Detecting extended radio emission: SNRs, Relics, Halos & Head-Tailed Galaxies

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Detecting extended radio sources

Methods of detecting extended radio sources from images usually rely on detection of contiguous pixels above some RMS noise level (such as Duchamp), or more recently "flood-fill" methods to detect sources which are enclosed by pixels which are above some RMS noise level.

What happens when the sources are broken?
What if they are very large and/or very faint?
How do you separate out different types of extended radio emission in catalogues?
How can you automatically deal with noise producing false positive detections?

Finding and classifying extended sources

Even in cases where other techniques can detect various different types of radio sources data volumes will be too large to manually collate samples.

A better approach is to have an automatic approach which generates a list of candidate objects of a certain class for an astronomer to inspect. It would be a bonus if the method could do a "better" job of finding a certain type of source than a person.
We investigated the circle Hough transform as a method for extracting and classifying certain types of extended radio emission.

The circle Hough transform

The circle Hough transform is an example of the family of transforms developed to detect tracks in bubble chambers.

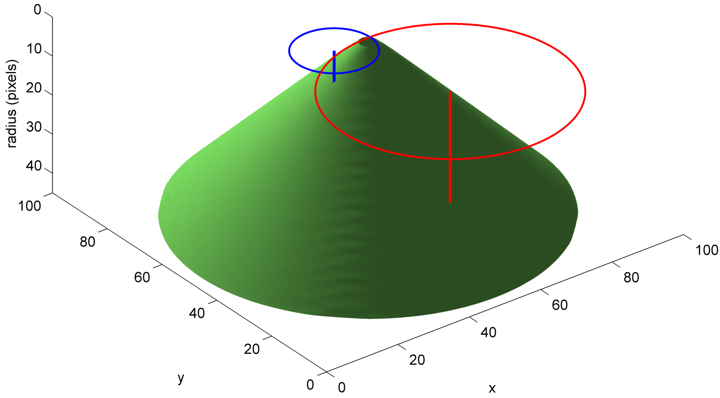
It is known to be robust in the presence of noise and copes well with broken features.

The circle Hough transform finds the location and radius of circular objects in an input image.

The Hough transform

- Each pixel in the input image "votes" for all possible circles that could pass through it.
- Votes are accumulated in a three-dimensional parameter space (Hough space), where two dimensions represent the location of the circle and the third the radius.
- Any circle that is present in the image will accumulate a statistically significant number of votes, leading to its detection.

Vote distribution



Hough distribution

Equivalently the transform can be viewed as performing a correlation with every possible circle in the image. Each test circle is characterised by its location and radius and the results of the correlations are stored in the corresponding location in Hough space.

Hough space must then be searched to find local maxima. In general this is a non-trivial problem.

- As astronomical images are relatively sparse, this is not such a problem as in some other applications.

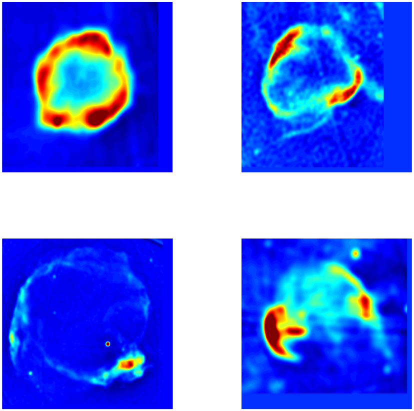
Case study: Supernova remnants

Currently three-quarters of the theoretically predicted SNRs are missing.

- Too faint?
- Too large?
- Simply missed?
- Theory could be wrong. . .

We used a modified (and optimised) Circle Hough transform on the Molonglo Galactic Plance Survey 2 (MGPS2) to test the algorithm to SNR of different complexities.

