- \( j \) characteristic footprinting scale of a source in \( I_{Dj,C} \)
- \( j \) largest spatial scale in a single-scale decomposition
- \( j \) weight enhancing contribution of high-res. images
- \( j \) source coordinates obtained in the detection process
- \( j \) source coordinates in the equatorial system parameter in the detection of noise peaks
Appendix C: Simulated star-forming region

To illustrate the spatial decomposition and all other processing steps of *getsources* in this paper, we use a simulated star-forming region that we constructed well before the launch of *Herschel* in order to have a reasonably realistic model; it is sufficient to give here the following brief description.25

The simulated star-forming region, placed at 140 pc, consists of a synthetic (scale-free) cirrus background fitted to a typical 100 μm intensity of the backgrounds in the Gould Belt survey and scaled to all other *Herschel* wavebands assuming a blackbody with a dust temperature of 17.5 K (cf. Lagache et al. 1999). The background was populated with 360 starless cores and 107 protostars with realistic intensity distributions, obtained from a large grid of 129 one-dimensional dust continuum radiative transfer models. The density distribution of the cores followed the structure of critical Bonnor-Ebert spheres, whereas the protostars had \( \rho \propto r^{-2} \) density profiles; both types of objects were embedded in background spherical clouds with a uniform density. The standard isotropic interstellar radiation field was shining on the outer edges of the clouds, making the temperature profile inverted (lower in the center) in all objects. Protostars, however, restored usual temperature distributions deeper towards their central parts, as they produced an accretion luminosity \( (L_{\text{acc}} \propto M) \); they had accreted half of the mass of the cores they formed from (the conceptual borderline between Class 0 and Class I objects, André et al. 2000). Starless cores consisted of low-, medium-, and high-density sub-populations and were distributed according to the \( M_{\text{BE}} \propto R_{\text{BE}} \) relation for the isothermal Bonnor-Ebert spheres \( (T_{\text{BE}} = 7, 14, 28 \text{ K}) \) in the area of the mass-radius diagram occupied by prestellar cores observed in the Orion and Ophiuchus star-forming regions (Motte et al. 1998, 2001). All populations span wide ranges of masses \((0.01 - 10 M_{\odot})\) and radii \((0.001 - 0.1 \text{ pc})\). Random noise (at the expected levels of the instrumental noise) was added to all pixels of the simulated images and the latter were convolved to the expected observational resolutions of 5, 7, 11, 17, 24, and 35″ in all PACS and SPIRE bands at 70, 100, 160, 250, 350, and 500 μm.

Appendix D: A look in the Fourier domain

The original images and their single-scale decompositions can be transformed into the Fourier domain. The successive unsharp masking described by Eq. (1) (Sect. 2.2) can also be formulated in terms of the Fourier transforms of the images. For those readers who are used to the transformations between the image and Fourier domains, we present some additional images that may be useful for better understanding of *getsources*.

In Fig. D.1, we show the amplitudes of the complex Fourier transform for the simulated star-forming region that is used in this paper to illustrate *getsources* (cf. Appendix C). In the simulated images, one exactly knows all individual components: the model sources, background, and noise; the amplitudes of the three components are displayed in the top panels of Fig. D.1. The Fourier transforms of the sources and noise are clearly dominated by the fact that the original images have a resolution of the 350 μm *Herschel* band: higher spatial frequencies have been suppressed by the convolution with the observational beam. Although the transform of the synthetic background is also shaped by the limited angular resolution at high frequencies, the steep power spectrum \( P(g) \propto g^{-3} \) of the synthetic background carries most of its power on large scales (cf. Appendix E) and hence the amplitude remains strongly peaked at zero frequency. The full simulated image has all components added together and at each spatial frequency the Fourier amplitude becomes a mixture of the noise, background, and sources that cannot be cleanly separated anymore (Fig. D.1, middle-left panel).

