ASTRONOMICAL OBJECT DETECTION WITH A ROBUST HIT-OR-MISS TRANSFORM

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ABSTRACT

Astronomical object detection is a particularly difficult but very challenging task. Indeed, astronomical images may contain a high noise level due to huge distance within the Universe or to the low photon flow collected on telescope mirrors [1]. Some astronomical objects of interest such as Low Surface Brightness (LSB) galaxies are characterized by a very low signal-to-noise ratio and thus are rather extracted manually and then are sometimes lost or not detected. In this paper, we propose an automatic approach using Mathematical Morphology, well-known for its appropriate care of spatial information (shape and luminance profile of LSB galaxies is known). In order to be able to detect objects in noisy environments, we propose a new morphological operator for template matching, namely a robust hit-or-miss transform.

1. INTRODUCTION

Astronomical imaging is a particularly challenging domain for image analysis and processing algorithms. Indeed, images are often very noisy and some tasks such as image segmentation or object detection may be rather difficult since many parameters should be taken into account simultaneously: shape, texture, spectral properties, doppler effect (redshift), large range of pixel values, but also the high noise level and possibly the other objects present in the image. In this paper we focus on the detection of a specific kind of faint objects, Low Surface Brightness galaxies (LSB) [2], an example of which is given in Figure[1] 1.

Since such astronomical images are characterized by a very low signal-to-noise ratio, no automatic detection method is widely accepted yet, and astronomers are rather using some fully (or quite fully) manual approaches [3]. However, the large amount of data (our dataset if composed of 18 images of 2048×4096 pixels with a double precision) makes the manual approach inadequate. Since noise is one of the most important criteria to deal with LSB detection, current developments towards an automatic detection method consists of explicit modeling of the noise, which can been achieved through Markovian methods. Even if these approaches help to increase the detection rate, they do not manage to take into account the spatial distribution of brightness (by means of a profile known analytically). Conversely, morphological methods, despite their lack of explicit noise modeling, are an interesting approach when knowledge about the ligthness spatial profile is available. In this article we will show how this knowledge can be involved in a morphological method for LSB detection, thus extending the possible use of Mathematical Morphology for astronomical imaging [4].

More precisely we propose to study how the hit or miss transform, a well-known morphological operator dedicated to template matching, can adequately tackle the problem of object detection in noisy grayscale images. To do so, we propose a new definition using a fuzzy formulation, and apply the proposed operator to an illustrative example: LSB galaxy detection.

2. GRAY LEVEL HIT OR MISS TRANSFORM

The Hit or Miss Transform (HMT) is a well-known morphological operator dedicated to template matching. Its recent extension to grayscale images [5] allows to consider the morphological framework as a reliable alternative to statistical approaches for template matching. In this transform, the input image I is scanned with two templates called structuring elements (SE): while the first (foreground) SE F is used to match the shape, the second (background) SE B is used to match the spatial neighbourhood of this shape. The pixels with a local neighbouring configuration fitting the two SEs are kept by the transform while the others are discarded. Contrary to binary images where the HMT is easily defined, the definition for grayscale images is more complex (in particular due to the fact that the definition of background and foreground is not intuitive in such images).

Nevertheless, in a recent work from Naegel et al. [6], the main solutions proposed in the literature have been reviewed and unified. We briefly recall here these definitions using the following notations. Let E be a digital space (*e.g.* $E = \mathbb{Z}^n$) and T be a set of gray levels. We require T to be a complete lattice with respect to the numerical order "$\leq$". We will next assume that $T = \mathbb{R} \cup \{+\infty, -\infty\}$ or $T = \mathbb{Z} \cup \{+\infty, -\infty\}$. We denote by $\perp$ and $\top$, respectively, the lowest and greatest elements of T. Let I and G be two functions of T^E, the set of functions going from a subspace of E to T. We call the support of I ($\text{supp}(I)$) and dual support ($\text{supp}^*(I)$) the set of points where I is strictly above $\perp$ and respectively under $\top$. Dilation $\oplus$ and erosion $\ominus$ of I by G at every point $p \in E$ are then given by:

$$(I \oplus G)(p) = \sup_{k \in \text{supp}(G)} (I(p-k) + G(k)) \tag{1}$$

[1] All images are given in inverse gray level to save ink.

