Detecting Faint Compact Sources using Local Features and a Boosting Approach

A. Torrent, M. Peracaula, X. Lladó, J. Freixenet
Vicorob Group
University of Girona
Girona, Spain
{*atorrent,martap,llado,jordif*}*@eia.udg.edu*

J.R. Sánchez-Sutil, J. Martí
Dept. of Physics
University of Jaén
Jaén, Spain
{*jrssutil,jmarti*}*@ujaen.es*

J.M. Paredes
Faculty of Physics
University of Barcelona
Barcelona, Spain
jmparedes@ub.edu

***Abstract*—Several techniques have been proposed so far in order to perform faint compact source detection in wide field interferometric radio images. However, all these methods can easily miss some detections or obtain a high number of false positive detections due to the low intensity of the sources, the noise ratio, and the interferometric patterns present in the images. In this paper we present a novel strategy to tackle this problem. Our approach is based on using local features extracted from a bank of filters in order to provide a description of different types of faint source structures. We then perform a training step in order to automatically learn and select the most salient features, which are used in a Boosting classifier to perform the detection. The validity of our method is demonstrated using 19 real images that compose a radio mosaic. The comparison with two well-known state of the art methods shows that our approach is able to obtain more source detections, reducing also the number of false positives.**

***Keywords*-Astronomical images; faint compact sources detection; Boosting classifier;**

I. Introduction

A great number of surveys providing images and catalogues of millions of astronomical objects have been done during the last years. The acquired images involve all kind of ground-based and space telescopes at different resolutions and different wavelengths (ranging from radiofrequencies to high energy gamma rays). Cross-identification of objects in these catalogues is essential to count and classify the vast amount of astronomical sources, and also to describe their physics and their relevance in the universe composition and evolution. Therefore, the development of robust algorithms for automated object detection in these images is necessary for the astronomical research community.

Recent wide field radiointerferometric surveys show a large amount of faint compact objects with intensities very close to noise levels. On top of that, the high dynamic range of this kind of images makes difficult the visualization of the full range of intensities of the global map (see for instance Taylor et al. [8] and Stil et al. [6]). Moreover, these images are usually very complex, presenting a diffuse interferometric pattern, deconvolution artifacts and grating rings produced by strong sources and, sometimes, by calibration problems. Hence, automatic detection methods working at low signal-to-noise ratios become necessary in order to create reliable catalogues of faint compact sources.

Several approaches have been proposed so far in order to perform this faint source detection process. Many of them are based on applying local thresholding techniques such as the SAD task of the AIPS (Astronomical Image Processing System) [7] and the well-known SExtractor [1]. However, these methods tend to miss detections or to detect false faint sources due to the fact that they have intensities close to noise levels.

In this paper we present a novel approach to perform the faint source detection in wide field radiointerferometric surveys. Our idea is inspired on the work of Murphy et al. [4] for object detection. Similar to their approach, we use a set of local features extracted from a bank of filters in order to provide a description of different types of faint source structures. Afterwards, we perform a training step in order to automatically learn and select the most salient features, which are then used in a Boosting classifier to perform the detection of faint sources. We also include in our approach a final step for reducing the false positive detections caused by the image noise. The experimental results with real data and the comparison with two of the most used methods in the astronomical community (SAD [7] and SExtractor [1]) illustrate the validity of our approach.

The rest of the paper is organized as follows. In section II we describe the boosting approach used to perform the detection. In section III we show experiments on different real images which validate our proposal. Finally, conclusions are given in section IV.

II. Our boosting detection system

Our approach for detecting faint compact sources is based on the work of Murphy et al. [4] for object detection. Similar to them, we first build a visual feature dictionary which is composed of faint sources patches. Afterwards, these dictionary words are used to extract local features from a training set. Finally, the system is trained using a Boosting classifier, which is our faint source detector. This idea of using local features to perform object detection and classification has been widely used during the last years [9], [10], [11]. In the following sections we will describe in

1051-4651/10 $26.00 © 2010 IEEE
DOI 10.1109/ICPR.2010.1117

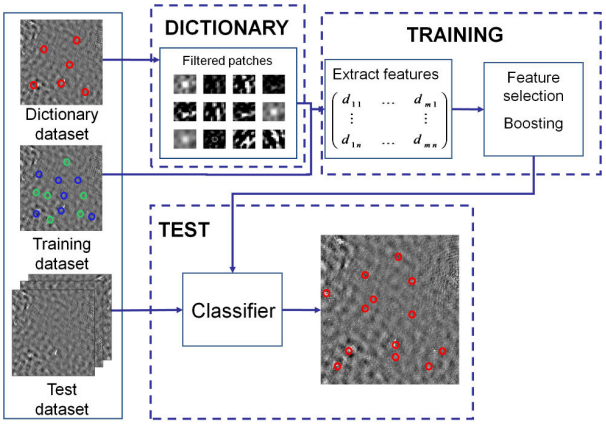

Figure 1. Graphical representation of our approach: 1) building the dictionary, 2) training process, 3) testing process with new images. Notice that different image sets are used for each step.

more detail the important aspects of our approach, which is divided in three main parts as illustrated in figure 1.

