A new source detection algorithm using FDR

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ABSTRACT

The False Discovery Rate (FDR) method has recently been described by Miller et al. (2001), along with several examples of astrophysical applications. FDR is a new statistical procedure due to Benjamini & Hochberg (1995) for controlling the fraction of false positives when performing multiple hypothesis testing. The importance of this method to source detection algorithms is immediately clear: To explore the possibilities offered we have developed a new task for performing source detection in radio-telescope images, Sfind 2.0, which implements FDR. We compare Sfind 2.0 with two other source detection and measurement tasks, Insad and SExtractor, and comment on several issues arising from the nature of the correlation between nearby pixels and the necessary assumption of the null hypothesis. The strong suggestion is made that implementing FDR as a threshold defining method in other existing source-detection tasks is easy and worthwhile. We show that the constraint on the fraction of false detections as specified by FDR holds true even for highly correlated and realistic images. For the detection of true sources, which are complex combinations of source-pixels, this constraint appears to be somewhat less strict. It is still reliable enough, however, for a priori estimates of the fraction of false source detections to be robust and realistic. Further investigation of the relationship between ‘source-pixels’ and ‘sources’ is nevertheless important to more strictly constrain the fraction of falsely detected sources.

Subject headings: methods: data analysis — methods: statistical — techniques: image processing

1. Introduction

Detecting and measuring the properties of objects in astronomical images in an automated fashion is a fundamental step underlying a growing proportion of astrophysical research. There are many existing tasks, some quite sophisticated, for performing such analyses. Regardless of the wavelength at which an image has been made however, each of these tasks has one thing in common: A threshold needs to be defined above which pixels will be believed to belong to real sources.

Defining this threshold is a complex issue and, owing to the unavoidable presence of noise, any chosen threshold will result in some true sources being overlooked and some false sources measured as real. Varying the chosen threshold to one extreme or the other will minimise one of these types of error at the expense of maximising the other. Clearly choosing a threshold to jointly minimise both types of error is not trivial, but even more problematic is that it is not even clear that one can, a priori, make a well defined estimate of the magnitude of each type of error. Typically this is done by comparing measured source counts with existing estimates for the expected number of sources. This is an unsatisfactory solution for surveys reaching to new sensitivity limits, or at pre-
viously uninvestigated wavelengths (where there can be no estimate of the expected number of sources from existing studies), and also for small area imaging where the properties of large populations are affected by clustering or small number statistics.

Throughout this paper we shall use the terms ‘source-pixel’ to mean a pixel in an image which is above some threshold, and thus assumed to be part of a true source. The term ‘source’ shall be used to mean a contiguous collection of ‘source-pixels’ which corresponds to an actual astronomical object, a star or galaxy for example, whose properties we are interested in measuring. Now consider the following possible criteria applied to some chosen threshold: (1) That there be no falsely discovered source-pixels; (2) That the proportion of falsely discovered source-pixels be some small fraction of the total number of pixels (background plus source); (3) That the fraction of falsely discovered sources over the total number of discovered sources be small. The first of these can be achieved by using a very high threshold called the Bonferroni threshold (Miller et al. 2001). This threshold is rarely used since, although guaranteeing no false detections, it detects so few real sources. The second criterion is most often applied in astronomy, and can be achieved by simply choosing the appropriate significance threshold. A threshold of 3$\sigma$, for example, ensures that 0.1% of the total number of pixels are falsely discovered. Unfortunately this is not the same as a constraint on the fraction of false detections compared to total number of detections. This quantity is a more meaningful measure to use in defining a threshold for the following reason. Consider a 3$\sigma$ threshold in an image composed of $10^6$ pixels ($1000 \times 1000$) and containing only gaussian noise would yield, on average, 1000 pixels above the threshold. If real sources are also present, these 1000 pixels appear as false source-pixels, and if it happens that only 2000 pixels are measured as source-pixels, then half the detections are spurious! If many more pixels belong to sources, of course, this threshold may be quite adequate.

The third criterion defines a more ideal threshold. Such a threshold allows one to specify a priori the maximum number of false discoveries, on average, as a fraction of the total number of discoveries. Such a method should be independent of the source distribution (i.e., it will adapt the threshold depending on the number and brightness of the sources). The False Discovery Rate (FDR) method (Benjamini & Hochberg 1995; Benjamini & Yekutieli 2001; Miller et al. 2001) does precisely this, selecting a threshold which controls the fraction of false detections. We have implemented the FDR technique in a task for detecting and measuring sources in images made with radio telescopes.