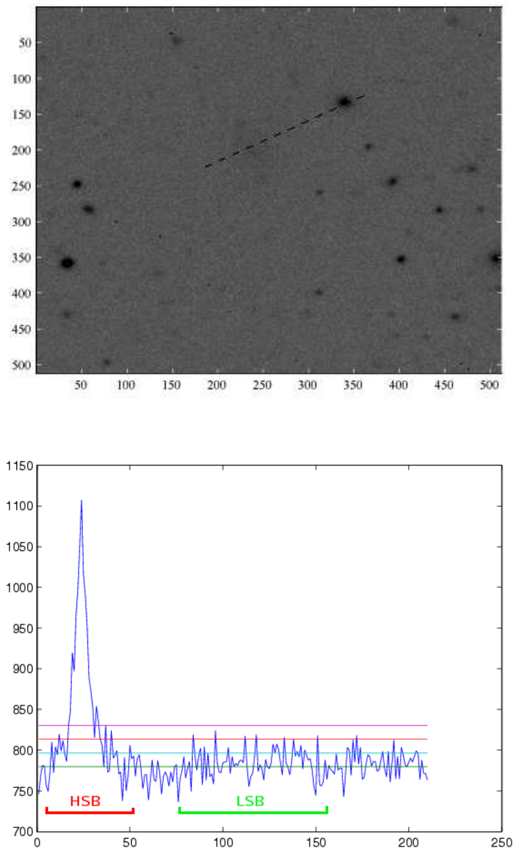


Figure 1: Illustration of a Low Surface Brightness (LSB) galaxy and comparison with an High Surface Brightness (HSB) galaxy: (top) an image containing both objects (LSB hardly visible) and (bottom) the image signal along a profile line.

$$(I \ominus G)(p) = \inf_{k \in \text{supp}(G)} (I(p+k) - G(k)) \qquad (2)$$

Finally we also define the dual G^* of the function $G \in T^E$ by:

$$\begin{aligned} G^* : E &\longmapsto T \\ p &\longrightarrow -G(-p) \end{aligned} \qquad (3)$$

The Ronse operator consists in assigning the maximum gray value where it is possible to fit both SEs:

$$RHMT_{[F,B]}(I)(p) = \begin{cases} (I \ominus F)(p) & \text{if } (I \ominus F)(p) \geq (I \oplus B^*)(p) \\ -\infty & \text{otherwise,} \end{cases} \qquad (4)$$

the Soille operator returns the difference between the highest and lowest value where it is possible to fit the SEs:

$$SHMT_{[F,B]}(I)(p) = \max\{(I \ominus F)(p) - (I \oplus B^*)(p), 0\}, \quad (5)$$

the Barat operator measures the distance between the best inner fit of F and the best outer fit of B (the lower is this value the best is the fit):

$$BHMT_{[F,B]}(I)(p) = (I \oplus B^*)(p) - (I \ominus F)(p), \qquad (6)$$

and finally the Khosravi-Schaefer operator differentiates from the others by using a single SE (here the result is always less or equal to 0 which is reached with a perfect match):

$$\begin{aligned} KHMT_{[F]}(I)(p) &= (I \ominus F)(p) - (-I \ominus (-F))(p) \\ &= (I \ominus F)(p) - I \oplus B^*)(p) \\ &= -BHMT_{[F,F]}(I)(p) \end{aligned} \qquad (7)$$

Nevertheless these definitions suffer from the relative inflexibility of morphological operators (erosion and dilation) used to define them, making them difficult to be applied in noisy images. Since our concern is to perform object detection in such images in the astronomical domain, we have evaluated how robust to noise these approaches were. Soille's and Ronse's HMT noise robustness is mainly determined by the distance between the two SEs F and B, the larger it is the more noise they can absorb but higher the number of false positive is. In Barat *et al* HMT or Khosravi-Schaefer HMT the distance between the two SEs is not important as it only results in a shift of the result. Thus the problem of determining a good distance is transformed in a thresholding problem. The important point is to understand that these problems are equivalent and that all of these formulations will react the same when a lot of noise is present. None of them will deal with this case accurately.