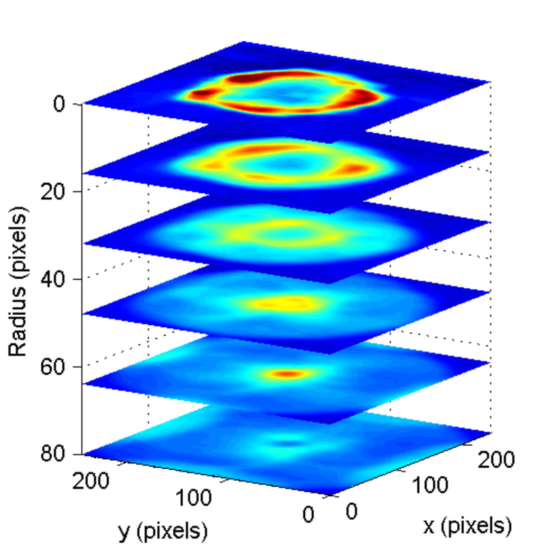
Some SNRs



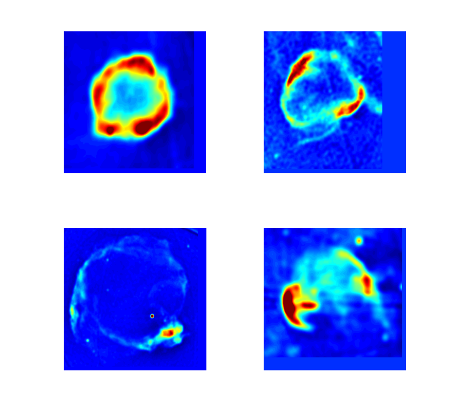
Supernova remnants are typically circular. However, the circles are often broken and/or distorted.

Four representative examples from the MGPS2 catalogue: G337.3+1.0, G302.3+0.7, G315.4-2.3 and G317.3-0.2

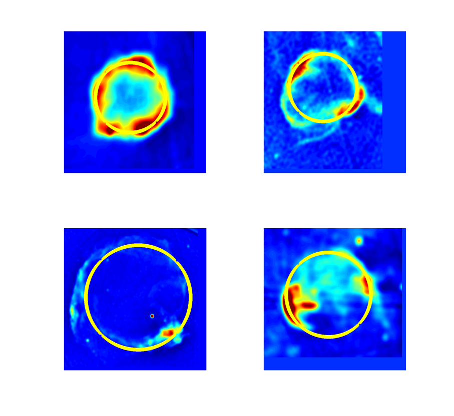
Hough space



Results



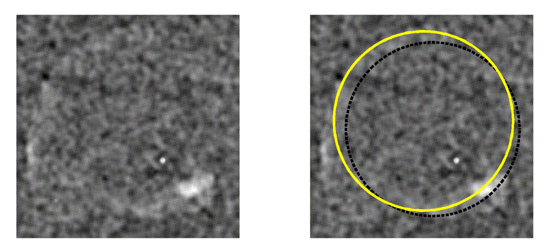
Input images



Results

Noise performance

We contaminated the input images with noise until the algorithm became approximately 50% reliable. This algorithm was able to cope with about twice as much noise as an astronomer.



Making is much better then contiguous pixel of "flood fill" techniques in such cases. Meaning it could potentially answer questions regarding the missing SNRs.

The pros

- Finds sources which would be otherwise undetectable automatically.
- Comes with automatic source classification.
- The transform is able to be generalized to other shapes, and combinations of shapes meaning things can also be rejected ie good automated artifact detection method.
- The Hough transform is well suited to running on a grid, where different machines process different parts of the sky.

The cons

- The Hough transform is quite slow, so it can't be run over the whole sky. The compute required in the traditional Hough transform goes as n^3, for images of n $\times$ n pixels.
  Chris has recast the transform to improve this to $\mathrm{n}^2\log(\mathrm{n})$ but even so it may need to be preceeded by a preprocessing stage to find promising areas of extended radio emission.
- The transform is able to be generalized to other shapes, but these are potentially even more compute intensive: $\mathrm{mn}^2\log(\mathrm{n})$, where m is a complexity measure.

So this is likely to be part, but not all of the solution. However, for perfoming an automated extraction of a particular class of extended radio source, it appears to work well.

The future

- Chris is currently extending this code to elliptical transforms using the faster method.
- We have offered a PhD project to port & optimize the current code to a grid for timing testing, and will be looking at how much the complexity of other shapes slows the computations. (In addition to the mechantronics PhD student working on further improving the algorithm.)
- We'd like to do 'multi-resolution' testing which is important for applications in robotics.
- We hope to test the automated source classification for different extended sources in the near future.

Further information is available in Hollitt (2009) and Hollitt & Johnston-Hollitt (2009).