Radio images were chosen for the current analysis for several reasons, including previous experience at coding of radio source detection tasks, but also since the conservative nature of constructing many radio source catalogues allows the value of this method to be emphasised. Traditionally radio source catalogues are constructed in a fashion aimed at minimising spurious sources, accomplished by selecting a very conservative threshold, which is usually 5$\sigma$ or even 7$\sigma$. This is partly driven by the difficulty of completely removing residual image artifacts such as sidelobes of bright sources, even after applying very sophisticated image reconstruction methods, and the desire to avoid classifying these as sources. Many of the issues surrounding radio source detection are described by White et al. (1997). While such a conservative approach may minimise false detections, it has the drawback of not detecting large numbers of real, fainter, sources important in many studies of the sub-$\mu$Jy and $\mu$Jy populations, for example. An FDR defined threshold may allow many more sources to be included in a catalogue while providing a quantitative constraint to be placed on the fraction of false detections.

Table 1 briefly describes the algorithms used in some common radio source detection and measurement tasks. There is much similarity in the selection of tasks available within the two primary image analysis packages, AIPS (Astronomical Image Processing System) and MIRIAD (Multichannel Image Reconstruction, Image Analysis and Display), as alluded to in the summaries given in this table, although the specifics of each such task certainly differ to a greater or lesser extent. In addition to these packages, AIPS++ also has a image measurement task, imagefitter, similar in concept to the Imfit tasks in AIPS and MIRIAD. A stand-alone task, SExtractor (Bertin & Arnouts 1996), is used extensively in image analysis for detecting and measuring objects, primarily in images
2. Simul 20

Simpl 20 grew out of an earlier implementation of Simul 10, which implemented a basic elementary peak-peak search to measure identified sources as is done in Inuit and Inupiaq. An important aspect of the source detection is that the FIR filter used in the implementation of Simul 10 is based on the same filter as used in the implementation of Simul 20, and it is useful to use both methods, particularly in the context of the FDR algorithm, which consists of two thresholding steps. The first step is to select a threshold value for the source detection, and the second step is to select a threshold value for the image quality assessment. The threshold value for the source detection is selected by minimizing the number of false alarms, and the threshold value for the image quality assessment is selected by minimizing the number of missed detections.

In the analysis below, we compare the effectiveness of the methods used in Simul 20 and the effectiveness of the methods used in Simul 10, and we find that the methods used in Simul 20 are more effective in terms of reducing the number of false alarms and missed detections. The differences in effectiveness are due to the fact that the methods used in Simul 20 are more robust to noise and variations in the input data. The method used in Simul 20 is based on the Gaussian kernel, which is more robust to noise and variations in the input data than the method used in Simul 10, which is based on the linear filter.

The Gaussian kernel is a good choice for the source detection task because it is robust to noise and variations in the input data. The Gaussian kernel is defined as a function of the distance between the source and the input data, and the Gaussian kernel is more robust to noise and variations in the input data than the linear filter. The Gaussian kernel is also more efficient than the linear filter, because it requires less computation to calculate the kernel.

The Gaussian kernel is used to calculate the threshold value for the source detection, and the threshold value for the image quality assessment is calculated by minimizing the number of false alarms and missed detections. The threshold value for the source detection is selected by minimizing the number of false alarms, and the threshold value for the image quality assessment is selected by minimizing the number of missed detections.
Table 1

<table>
<thead>
<tr>
<th>AIPS</th>
<th>miriad</th>
<th>Short description</th>
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<tbody>
<tr>
<td>IMFIT/JMFIT</td>
<td>Imfit</td>
<td>fits multiple gaussians to all pixels in a defined area.</td>
</tr>
<tr>
<td>SAD/VSAD/HAPPY</td>
<td>Imsad</td>
<td>defines islands’ encompassing pixels above a user defined threshold, and fits multiple gaussians within these areas.</td>
</tr>
<tr>
<td>Sfind 2.0</td>
<td></td>
<td>defines threshold using FDR to determine pixels belonging to sources, and fits those by a gaussian.</td>
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</table>

lated to the synthesised beam size, or point-spread function (PSF). If \( n \) is the (integer) number of pixels representing the PSF we define \( c_N = \sum_{i=1}^{n} \frac{1}{i} \). This will be discussed further in Section 4. A diagrammatic example of the threshold calculation is shown in Figure 1. It becomes obvious from this Figure that increasing or decreasing the value chosen for \( \alpha \) corresponds to increasing or decreasing the resulting \( p \)-value threshold, \( p_{\text{ext}} \), and the number of pixels thus retained as source-pixels. The FDR formalism ensures that the average fraction of false source-pixels will never exceed \( \alpha \). As described in Miller et al. (2001), this explanation of implementing FDR does not explain or justify the validity of FDR. The reader is referred to Miller et al. (2001) for a heuristic justification, and to Benjamini & Hochberg (1995) and Benjamini & Yekutieli (2001) for the detailed statistical proof.

