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LSB Galaxies Detection Using Markovian Segmentation on Astronomical Images

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Abstract. We have designed a new technique for the detection of Low Surface Brightness galaxies based on local background/source separation using Markovian analysis. This method helps to estimate smooth local variations of the background and therefore allows for determining source candidates as faint as LSB galaxies. For each source an average density profile is computed, the shape of which can help to sort out stars and bright objects. A list of LSB candidates is provided, for which position, profile and surface brightness are examined thoroughly. The results are very promising. This approach has been compared to the SExtractor source detection tool and to a previous original analysis by S. Sabatini et al. on the same INT image dataset of the Virgo Cluster. Detection rate, source selection criteria and calculation loop improvements are discussed.

1. Introduction

This paper presents a method for the detection and analysis of Low Surface Brightness galaxies (LSB). Detecting such objects has a cosmological interest as it could improve statistical knowledge about the morphology of far galaxies, provide more information about the spatial distributions of galaxies in general and give hints to study the baryonic mass generally attached to galaxies. Detecting very faint objects using local background estimations and profile assumptions have been successfully carried out using Sextractor tools for instance, but this approach fail in the case of crowded fields or very faint object close to the background luminosity. We propose a Markovian approach to disentangle the influence of background noise and local environment on the detection of source candidates. We describe the various steps of the methods and how it was applied on a first subset of test images.

2. Description of the Method

A general overview of the process is given in Figure 1. The first difficult step is to define appropriate source candidates before the exploration of isolines in the sources'luminosity and then derive what kind of objects are observed.

First a segmentation map is computed. The luminosity distribution of the pixels within an image is partitioned in various classes of pixel values assuming

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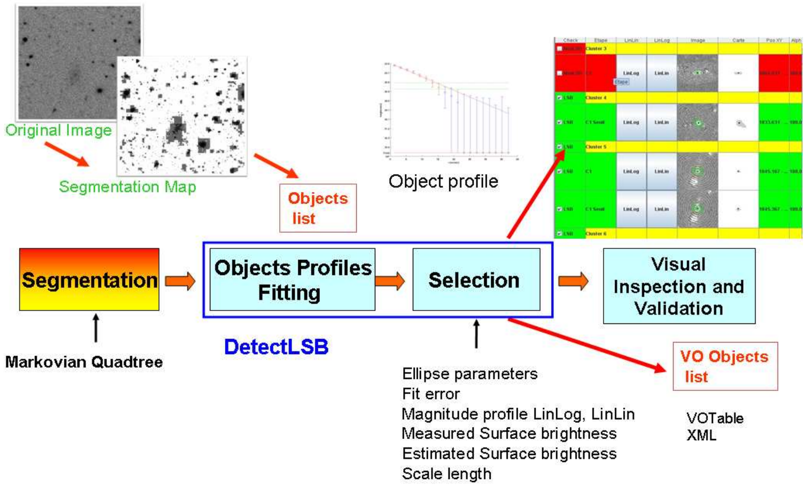

Figure 1. Overview of the detection and analysis method proposed

a Gaussian probability law for each class and gaussian additive noise. The labeling process is considered as a Markovian phenomenon, organised on a quadtree. Each label or class number to be set for a pixel only depends on the label attached to its upper scale parent in the tree (Collet et al. , 2003) (see Figure 2). A segmentation map is computed, with 5 to 6 classes $C_0, .., C_5$, C_0 correspon-

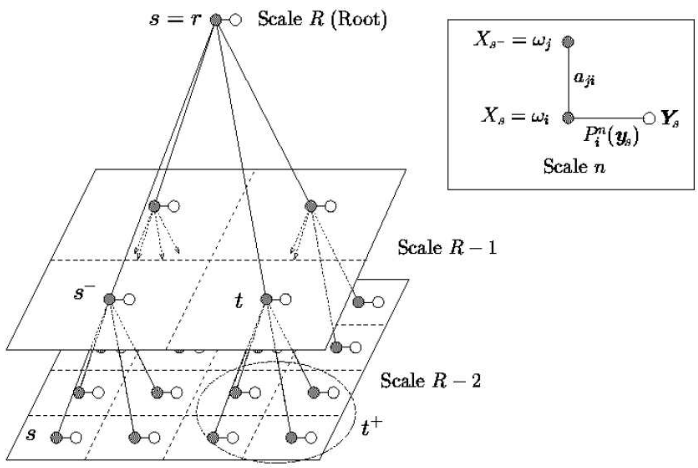

Figure 2. Markovian Quadtree used for the labeling process

ding to background pixels. Then a binary map discriminating detections from background is obtained by adjusting a threshold value between the averaged luminosity of the fainter classes, between C_1, C_2 typically.
The detection map (Fig. 1) shows pixel aggregates which provide knots to be used as first guess for object detection. The center of mass of each pixel knot

is used as input center to fit elliptic profiles on the local pixel values. Once the best ellipse is found, an average profile is computed. We assume LSB galaxies to have a decreasing exponential profile for the disc component in the form of:

$$f(r) = U_0 * \exp(-r/r_0) \tag{1}$$

where r is the radius and r_0 the scale length of the object. The profile is shown on logarithmic scale then fitted with a line to give evidence of an exponential decrease, and estimate the value of r_0. The surface brightness of the object averaged on central pixels is also computed. Figure 3 shows the profiles obtained for one detected object. Compact sources like stars have a very steep decrease