3. A ROBUST HMT

In order to ensure a better robustness to noise of the morphological HMT operator, we propose to adapt the idea from Maragos [7] for binary images to grayscale images. In the original paper from Maragos [7], a fuzzy HMT is introduced to continue using well defined SEs, close to each other and performing reasonably well in noisy environment. It consists in measuring a ratio between the number of pixels that actually fit in the SEs and the total number of pixels contained in the SEs. Hence, instead of looking for positions where the two SEs perfectly fit the image, it measures how well the SEs fit the image everywhere.

To extend this proposal to grayscale images, we consider that the foreground and background SEs describe respectively a local lower and upper bound for the image. The fitting process consists in measuring the ratio between the number of pixels in the neighbourhood between these two bounds and the total number of pixels in the area covered by the SEs. The result is a score between 0 (no points of the neighbourhood fit in the bounds) and 1 (all pixels of the image are between lower and upper bounds). Contrary to Ronse and Soille's HMT where the distance between SEs F and B and so the global shape of the pattern has to be modified to tolerate noise, in the proposed approach SEs can keep a well defined shape and tolerate fluctuations due to noise.

We now assume that T is an infinite set of gray values with a total ordering relation noted $\leq$ (*e.g.* $T \subset \mathbb{Z}$). Formally we have to decompose the image I and pair of SEs (F,B) as *suprema* of impulses and then consider each triplet I, F, B of impulses independently. Let $i_{(p,t)}$ be an impulse at point $p \in E$ of level $t \in T$.

$$\forall x \in E, \;\; i_{(p,t)}(x) = \begin{cases} t & \text{if } p = x \\ -\infty & \text{otherwise.} \end{cases} \qquad (8)$$

For practical reason and because the positions of the impulses have no influence on the following definition we write

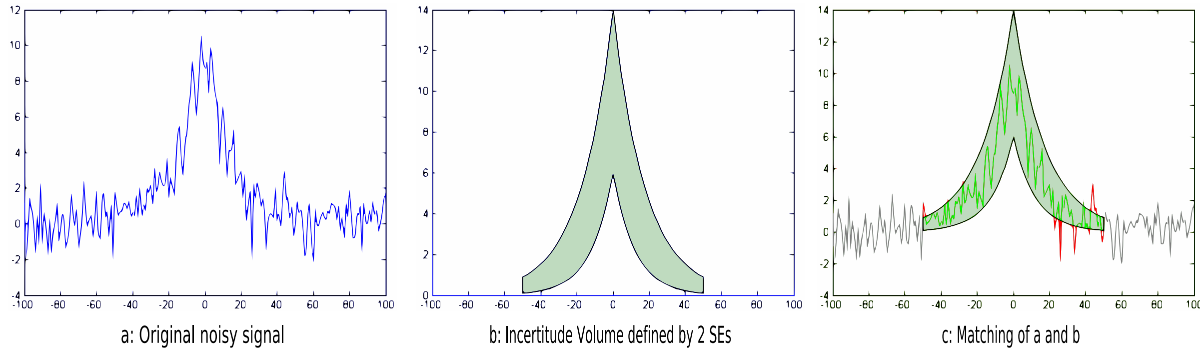


Figure 2: Example of application of the fuzzy hit-or-miss transform to detect an exponential profile with gaussian noise. Image (a) represents a 1D noisy signal (SNR$\approx 9dB$). Image (b) represents the incertitude area defined by the 2 SEs F and B. Image (c) shows how well the pattern can fit the signal.

i_t for $i_{(0,t)}$. Let us write $IC^t_{F,B}(v)(p)$ the proposition "pixel value v is comprised between $F+t$ and $B+t$ at point q", we have

$$IC^t_{F,B}(q)(v) \iff i_{F(q)+t} \leq i_v \leq i_{B(q)+t} \quad (9)$$

$$\iff i_v \oplus i_{B(q)+t} \leq t \leq i_v \ominus i_{F(q)+t} \quad (10)$$

A proof of equivalence between eq. 9 and 10 can be found in [6].