Our source extraction method attempts to give a practical solution to the problem of separating sources from all other components by decomposing the original images in a large number of fine spatial scales using a procedure that involves successive convolution and subtraction of the images (cf. Sect. 2.2, Eq. (1)). In effect, such a decomposition creates a set of the filtered “single-scale” images \( I_{\lambda j} \), each containing considerable signals from only a limited range of spatial scales (or frequencies) that are determined by the size \( S_{\lambda} \) of the smoothing Gaussian beam. Consequently, in the Fourier domain, the single-scale images look like toroidal structures of variable widths heavily overlapping with each other over a substantial range of frequencies (Fig. D.1). By construction, the simulated sky does not include any asymmetric or highly-elongated (filamentary) structures, therefore the toroids look very regular and symmetric in the Fourier domain. The actual fields observed by *Herschel* are, however, more complicated, containing lots of filamentary structures, that make the toroids less symmetric. To illustrate their appearance in the real observations, we present in Fig. D.2 Fourier amplitudes of a few single-scale images for the Aquila and Rosette star-forming regions.

The Fourier space representation is useful for understanding some aspects of our method, as well as for image convolution (for which we apply a discrete fast Fourier transform algorithm). However, *getsources* is not entirely translatable into the Fourier domain and remains fundamentally the image-oriented method of source extraction.

Appendix E: Power spectra of image components

The ability to detect compact sources, such as dense cores, in the wide-field images obtained as part of the Gould Belt and

\[ \gamma \] weighting power-law exponent defining \( w_{\lambda j} \)

\[ \Delta \] pixel size (the same for all images in an extraction)

\[ \lambda \] wavelength (central wavelength of a waveband)

\[ \mu_{\lambda j} \] third statistical moments about the mean value

\[ \mu_{\lambda} \] fourth statistical moments about the mean value

\[ \sigma_{\lambda j} \] iterated cleaning thresholds (cut-off levels)

\[ \sigma_{\lambda} \] standard deviation in a single-scale image

\[ \sigma_{\lambda,T} \] standard deviation in a full image

\[ \sigma_{\lambda,b} \] standard deviation in a detection image at scale \( j \)

\[ \sigma_{\lambda,IP} \] uncertainty of the peak intensity \( F_{\lambda,IP} \) of a source

\[ \sigma_{\lambda,T} \] uncertainty of the total flux \( F_{\lambda,T} \) of a source

\[ \Pi_{l}, \Pi_{m} \] pixels \( l, m \) in the clean combined images \( I_{\lambda j} \)

\[ \Theta_{T,Ed} \] position angle of the elongation of a footprint

\[ \Theta_{\lambda,Ed} \] position angle of the elongation of a source

\[ \Xi_{\lambda} \] global significance over all wavelengths \( \lambda \)

\[ \Xi_{\lambda,i} \] monochromatic significance of a source \( i \) at \( \lambda \)

\[ \Xi_{\lambda,el} \] reliable level of significance for extracted sources

\[ \Xi_{\lambda,en} \] tentative level of significance for extracted sources

\[ \Omega_{l} \] global signal-to-noise ratio over all wavelengths

\[ \Omega_{\lambda,i} \] monochromatic signal-to-noise ratio of a source \( i \)

\[ \omega_{\lambda} \] sub-levels of intensities during source detection.

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25 Full description of this and other synthetic skies will be given in another paper (Men’shchikov et al., in prep.) devoted to benchmarking of source extraction algorithms.
HOBYS surveys with Herschel is primarily limited by the confusion arising from the small-scale cloud structure. In contrast, the instrumental noise and mapping artifacts are often negligible. An important property of the background cloud fluctuations is that they do not follow Gaussian statistics. In particular, it is well known that the power spectrum of interstellar cloud fluctuations strongly depends on spatial scales ($P(q) \propto q^{-3}$, where $q$ is spatial frequency; e.g., Roy et al. 2010, and references therein).
Fourier transform of the actual star-forming regions observed by Herschel at 350 μm with a 25″ resolution. Shown are the amplitudes of the decomposed images of Aquila (top left to right) and Rosette (bottom left to right); the scale sizes $S_j$ are annotated at the bottom of the panels. For the original Aquila images with 4096 × 4096 3″ pixels and Rosette images with 2048 × 2048 3″ pixels, the panels present the Fourier amplitudes within the range of spatial frequencies from zero to one-third of the Nyquist frequency (0.17 arcsec$^{-1}$). For better visibility, the spatial frequencies and the pixel values are somewhat limited in range; the color coding is linear.