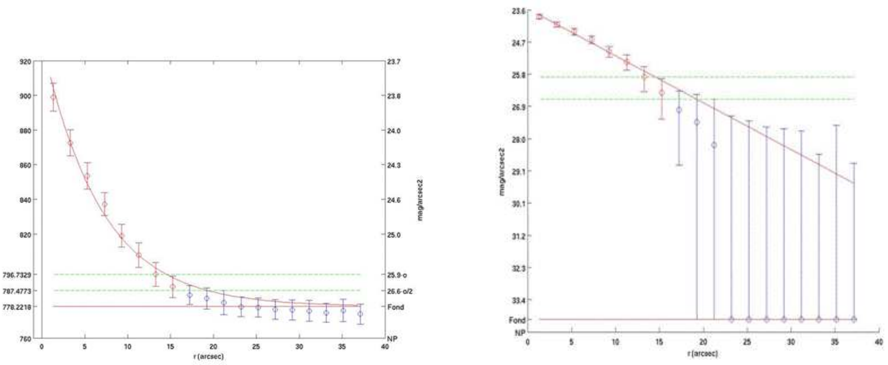

Figure 3. Averaged profile obtained for a detection. Left: linear scale. Right: on the logarithmic scale, the line fits more than 3 points above the background and gives evidence of a LSB profile.

comparable to the PSF function which is easily recognised on the profile on a linear scale. Some of the very faint detections occur to be located between brighter sources and show shifted profile with the peak shifted at r >> 0.
Finally all measurements and profiles are gathered in HTML files with thumbnails images, the two luminosity curves and fit and measurements. Sources with a good fit of at least 3 points aligned above the background level are stored in the LSB candidates file while stars and multiple detections are stored in another file for visual validation. The algorithm allows to classify LSB candidates, but requires astronomers expertise in many cases. We provide an interactive Java interface called LSBExplorer to navigate in the results files ,gather the expert's evaluation (see Fig 4) and produce VO compatible output formats (VOtable). The processing is prototyped in MathLab, reusing existing building blocks for the Markovian segmentation.

3. Data Description and Results

We have applied this processing on a subset of 18 B-images of the Isaac Newton Telescope WFCS (Wide Field Camera Survey) for the Virgo cluster. This data set was analysed by Sabina Sabatini et coll. (Sabatini et al. 2005), and provided to us as a training set. A cross match of our detections with the published catalog

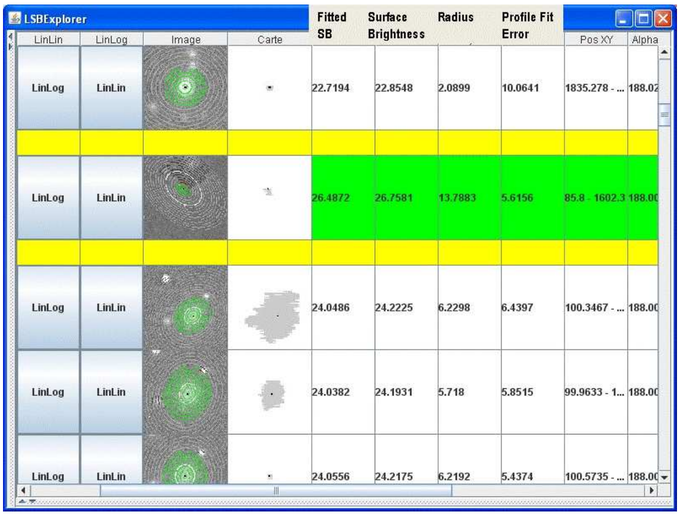

Figure 4. Results browsed by the LSBExplorer interface: inspection of the region of interest, profiles and fit are available as well as an interactive validation of objects as LSB or non LSB.

provided by Sabatini et al. shows 80 % of match. A few new LSB candidates are found in the case of bright neighbors. The validation of such a method on the full data set (80 images of 4096×2048 pixels i.e 2.5 Go) is still an ongoing task, but first results are promising. One of the limitation of the algorithm is the segmentation map size, which cannot exceed 1024×1024 pixels. This can be overcome with an appropriate tiling of the original images and screaming out of multiple detections. Various criteria about the slope of the profile near the center have been tried out but with little success. We concentrate on a minimum of selection rules in order to optimise the computing performance for the whole data set.

4. Conclusion

This pipeline offers semi-automatic processing for LSB detection and allow to examine very large collections of data. The astronomer's expertise is involved only in the last evaluation step which allows for automatic processing. The primary step of Markovian segmentation is also applicable on multiband images which could help to collect and distinguish more LSB candidates.

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