Let us define $S = \text{supp}(F) \cup \text{supp}^*(B)$ and $\text{card}(S)$ the cardinality of the set S, the proposed fuzzy HMT is then defined by:

$$FHMT_{[F,B]}(I)(p) = \max_{t \in T} \frac{\text{card}\{q \in S \,|\, IC^t_{F,B}(q)(I(p+q))\}}{\text{card}(S)} \quad (11)$$

hence it evaluates the best ratio of pixels satisfying requirements of proposition 10 with SEs F and B translated at all possible gray levels.

However, application of this operator is not straightforward. Indeed T is theoretically an infinite and perhaps continuous set, thus it is not directly possible to determine at which level t the score in equation 11 will be maximized. In fact the interval of possible values for t can be restricted quite easily by a local analysis of pixel values. For example in Figure 2, we can estimate that upper part of our pattern should be between gray levels 6 and 14, and this can obviously be done by applying a simple mean filter and keep the resulting value as an estimation of t. One can then compute score for different values near this estimation. This solution obviously depends on the possibility to extract a main feature from the pattern (for example "the peak" in Figure 2) that can be used to perform a first and quick estimation of t.

Another issue is how to determine ideal distance between the two SEs. Indeed it can be estimated from local noise information. For example assuming that our image is corrupted by a gaussian noise $\mathcal{N}(0,\sigma^2)$, and that we are looking for a pattern given by function P: we can set $F = P - \sigma$ and $B = P + \sigma$. Then, according to noise statistic we can expect to have a matching score of about 68% in a correct case.

4. APPLICATION TO LSB GALAXY DETECTION

Since the discovery of the various surface brightness of galaxies, astronomers have become more and more interested in a way to automatically detect very faint objects in astronomical images. Low Surface Brightness Galaxies (LSB) [2] are galaxies with a central surface brightness higher than 22.5 $mag.arcsec^{-2}$ (the magnitude is an inverse logarithmic scale used in astronomy because of its similarities with the human eye behavior). Traditional method of sigma clipping (*i.e.* adaptive threshold method) used commonly in astronomy is not able to detect such object as they are eliminated with the background (see Figures 1 and 5(a) for LSB illustrative examples).

The whole process of LSB galaxies detection is decomposed in two steps: first, a segmentation map of interesting objects is built, and then objects present in segmentation map are characterized using physical criteria. Astronomers of the CDS (Centre de Données astronomiques de Strasbourg[2]) have recently developed such a tool that performs an automatic characterization of astronomical objects through a 2D galaxy model fitting [8]. The goal here is to evaluate the proposed FHMT for automatically building a segmentation map of potential LSB galaxies, complementary to other existing works relying on Markovian approaches. The detection algorithm is fully automatic and decomposed in several steps as shown in the Figure 3.

From the main features of LSB galaxies [2], several patterns of various shapes and orientations are built, thus resulting in a final set of 640 templates or SEs (see for example Figure 4.) All SEs are then convolved with a gaussian kernel of 5×5 pixels to reproduce the point spread function (PSF) of the telescope (seeing and optics deformations). This is an approximation because PSF depends of the image and the location in the image, but this approximation is negligible in comparison with shape uncertainties. Finally from each pattern are built two SEs (background and foreground) of same orientation and elongation, but with two brightness profiles shifted from a distance adjusted dynamically with respect to local noise statistic.

Because the objects we are looking for are very close to the background in terms of photometry, we also need to compute a precise map of the background (*i.e.* evaluate the intrinsic luminosity of the sky at all points). Thus we follow the classical approach used in astronomical imaging and apply the sigma clipping method, which consists in iteratively thresholding the image based on the average and deviation