Finally, once the FDR threshold is defined, the pixels with \( p < p_{\text{ext}} \), corresponding to source-pixels, can be analysed. Each of the source-pixels are investigated in turn as follows. A hill-climbing procedure starts from the source-pixel and finds the nearest local maximum from among the contiguous source-pixels. From this local peak, a collection of contiguous, monotonically decreasing pixels are selected to represent the source. At this point, it is possible to either (1) use all of the pixels around the peak which satisfy these criteria, or (2) use only those which are themselves above the FDR threshold. The latter is the default operation of Sfind 2.0, but the user can specify an option for choosing the former method as well. The former method, which allows pixels below the FDR threshold to be included in a source measurement, may be desirable for obtaining more reasonable source parameters for sources close to the threshold. In either case, the resulting collection of source-pixels is fit in a least-squares fashion by a two-dimensional elliptical gaussian. If the fit is poor, the source is rejected. If the fit was accepted the source is is characterised by the fitted gaussian parameters, and the pixels used in this process are flagged as already belonging to a source to prevent them from being investigated again in later iterations of this step. On completion, a source catalogue is written by the task, and images showing (1) the pixels above the FDR threshold, and (2) the normalised image, may optionally be produced.

3. Task comparisons

To compare the effectiveness of Sfind 2.0, Imsad and SExtractor, one hundred artificial images 361 × 391 pixels in size were generated. Each of these contained a different instance of random gaussian noise and the same catalogue of 72 point sources with known properties (position and intensity). The artificial images were convolved with a gaussian to mimic the effects of a radio telescope PSF. The test images have 2′ pixels, and the gaussian chosen to represent the PSF has FWHMa of 11″73 × 3″52 with a position angle of 16.3°. The (convolved) artificial sources in the absence of noise can be seen in Figure 2, along with one of the test images.

On each image, Sfind 2.0 was run with \( \alpha = 0.01 \), 0.05 and 0.1, and the resulting lists of detected sources compared with the input catalogue. By way of an example, the sources detected in a sin-
ingle test of Sfind 2.0 are shown in Figure 3, which indicates by an ellipse the location, size and position angle of each detected source. This example demonstrates the difficulty of detecting faint sources, and the ability of noise to mimic the characteristics of faint sources.

3.1. Source pixel detection

Miller et al. (2001) examined the simplest possible scenario, source-pixels placed on a regular grid in the presence of uncorrelated gaussian noise. Here we investigate a much more realistic situation. The ‘source-pixels’ now lie in contiguous groups comprising ‘real’ sources in the sense that the whole image (background and sources) has been convolved with a PSF. The number of pixels in each source above a certain threshold will vary depending on the intensity of the source. We now confirm that the FDR method works consistently on these realistic images.

To verify the reliability of the FDR defined threshold, the number of pixels detected above the FDR threshold in each test were recorded along with the number which were unassociated with any true source. The distribution of this fraction of false FDR pixels should never exceed the value specified for $\alpha$, and this can be seen in the histogram in Figure 4. This Figure also shows how the distribution of falsely detected pixels changes with the form chosen for $c_N$, emphasising that the assumption of complete independence of the pixels is not justified (as expected), but neither is the image fully correlated, evidenced by the conservative level of false detections seen under this assumption. Our choice for the form of $c_N$, which is not in fact a result of the rigorous statistical proof, appears to be a feasible and reliable intermediate for such ‘partially correlated’ images.

3.2. Source detection

The FDR formalism ensures that the average fraction of falsely detected pixels will be less than $\alpha$. The connection between numbers of pixels and numbers of sources is complex, however, and the same criterion cannot be said to be true for the fraction of falsely detected sources. The fraction of falsely detected sources in each image, as well as the fraction of true sources not detected, are shown in Figure 5 as distributions for each tested value of $\alpha$. By construction, a number of the artificial sources have intensities comparable to or lower than the noise level in the images, so not all sources will be able to be recovered in every image. This is reflected in the fact that somewhat more than 5% of sources are missed (by all tasks tested) even with very liberal thresholds.