A. Building the dictionary

The first task of our system consists in building a visual feature dictionary. The definition of this dictionary contains the visual words (patches) that will be then used to extract features for training and testing. First of all, we randomly select a set of wide field aperture synthesis radio images to create the dictionary. Afterwards, these images are convolved with a bank of filters composed by: a delta function, which does not change the image; 4 gaussian derivatives; a laplacian filter; a corner detector; and 2 sobel filters. All the filtered images are then used to extract different patches centered on faint sources. Figure 2 shows the building dictionary process. These patches become the words of our dictionary. Notice that as well as the patch, the used filter is also needed to extract the image features, since each patch is convolved with the corresponding filtered image.

When the dictionary has been built, the pixels of an image can be characterized using the following equation:

$$v = (I * f) \otimes p \tag{1}$$

where v are the characterized image pixels, I is the original image, f is the filter, and p is the filtered patch. Therefore, the image is convolved ($*$) with the filter and then a normalized cross correlation ($\otimes$) with the patch is performed. As a result we obtain a probability image with high values on the regions similar to the patch.

B. Training and testing processes

The goal of the training process is to learn which features are the best in order to detect faint compact sources. Our training data is created as follows. Instead of using all the pixels of the training images, which will be computational expensive, we select some points for each training image. In particular, we select the center of the faint sources (positive training samples) and some random locations of the background (negative training samples). Afterwards, we apply a Boosting algorithm on these samples to perform the training. Boosting algorithms are based on the simple idea that the sum of weak classifiers can produce a strong classifier. In our system we used the gentleBoost algorithm proposed by [2], since it was demonstrated in [3] that it is more numerically stable than other confidence-rated variants of Boosting. The weak classifiers h_t are simple regression stumps with one of the features, so at each round the feature with less error is selected. The weak classifier function used is shown in equation 2,

$$h_t(x) = a(x_i > th) + b \tag{2}$$

where x is the data, x_i is the i'th dimension (feature) of x, and th is a threshold that determines if the data belongs to the object class or not. Note that a and b are parameters selected to minimize the error function of equation 3 given the chosen feature x_i and threshold th.

$$e = \sum (w(y - (a(x_i > th) + b))^2) \tag{3}$$

where y are the labels and w are the training data weights updated at each round. Equation 4 is then used to update the data weights.

$$w_{t+1} = w_t e^{y \cdot h_t(x)} \tag{4}$$

Our final faint source classifier $H(x)$ is the sign of the result of the weak classifiers sum. Once this pixel-based classifier is built, we can move to the testing process where the classifier is applied to new images in order to perform the faint compact source detection.

As a final step of our system and in order to remove possible false positive detections, we discard detections according to their intensity noise level of the neighbourhood pixels. In particular, as the noise in radioastronomical images follows a Gaussian distribution, we determine the noise level N fitting a Gaussian function to the intensity histogram of the neighbourhood. N is defined as the half-width fitted Gaussian at a fraction $\frac{1}{fr}$ of the fitted Gaussian height. Afterwards, we filter those pixels detections with intensity levels under q times the image neighbourhood noise level N. Notice that these q and fr parameters have to be properly tuned. This point will be further discussed in the following section.

III. Experimental results

To validate the performance of our approach we use the 19 deep radio images obtained by Paredes et al. [5] at 610 MHz (49 cm) to survey a $2.5° \times 2.5°$ region centered on the MGRO J2019+37 peak of high energy gamma-rays emission. Each image is of size 3385×3397 pixels and covers a $28'$ radius circular region. All these images are

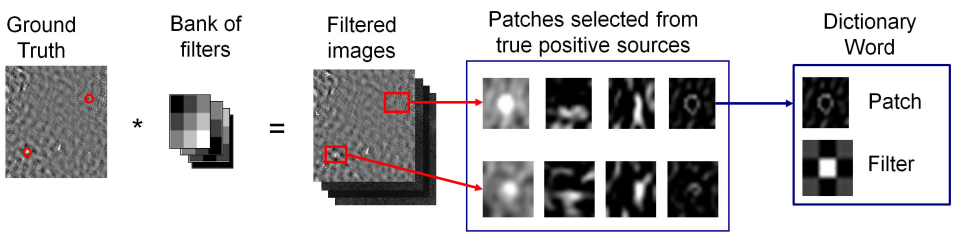

Figure 2. Dictionary building process.

