New Astronomy 36 (2015) 86–99

Contents lists available at ScienceDirect

New Astronomy

journal homepage: www.elsevier.com/locate/newast

Exploring three faint source detections methods for aperture synthesis radio images

M. Peracaula [a], A. Torrent [a], M. Masias [a,*], X. Lladó [a], J. Freixenet [a], J. Martí [b], J.R. Sánchez-Sutil [b], A.J. Muñoz-Arjonilla [b], J.M. Paredes [c]

[a] Departament d'Arquitectura i Tecnologia de Computadors, Universitat de Girona, Spain
[b] Departamento de Física, Universidad de Jaén, Spain
[c] Departament d'Astronomia i Meteorologia and Institut de Ciències del Cosmos, Universitat de Barcelona, Spain

HIGHLIGHTS

- Three new approaches for detecting faint sources in radio interferometric images are presented.
- The first approach is based on local thresholding in different wavelet scales.
- The second approach uses spatial coherence of pixel neighbourhoods.
- The third approach is based on feature extraction and pixel classification.
- The performance of the methods is compared to reference state-of-the-art algorithms.

ARTICLE INFO

Article history:
Received 10 January 2014
Received in revised form 1 October 2014
Accepted 17 October 2014
Available online 24 October 2014

Communicated by G. Brunetti

Keywords:
Methods: data analysis
Techniques: image processing

ABSTRACT

Wide-field radio interferometric images often contain a large population of faint compact sources. Due to their low intensity/noise ratio, these objects can be easily missed by automated detection methods, which have been classically based on thresholding techniques after local noise estimation. The aim of this paper is to present and analyse the performance of several alternative or complementary techniques to thresholding. We compare three different algorithms to increase the detection rate of faint objects. The first technique consists of combining wavelet decomposition with local thresholding. The second technique is based on the structural behaviour of the neighbourhood of each pixel. Finally, the third algorithm uses local features extracted from a bank of filters and a boosting classifier to perform the detections. The methods' performances are evaluated using simulations and radio mosaics from the Giant Metrewave Radio Telescope and the Australia Telescope Compact Array. We show that the new methods perform better than well-known state of the art methods such as SExtractor, SAD and DUCHAMP at detecting faint sources of radio interferometric images.

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1. Introduction

A large number of astronomical deep field surveys appeared over the last few years and with them the need of creating reliable catalogues. This situation brought up the necessity of having fast and robust tools for automated source detection and classification. An especially relevant case are mosaicked maps produced from wide-field images. These images typically contain both some very bright sources as well as a large number of faint objects and diffuse emission with intensities close to the image background noise. Inaccuracies in the calibration and imaging of radio interferometric data limit the dynamic range, leaving bright sources surrounded by residual PSF sidelobes.

The development of robust algorithms for automated object detection with these images is necessary for the astronomical research community. The main reason for this is that they are more efficient, fast and accurate than manual inspection. The robust detection of sources is an essential first step in the extraction process (the extraction of characteristics of the sources present in an astronomical image).

Radio astronomy is under expansion. A new generation of radio telescopes is already being built around the world. Along the next ten years the Square Kilometre Array (SKA) will start providing observations many times more sensitive than the current ones at wavelengths ranging from centimetres to metres. It will consist of many antennas deployed in both Australia and South Africa.

* Corresponding author.
E-mail address: mmasias@eia.udg.edu (M. Masias).

http://dx.doi.org/10.1016/j.newast.2014.10.006
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Before the SKA, however, several other new-generation telescopes are being built or already in use. For many years the Very Large Array (VLA; USA), the Giant Metrewave Radio Telescope (GMRT; India) and the Australia Telescope Compact Array (ATCA; Australia) have been providing radio astronomers with images. The new generation of radio telescopes includes the Low-Frequency Array (LOFAR; the Netherlands), the Australian Square Kilometre Array Pathfinder (ASKAP; Australia) and the MeerKAT (South Africa). All these telescopes are, or will be, used for deep, large-area continuum surveys. For more details we refer the reader to Hancock et al. (2012), Whiting (2012) and Hales et al. (2012).

Automated detection of compact sources in astronomical images has been classically produced using thresholding techniques based on local noise estimation. Several packages such as SExtractor (Bertin and Arnouts, 1996), SAD (AIPS) (Greisen, 2003) and SFind (Hopkins et al., 2002) follow this strategy. Although these methods were developed more than ten years ago they are still widely used by the astronomical community due to their good performance. New packages following a similar strategy such as AEGEAN (Hancock et al., 2012), DUCHAMP (Whiting, 2012) and BLOBCAT (Hales et al., 2012) have appeared over the last few years. These tools claim to provide as reliable[1] and complete[2] detections as the classical software, even at low signal-to-noise regime (they use, for instance, noise removal and deblending steps). A summary of these methods can be found in the work of Hancock et al. (2012).