The histograms in Figure 5(a) show that for $\alpha = 0.1$, where up to 10% of pixels could be expected to be false, the fraction of false sources is not much more. The result for $\alpha = 0.05$, is also quite reasonable, although for $\alpha = 0.01$ the outliers are further still, relatively speaking, from the expected fraction. While the strict constraint applicable to the fraction of false source-pixels no longer holds for false sources, it still seems to be quite a good estimator. For the case where only the peak pixel is required to be above the FDR threshold, Figure 5(c), the fractions of falsely detected sources are not so strongly constrained. For $\alpha = 0.1$, the fraction may be almost twice that expected. In both cases, although with greater reliability in the former, this allows the FDR method to provide an estimate of the fraction of false sources to expect. Even though the constraint may not be rigorous, and clearly the estimate will be much more reliable in the case where all source-pixels are required to be above the FDR threshold, the FDR method allows a realistic a priori estimate of the fraction of false detections to be made. This feature is not possible with the simple assumption of, say, a $5\sigma$ threshold.

To test Imasad and SExtractor in the same fashion as Sfind 2.0, a choice of threshold value as a multiple of the image noise level ($\sigma$) was required. Simply selecting a canonical value of $3\sigma$, $5\sigma$ or $7\sigma$, for example, would complicate the comparison between these tasks and Sfind 2.0, as this would be testing not only different source measurement routines but also potentially different thresholds. The values of $\alpha$ selected for testing Sfind 2.0 result in threshold levels which correspond approximately, (since the noise level varies minimally from image to image), to $4.1\sigma$, $3.6\sigma$ and $3.3\sigma$. A $5\sigma$ threshold in these simulations would correspond to a value of $\alpha \approx 0.0001$.

In a brief aside, it should be emphasised that this particular correspondence between a choice of $\alpha$ and a particular $\sigma$-threshold is only valid for the noise and source characteristics of the images used.
in the present simulations. For images with different noise levels or different source intensity distributions, any particular value of \( \alpha \) will correspond to some different multiple of the local noise level. The primary advantage of specifying an FDR \( \alpha \) value over choosing a 5\( \sigma \) threshold, say, is that the FDR threshold is adaptive. The FDR threshold will assume a different value depending on the source intensity distribution relative to the background. This point is made very strongly in Miller et al. (2001) in the diagrams of their Figure 4. As a specific example in the context of the current simulations, we investigated additional simulated images containing the same noise as in the current simulations but containing sources having very different intensity distributions. We chose one intensity distribution such that every source was 100 times brighter than in the current simulations and one such that every source was 100 times fainter. In the brighter case, the FDR threshold for \( \alpha = 0.01 \), ensuring that on average no more than 1\% of source-pixels would be falsely detected, corresponded not to 4\( \sigma \), but to about 400\( \sigma \). The simple assumption of a 4\( \sigma \) or 5\( \sigma \) threshold in this case would introduce more false detections. In the fainter case, where almost all the artificial sources are comparable to the noise level, the same FDR threshold corresponds to about 1.6\( \sigma \). Of course in this case almost no sources are detected, for obvious reasons, but the same constraint on the fraction of falsely detected pixels applies. In this case a 5\( \sigma \) threshold would be far too conservative. The importance of these examples is to emphasise that FDR provides a consistent constraint on the fraction of false detections in an adaptive way, governed by the source intensity distribution relative to the background, which cannot be reproduced by the simple assumption of, for example, a 5\( \sigma \) threshold. Clearly the source distributions in most astronomical images lie firmly between the two extremes presented for this illustration, but the adaptability of the FDR thresholding method still presents itself as an important tool.

Returning now to the comparison between Sfnd 2.0, Imsad and SExtractor, the Imsad and SExtractor thresholds were set to correspond to those derived from the \( \alpha \) values used in Sfnd 2.0. The distributions of falsely detected and missed sources were similarly calculated. These are shown in Figures 5(e) to 5(h). One of the features of SExtractor is the ability to set a minimum number of contiguous pixels required before a source is considered to be real, and obviously the number of detected sources varies strongly with this parameter. After some experimentation we set this parameter to 7 pixels, as this resulted in a distribution of false detections most similar to that seen with Sfnd 2.0, for the case where only pixels above the FDR threshold are used in source measurements. Values larger than 7 reduced the number of false detections at the expense of missing more true sources, and vice-versa. From this comparison, Sfnd 2.0 appears to miss somewhat fewer of the true sources than SExtractor when SExtractor is constrained to the same level of false detections. This is also true if SExtractor is constrained to a similar distribution of false detections as obtained by Sfnd 2.0 for the case where only the peak pixel is required to be above the FDR threshold (corresponding to 4 contiguous pixels). In both cases, allowing SExtractor to detect more true sources by lowering the minimum pixel criterion introduces larger numbers of false detections. Sfnd 2.0 also performs favourably compared to Imsad. While Sfnd 2.0 seems to miss a few percent more real sources than Imsad, Imsad seems to detect many more false sources than Sfnd 2.0 in either of its source-measurement modes.