[2] `http://cdsweb.u-strasbg.fr/`

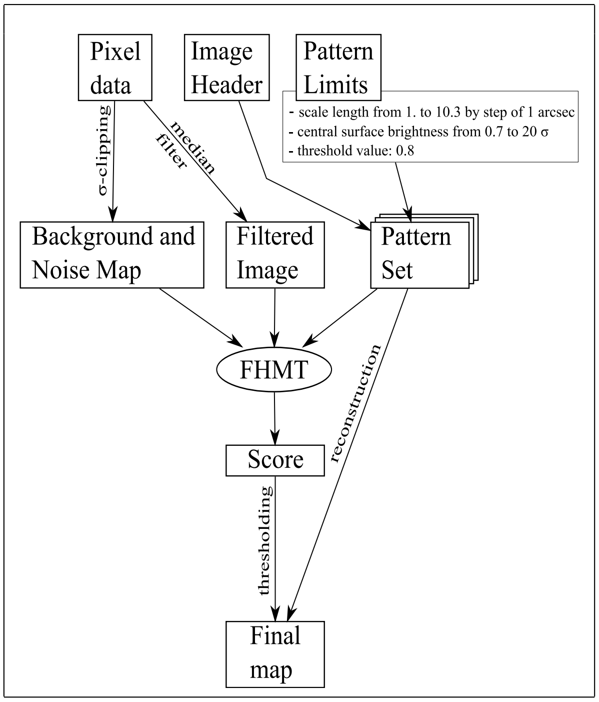


Figure 3: Scheme of the LSB galaxy detection method. The algorithm takes three inputs: image pixels values, image header, and pattern limits (based on physical criteria.) The whole procedure is automatic.

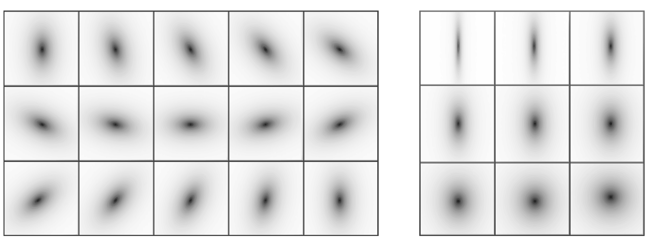


Figure 4: Example of SEs obtained with a variation of orientation (left) and of elongation (right) convolved with a gaussian point spread function.

statistical measures [9].

Next the original image is preprocessed with a median filter to reduce noise. Filtered image, background map, and pattern set are then used to calculate FHMT. Estimation of the best gray level t for vertical translation of SEs is done using a median filter (5×5). We translate foreground (resp. background) SE to local background level and stretch it so that its highest value is $t - \sigma$ (resp. $t + \sigma$) with σ the local deviation of noise. Matching scores between each pattern and median filtered image is then computed and the best one is kept as the result (Figure 5(b)).

In the next step, the score map is binarized using a threshold. The threshold value offers a good tuning option and was determined to minimize false negative rate and, with less importance, minimize false positive rate. We found that a score of 80% offers a good compromise. The use of the same threshold for every observation is not a problem. As all parameters of the algorithm are set automatically according to observation parameters and statistics, the score gives an absolute measure which is independent of the observation.

Once we have a binary map, we need to reconstruct the final map. To do this, each pixel of the binary map is dilated by the support of the pattern that gives the maximum score in this position (Figure 5(c)).