As illustrated in Fig. E.1, which shows the power spectrum of a SPIRE 250 μm image of the Polaris cirrus cloud (see also Fig. 3 of Miville-Deschênes et al. 2010). In practice, this means that the background fluctuations are much stronger on larger scales and, unlike Gaussian fluctuations, cannot be characterized by a single value of the standard deviation. Indeed, they are better described by a wide range of standard deviations, as reflected in their power spectrum (Fig. E.1). Accordingly, the probability density function (PDF) of submillimeter intensity (or column density) variations in the Herschel images of Galactic fields is not Gaussian, but typically lognormal in non-star-forming clouds, such as Polaris (Schneider et al., in prep.; see also Kainulainen et al. 2009).

In contrast to the astrophysical backgrounds, the instrumental noise fluctuations are approximately Gaussian, having a flat power spectrum, essentially independent of spatial frequency (white noise). This is illustrated in Fig. E.1, which shows the estimated power spectrum of the instrumental noise in a typical Herschel image at 250 μm, derived from the power spectrum of the PACS 70 μm image of the Polaris field with no significant cloud emission (cf. Men'shchikov et al. 2010; Miville-Deschênes et al. 2010; André et al. 2010). For a better comparison with the power-law cirrus profile in Fig. E.1, the spatial frequencies sampled in the original PACS 70 μm data were scaled down by a factor 70/250, to represent the typical range of spatial frequencies in the SPIRE 250 μm images of the Herschel Gould Belt survey. Likewise, the power spectrum of the intensity distribution of a Gaussian source with a half-maximum width $D$ is itself Gaussian and thus flat approximately up to its half-maximum width $2^{3/2} \ln 2 (\pi D)^{-1}$ in spatial frequencies.

Figure E.1 illustrates why decomposing the observed images into a finely-spaced set of filtered images is advantageous for source extraction. Given the typical power spectra of the background fluctuations, instrumental noise, and Gaussian-like sources, the maximum contrast of a source with a size $D$ over the background fluctuations is obtained at spatial frequencies $0.46 D^{-1}$ or, equivalently, for spatial scales close to $2.2 D$. By performing source detection in a fine grid of single-scale images, getsources can automatically identify and use the scale at which the contrast of each source over the background is maximized, thereby improving source detectability.

Another great advantage of the fine spatial decomposition employed by getsources (Sect. 2.2) is that the emission fluctuations in the decomposed single-scale images of interstellar clouds follow Gaussian statistics much more closely than the...
Cloud fluctuations in the observed images containing all spatial scales (cf. Fig. 5). This is because each single-scale image of a cirrus cloud can be characterized by a single standard deviation value much better than the original image, since it selects only a narrow range of spatial frequencies from a power-law spectrum of standard deviations, such as that shown in Fig. E.1.

Appendix F: Estimating shapes of sources

We derive the source coordinates, sizes, and orientations from the background-subtracted, deblended intensity distributions over the pixels of their footprints using the first and second moments

\[ E(x) = \frac{\int x I(r) d^2r}{\int I(r) d^2r}, \]

\[ E(y) = \frac{\int y I(r) d^2r}{\int I(r) d^2r}, \]

\[ E(\tilde{x}^2) = \frac{\int \tilde{x}^2 I(r) d^2r}{\int I(r) d^2r}, \]

\[ E(\tilde{y}^2) = \frac{\int \tilde{y}^2 I(r) d^2r}{\int I(r) d^2r}, \]

\[ E(\tilde{x} \tilde{y}) = \frac{\int \tilde{x} \tilde{y} I(r) d^2r}{\int I(r) d^2r}. \]

where \(x, y\) are the Cartesian coordinates of a vector \(r = (x, y)\) and the pixel coordinates relative to the source barycenter are given by \(\tilde{x} = x - E(x)\) and \(\tilde{y} = y - E(y)\). Let us write the covariance matrix

\[ M = \begin{bmatrix} E(\tilde{x}^2) & E(\tilde{x} \tilde{y}) \\ E(\tilde{x} \tilde{y}) & E(\tilde{y}^2) \end{bmatrix} = \begin{bmatrix} \sigma_{xx} & \sigma_{xy} \\ \sigma_{xy} & \sigma_{yy} \end{bmatrix} \]