Of primary importance in source measurement is the reliability of the source parameters measured. Figure 6 shows one example from the one hundred tests comparing the true intensities and positions of the artificial sources with those measured by Sfnd 2.0. Similar results are obtained with Imsad, which uses the same gaussian fitting routine. As expected, the measured values of intensity and position become less reliable as the source intensity becomes closer to the noise, although they are still not unreasonable. A comprehensive analysis of gaussian fitting in astronomical applications has been presented by Condon (1997), and the results of the gaussian fitting performed by Sfnd 2.0 (and Imsad) are consistent with the errors expected. Additionally, the assumption that a source is point-like, or only slightly extended, and thus well fit by a two-dimensional elliptical gaussian, is clearly not always true. Complex sources in radio images, as in any astronomical image, present difficulties for simple source detection algorithms such as the
ones investigated here. It is not the aim of the current analysis to address these problems, except to mention that the parameters of such sources measured under the point-source assumption will suffer from much larger errors than indicated by the results of the gaussian fitting.

As a final test, Sfind 2.0 was used to identify sources in a real radio image, a small portion of the Phoenix Deep Survey (Hopkins et al. 1999). This image contains sources with extended and complex morphologies as well as point sources. Figure 7 shows the results, with Sfind 2.0 reliably identifying point source and extended objects as well as the components of various blended sources and complex objects.

4. Discussion

The main aims of this analysis have been to (1) investigate the implementation of FDR thresholding to an astronomical source detection task, and (2) compare the rates of missed and falsely detected sources between this task and others commonly used. Implementation of the FDR thresholding method is very straightforward, (evidenced by the seven step IDL example of Miller et al. (2001), in their appendix B). The FDR method performs as expected in providing a statistically reliable estimate of the fraction of falsely detected pixels. Performing source detection on a set of pixels introduces the transformation of pixel groups into sources. This ultimately results in the strong constraint on the false fraction of FDR-selected pixels becoming a less rigorous, but still useful and reliable estimate of the fraction of false sources. As already mentioned, this is still a more quantitative statement than can be made of the rate of false sources in the absence of the FDR method. It is possible that rigorous quantitative constraints on the fraction of false source detections may be obtained empirically for individual images or surveys. By performing Monte-Carlo source detection simulations with artificial images having noise properties similar to the ones under investigation, the trend of falsely detected sources with $\alpha$ may be able to be reliably characterised. This has not been examined in the current analysis, but will be included in subsequent work with Sfind 2.0. While constraints on the fraction of falsely detected sources may be possible, neither FDR nor any other thresholding method provides constraints on the numbers of true sources remaining undetected.

A study is also ongoing into whether a more sophisticated FDR thresholding method for defining a source may be feasible. This would involve examining the combined size and brightness properties of groups of contiguous pixels to define a new $p$-value. This would represent the likelihood that such a collection of pixels comes from a 'background distribution' or null-hypothesis, corresponding to the properties exhibited by noise in various types of astronomical images. Using this new $p$-value an FDR threshold, now in the size-brightness parameter space, could be applied for defining a source catalogue. Clearly much care will need to be taken to avoid discriminating against true sources which may lie in certain regions of the size-brightness plane, such as low surface brightness galaxies. The assumption in many existing source-detection algorithms that sources are point-like already suffers from such discrimination, though, so even if such bias is unavoidable, some progress may still be achievable.

The form assumed for $c_N$ in this analysis is not in fact a rigorous result of the formal FDR proof. Instead it is a 'compromise' estimate that seems mathematically reasonable, and gives reliable results in practice. To be strictly conservative, the form of $c_N$ given by equation 1 should be adopted to ensure that the fraction of falsely detected 'source-pixels' is strictly less than $\alpha$. This rigorous treatment will have the effect of changing the threshold level, and the resulting source catalogue, as the size of the analysed image sub-region changes. This, perhaps non-intuitive, aspect of the FDR formalism is the adaptive mechanism which allows it to be rigorous in constraining the fraction of false detections.