partly overlapped in a hexagonal pattern to compose a final mosaic (see Figure 3). These images are an ideal benchmark set for automated detection methods since: 1) they show a significant amount of detail due to its high spatial dynamic range; 2) they have a remarkable population of compact sources (i.e. star-like objects) and show extended diffuse emission; 3) they also show unwanted interferometric pattern mainly caused by deconvolution artifacts and grating rings from strong sources both inside and outside the primary beam; and 4) they have been previously used to create two different catalogues using the SAD task of AIPS [7] and the SExtractor [1]. Therefore, enabling a quantitative comparison with them.

Before obtaining the final results with this data set, we optimized the parameters involved in our detection approach. For instance, regarding the number of images and visual words used for building the dictionary, we observed that increasing them the detection results were not significantly improved, while the computational time of the whole process dramatically increased. As a result, we decided to use a set of 3 images and around 3000 visual words (100 sources $\times$ 3 patch sizes $\times$ 10 filters) for describing the different types of faint source structures. These values were empirically obtained, providing a good trade-off between performance and feature vector length. Regarding the number of images and the number of positive and negative samples used for training, we noticed as expected that better results were obtained when increasing them. In this work, in order to perform the quantitative evaluation of our experiments we used a 6-folder cross-validation methodology. The 19 images were divided into 6 different groups, from where 1 was used to create the dictionary (3 images), 4 groups were used to train the Boosting classifier (12 images), while the remaining group was used for testing. This procedure was repeated until all image groups were used for testing. Notice that each image appears in the test set only once. Regarding the number of samples, for each training we used approximately 400 positive source samples and 7000 negative samples randomly selected from the images. Regarding the parameters q and fr used during the false positive reduction step, we empirically selected $q = 3.5$ and $fr = 6$ since allowed to reduce the number of false positives, without affecting the true positive detections. These parameters turn out to provide the best overall performance.

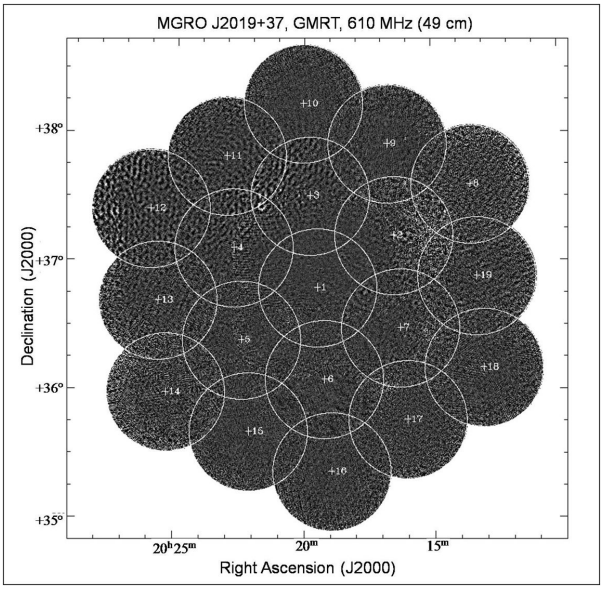

Figure 3. 19 deep radio images obtained by Paredes et al. [5]. All these images are partly overlapped to compose a final mosaic.

Table I shows the quantitative analysis in terms of number of true positive (TP) and false positive (FP) detections obtained for the 19 images. Figure 4 illustrates the obtained results on fields 14 and 15 using our Boosting approach, SAD and SExtractor (blue, red and green respectively). Moreover, Table I also includes the quantitative comparison with the two catalogues obtained using SAD and SExtractor methods. Analyzing these results one can see that our Boosting approach succeeds in reducing the number of FP with respect to SAD and SExtractor, while the number of TP detections increases, being even better than those reported by the other methods. We want to stress that some of these TP were not coincident. Our approach found 397 TP coincident with the results reported by SAD (87%) and 461 with respect to the results reported by SExtractor (97%). 375 TP were coincident in all the approaches. Regarding the false positive detections, our approach found 71 FP after correctly discarding 168 detections during the FP reduction step.

Table I
QUANTITATIVE ANALYSIS, COMPARING OUR APPROACH WITH SAD AND SEXTRACTOR METHODS.