where \(\sigma_{xx}\) and \(\sigma_{yy}\) are the variances and \(\sigma_{xy}\) is the covariance of the intensity moments. For such a symmetric matrix \((\sigma_{xy} = \sigma_{yx})\), one can find eigenvalues \(\Lambda\) by solving the characteristic equation

\[ \det (M - \Lambda I) = 0, \]

where \(I\) is the identity matrix. This leads to the quadratic equation

\[ \Lambda^2 - (\sigma_{xx} + \sigma_{yy})\Lambda + \left(\sigma_{xx}\sigma_{yy} - \sigma_{xy}^2\right) = 0 \]

with the following two roots \(\Lambda^+\) and \(\Lambda^-:\)

\[ \Lambda^\pm = \frac{\sigma_{xx} + \sigma_{yy} \pm \sqrt{\left(\sigma_{xx} - \sigma_{yy}\right)^2 + 4\sigma_{xy}^2}}{2} \]

defining the major and minor axes of an ellipse. The major axis forms an angle \(\theta\) with the \(x\)-axis, given by

\[ \tan(2\theta) = \frac{2\sigma_{xy}}{\sigma_{xx} - \sigma_{yy}}. \]

The major and minor FWHM sizes, as well as the position angle (east of north) of a source \(i\) at wavelength \(\lambda\), are finally computed from

\[ A_{\lambda i} = (\Lambda^+ 8 \ln 2)^{1/2}, \]

\[ B_{\lambda i} = (\Lambda^- 8 \ln 2)^{1/2}, \]

\[ \Theta_{\lambda i} = \pi - \arctan \theta. \]

Appendix G: Installing and using getsources

The source extraction method described above has been developed by A.M. (since July 20, 2008) as a Bash script called getsources and a suite of the FORTRAN utilities executed by the script that perform most of the work. This ensures a high degree of portability and efficiency, as these two languages are the de facto standards in the worlds of the UNIX-like operating systems and numerical computations. Either Mac OS X or Linux and either ifort 11.1 or gfortran 4.5 can be used to install getsources; other systems and compilers have not been tested. A preparation script called prepareobs makes use of Swarp (Bertin et al. 2002) for image resampling and reprojection. To read and write images in the FITS format, getsources uses the CFITSIO library (Pence 1999); to convolve images, the fast Fourier transform routine rfft3 (Press et al. 1992) is used; the source coordinates \((\alpha, \delta)\) are computed by the utility xy2sky from WCSTools (Mink 2002).

The total processing times are proportional to the numbers of pixels, spatial scales, wavelengths, iterations, and potential sources detected, depending also on the computer CPUs available. The extraction time may vary between few minutes and a week, the latter being the longest time we have experienced and it refers to a 6-wavelengths extraction for 5:2 × 5:2 images with
To optimize the processing times, it is a good idea to test available ones much faster, running the extraction may want to split them into several sub-fields to obtain extraction results in parallel, one wavelength per CPU, as they are decomposed in parallel, one wavelength per CPU, as they are decomposed and cleaned independently of each other. If the computational time becomes an issue for enormously large images, the users can also use special mask images to exclude problematic (e.g., saturated) areas at some of the wavelengths to avoid using those areas in combining images over wavelengths and in detecting sources. Users can re-run only selected steps of the extraction and also restart the detection and measurements from any intermediate scale or iteration. There are also other possibilities; users are welcome to request information on their specific needs from the author.

The source extraction code with an installation guide and a quick start guide are freely available upon request or they can be downloaded from our web pages. Users installing getsources on their computers are advised to test it on a multi-wavelength extraction using Herschel images of the galaxy NGC 4559 that was chosen as our validation field (the galaxy was observed as part of the KINGFISH project, see Kennicutt et al. 2011). This relatively quick extraction performed by the author can also be requested or downloaded by the users who wish to validate their installation and verify that they are able to reproduce the reference extraction results.

References


26 To optimize the processing times, it is a good idea to test available disk storage for speed. The script lospeed enables comparisons of available hard drives by reading and writing a FITS image multiple times. One can perform tests of the local and network disks, as well as of the virtual disks.