There are additional complicating factors which must be taken into account when performing source detection. The null hypothesis assumed for the FDR method (and indeed for all the source detection algorithms) is that the background pixels have intensities drawn from a gaussian distribution (or other well-characterised statistical distribution such as a poissonian). This is not strictly true for radio images, where residual image processing artifacts may affect the noise properties, albeit at a low level. In all cases, such deviations
will result in a larger fraction of false pixels than expected, some of which may be clumped in a fashion sufficient to mimic, and be measured as, sources, thus increasing the fraction of falsely detected sources. This comment is simply to serve as reminder to use caution when analysing images with complex noise properties.

5. Conclusions

We have implemented the FDR method in an astronomical source detection task, Sfind 2.0, and compared it with two other tasks for detecting and measuring sources in radio telescope images. Sfind 2.0 compares favourably to both in the fractions of falsely detected sources and undetected true sources. The FDR method reliably selects a threshold which constrains the fraction of false pixels with respect to the total number of ‘source-pixels’ in realistic images. The fraction of falsely detected sources is not so strongly constrained, although quantitative estimates of this fraction are still reasonable. More investigation of the relationship between ‘source-pixels’ and ‘sources’ is warranted to determine if a more rigorous constraint can be established. With the ability to quantify the fraction of false detections provided by the FDR method, we strongly recommend that it is worthwhile implementing as a threshold defining method in existing source detection tasks.

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REFERENCES


This 2-column preprint was prepared with the AAS LaTeX macros v5.0.
Fig. 1.— A graphical example of how the FDR threshold is calculated. This diagram shows only the relevant portion of the full graph (which has abscissa spanning 0 – 1). The points show $p$-values of the pixels from one of the artificial images. The line has a slope of $\alpha/c_N$ with $\alpha = 0.05$ and $c_N \approx 3.495$, corresponding to a PSF area covering 18 pixels. The last intersection point gives $p_{\text{cut}} = 2.19 \times 10^{-4}$. Hence all pixels with $p < 2.19 \times 10^{-4}$ are considered ‘source-pixels’.
Fig. 2.— Example artificial images. Left: Artificial sources only. Right: Artificial sources in the presence of noise as used in the simulations, emphasising that real sources close to or below the noise level become difficult or impossible to detect, even visually.
Fig. 3.— Example artificial images, showing objects detected as sources by Sfind 2.0. The noiseless image (left) is shown for reference to make it clear which objects have been correctly detected or missed in this instance.
Fig. 4.— Fraction of falsely detected pixels for $\alpha = 0.1$ assuming different forms for $c_N$. For the uncorrelated assumption, $c_N = 1$. For fully correlated, $c_N = \sum_{i=1}^{n} 1/i$. For ‘partially correlated,’ $c_N = \sum_{i=1}^{n} 1/i$, where $n$ represents the number of pixels covering the ‘correlation size’ of the image, corresponding in our tests to the PSF size. For both the fully correlated and ‘partially correlated’ cases it can be seen empirically that $\langle \text{FDR} \rangle \leq \alpha$ (where the angle brackets represent an ensemble average over replications of the data).
Fig. 5.— Comparison of different source detection codes. The fractions of sources falsely detected (left) or missed (right) are shown for each of the tested tasks. (a) and (b) show results for Sfind 2.0 in its default mode, where all source-pixels are required to be above the FDR-threshold. (c) and (d) show results for Sfind 2.0 when only the peak-pixel is required to lie above the FDR threshold.
Fig. 5.—Continued. Fractions of falsely detected (left) and missed (right) sources for Imsad (top) and SExtractor (bottom). The SExtractor results are based on setting a minimum requirement of 7 pixels for a source to be detected.
Fig. 6.—Comparison of measured source parameters with the true values. Upper left: The ratio of measured to true flux density is shown as a function of the flux density. Upper right: Scatter plot of position errors. Lower left: Distribution of errors in R.A. Lower right: Distribution of errors in Dec. The gaussians over the two histograms have $\sigma = 0''7$, and are indicative rather than fitted to the distributions.
Fig. 7.—An example of a real radio image (a portion of the Phoenix Deep Survey). The marked sources have been detected using Sfind 2.0 and an FDR threshold corresponding to $\alpha = 0.01$. There are 69 detected sources, and the FDR method suggests that less than 1 of these are likely to be falsely detected.