Faint compact sources presenting intensity values close to the image background noise are easily missed by threshold-based methods. Different techniques were proposed to address this issue (Masias et al., 2012). In the current paper we explore the performance of three novel approaches based on fundamentally different strategies to detect sources at low signal-to-noise ratio. The first two algorithms are based on unsupervised strategies: the first uses a multiscale transform, while the second uses pixel structural behaviour. The third algorithm presents a supervised strategy that includes local feature extraction and a classification process.

In order to evaluate the performance of these three methods, we used realistic simulations and real data from the deep radio maps obtained by Paredes et al. (2009) with the Giant Metrewave Radio Telescope (GMRT) and Hopkins et al. (2003) with the Australia Telescope Compact Array (ATCA). These images constitute an excellent benchmark for automated detection methods. Their main characteristics are: (1) a significant amount of detail due to their high dynamic range; (2) a large population of compact sources over a wide flux density range; and (3) unwanted patterns commonly known as sidelobes caused mainly by data problems, and by inaccuracies in calibration and imaging.

An important contribution of our study is the comparison of the new proposals with the well-known state of the art methods SExtractor, SAD (within AIPS) and DUCHAMP. The first two are well-known robust astronomical methods while the last one is a recent method that provides reliable and complete detections more quickly than the rest of recently emerged methods.

The rest of the paper is organised as follows: in Sections 2–4 we introduce and analyse the three new algorithms; Section 5 is devoted to presenting the images used to test the new algorithms; the test results are shown in Section 6; and finally, conclusions are presented in Section 7.

2. Algorithm I: WALT – multiresolution analysis on thresholded images

The first method (based on Peracaula et al., 2009b) incorporates the concept of multiscale analysis, which is applied in Computer Vision generally when the image to segment shows objects with very different sizes or patterns organised in a hierarchical structure (Mallat, 1989a,b). In these cases, there is not an optimal resolution for analysing the image, and algorithms to process it at different resolutions are needed. In multiscale approaches, the image is decomposed into components at different scales (spatial frequencies) and sources become highlighted in some of these scales depending on their morphology. Especially suited for this purpose are algorithms that decompose the image through a wavelet representation, using discrete versions of the wavelet transform (Shensa, 1992; Starck and Murtagh, 2006; Starck and Bobin, 2010).

Astronomical images often display hierarchically organised structures of objects with irregular patterns that can be represented at different spatial frequencies. Therefore, the analysis of such images with the purpose of detecting and classifying emitting sources is a clear example where multiscale methods can be conveniently applied (Bijaoui and Rué, 1995).

Within this approach, wavelet decomposition is used as a tool to detect and separate objects of astronomical interest that can be represented at different spatial frequencies.

2.1. Wavelet representation using the "à trous" algorithm

Multiscale Vision Models (Bijaoui and Rué, 1995) decompose an image in J scales or wavelet planes and independently segment each of the images representing a scale. Low index scales highlight high spatial frequencies, whereas high index scales highlight low spatial frequencies. The mathematical decomposition of an image in a set of wavelet planes requires that, at each scale, the wavelet coefficient mean must be zero (it is an intrinsic property). Due to this fact, high pixel intensities resulting from bright sources in a given wavelet plane are compensated with negative values in their surroundings to preserve the zero-mean property (Starck and Murtagh, 2006). These negative values create artifacts that complicate the analysis, therefore the need to remove bright sources beforehand.

Since astronomical sources are mostly isotropic, e.g. stars, clusters or galaxies, astronomers generally choose to use a wavelet transform that does not privilege any orientation in the image and also maintains the sampling at each scale (Starck and Murtagh, 2006). For this reason, one of the widely used transforms in this field is the stationary wavelet transform (SWT) also called "à trous" algorithm. The SWT decomposes an image $I(i,j)$ in N scales or wavelet planes $W_n(i,j)$ and a smoothed array $F_N(i,j)$ using a smoothing filter h, associated to the wavelet scaling function, in the following way:

$$I(i,j) = F_N(i,j) + \sum_{n=1}^{N} W_n(i,j), \tag{1}$$

where $F_N(i,j)$ and $W_n(i,j)$ are calculated through the following iterative process:

$$\begin{aligned} F_0(i,j) &= I(i,j), \\ F_n(i,j) &= \langle H_n, F_{n-1}\rangle(i,j), \\ W_n(i,j) &= F_{n-1}(i,j) - F_n(i,j), \end{aligned} \tag{2}$$

with $n = 1, \ldots, N$ and

$$\langle H_n, F_{n-1}\rangle(i,j) \equiv \sum_{k,l} h(k,l) F_{n-1}(i + 2^{n-1}k,\ j + 2^{n-1}l), \tag{3}$$

where the set $W_1, W_2, \ldots, W_N, F_N$ represents the wavelet transform of the data.

Following Starck and Murtagh (2006) and references therein, we will use the B_3-spline function as the scaling function, which is very similar to a Gaussian one. In this way, the mask associated with the filter h takes the following form:

[1] Most of the detections correspond to true sources.
[2] Most of the sources in the image are found.

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