Approach	TP Detections	FP Detections
Boosting	501	71
SAD [7]	455	474
SExtractor [1]	473	266

IV. CONCLUSIONS

A novel approach for the detection of faint compact sources in wide field interferometric radio images has been proposed. The description of different faint source structures have been done using local features extracted from a bank of filters. Moreover, a Boosting classifier has been used to automatically select the most salient features and to perform the faint source detection. Finally, a false positive reduction step have been applied to filter false detections caused by the noise ratio and the interferometric patterns of the images. The experimental results and the comparison with SAD and SExtractor methods have shown that our approach is able to obtain a reliable number of true positive detections, while reducing greatly the number of false positives. Finally, we want to emphasize the simplicity of implementing our Boosting approach (our code is available at *http://eia.udg.edu/∼atorrent/sourcedetection*).

ACKNOWLEDGEMENTS

This work has been supported by Ministerio de Educación y Ciencia of Spain under grants AYA2007-68034-C03-(01/02/03) and DPI2007-66796-C03-02. A. Torrent holds a FPU grant AP2007-01934.

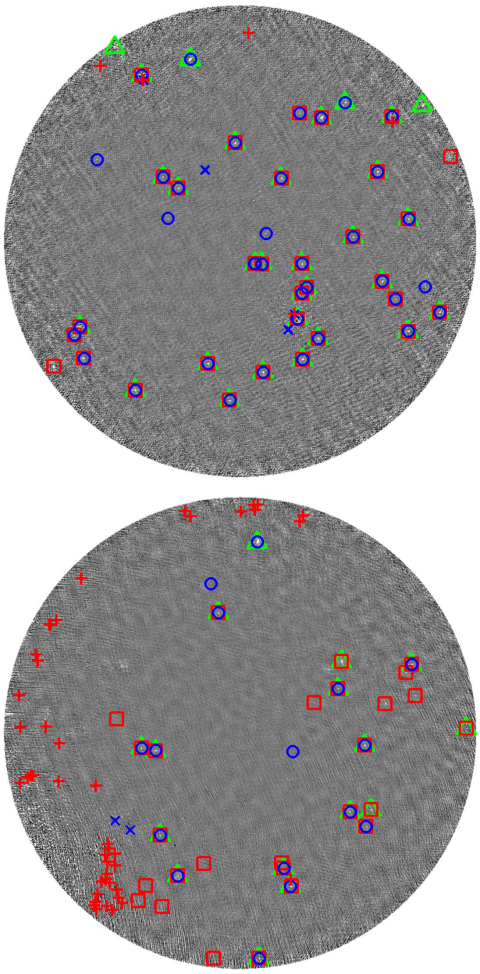

Figure 4. Results of fields 14 and 15. Blue, red and green colors refer to Boosting, SAD and SExtractor results respectively. Symbols + and × indicate FP, while the rest are all TP.

REFERENCES

[1] E. Bertin and S. Arnouts. SExtractor: Software for source extraction. *Astronomy & Astrophysics Supplement*, 117:393–404, June 1996.

[2] J. Friedman, T. Hastie, and R. Tibshirani. Additive logistic regression: a statistical view of boosting. *The Annals of Statistics*, 38(2):337–374, 2000.

[3] R. Lienhart, A. Kuranov, and V. Pisarevsky. Empirical analysis of detection cascades of boosted classifiers for rapid object detection. In *Pattern Recognition Symposium*, pages 297–304, 2003.

[4] K. Murphy, A. Torralba, D. Eaton, and W. T. Freeman. Object detection and localization using local and global features. In *Toward Category-Level Object Recognition*, pages 382–400, 2006.

[5] J. Paredes et al. Radio continuum and near-infrared study of the MGRO J2019+37 region. *Astronomy and Astrophysics*, 508:241–250, 2009.

[6] J. Stil et al. The vla galactic plane survey. *The Astronomical Journal*, 132(3):1158–1176, 2006.

[7] A. I. P. System. http://www.aips.nrao.edu/.

[8] A. Taylor et al. The canadian galactic plane survey. *The Astronomical Journal*, 125(6):3145–3164, 2003.

[9] B. Wu and R. Nevatia. Optimizing discrimination-efficiency tradeoff in integrating heterogeneous local features for object detection. In *CVPR*, 2008.

[10] J. Zhang, M. Marszalek, S. Lazebnik, and C. Schmid. Local features and kernels for classification of texture and object categories: A comprehensive study. *IJCV*, 73(2):213–238, June 2007.

[11] Z. Zhang, M. Li, K. Huang, and T. Tan. Boosting local feature descriptors for automatic objects classification in traffic scene surveillance. In *ICPR*, pages 1–4, 2008.