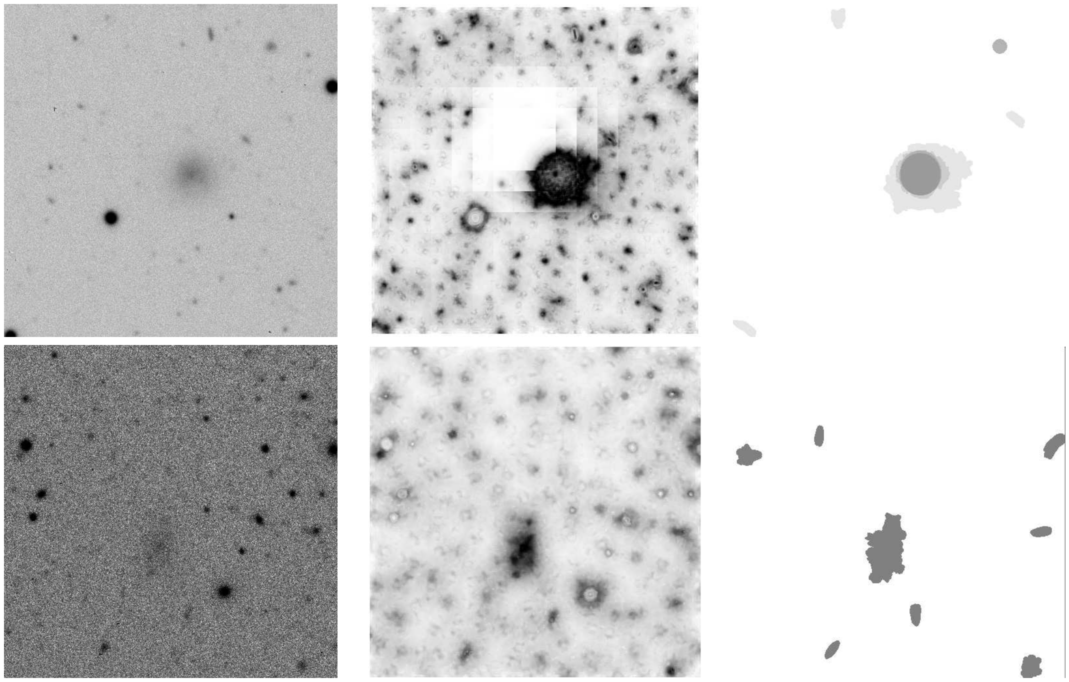
It is very important for astronomers to know the detection limits of the algorithm they are using. This information is used to determine the statical bias of their conclusions due to selection effects of the algorithm. First, some experiments were performed to check the method accuracy on simulated dataset designed with astronomers of the CDS to ensure valid physical properties of the objects and images. We have observed that the method is able to detect LSB galaxies with a low SNR ($\sim 0dB$.)

Next the FHMT operator was applied on a test set of 16 blue band (a filter centered at wavelength of 4500 Angström corresponding to blue color is used) images of 2048×4096 pixels coming from the INT Wide Angle Survey[3]. The dataset covers the Virgo cluster which has the advantages to be close to our Galaxy and in a relatively sparse area of the sky. Moreover LSB galaxies population in this survey has already been studied by astronomers [3], which gives us a reference catalog to evaluate our results. The algorithm has been run over the whole dataset and segmentation maps were used as entry for the CDS characterization tool DetectLSB. At the end of the process, this tool provides HTML files describing potential LSB galaxies found and XML catalogs in the VOTable standard [8]. A full analysis of the result for two images was performed in collaboration with an astronomer. Reference catalog contains 9 LSB galaxies in these fields. The algorithm proposed 23 candidates. It found 6 objects of the reference catalog and provided 8 new LSB galaxies. Spurious detections were mainly due to artifacts created by two close sources (when wings of two close objects intersect, they locally create an artificial raise of luminosity) or very distant galaxies (galaxy's brightness is then decreased by absorption of intergalactic environment). That leads to a total of 17 interesting objects for the 2 images. The recall of the method is then 0.82 and the precision is 0.6. One can note that the 3 LSB galaxies missed from the reference catalog were correctly segmented by FHMT but were rejected by the characterization algorithm. A comparison of the new catalog for the whole set of 16 images with the existing one gives us a recovery rate of 87% and several new candidates. These candidates have now to be analysed by astronomers' community before any conclusion can be drawn on them. It will allow to perform a comparison with other approaches such as the Markovian one [8].

5. CONCLUSION

We have addressed the peculiar problem of object detection in very noisy environment using the morphological HMT. As an alternative to statistical approaches which accurately model the noise information but sometimes fail to deal correctly with shape knowledge, we believe the morphological HMT is a reliable solution as long as it can deal with noisy images. We have studied existing formulations of HMT and observed that they were not adapted to the case of noisy images, thus we proposed a formulation of a robust HMT. Following a fuzzy framework, it relies on two structuring elements: the foreground and the background one and consists

[3] `http://www.ast.cam.ac.uk/~rgm/int_sur/`



(a) (b) (c)

Figure 5: Application of FHMT to LSB detection, easy (top) and hard (bottom) cases. From left to right: contrast-stretched view of the original image of 512×512 pixels with an LSB galaxy at center, score map obtained after application of FHMT, and final map containing different classes proportional to the object luminosity allowing deblending capabilities for overlapping object having different luminosities.

in measuring the ratio of the image area that fit the SEs compared to the total area covered by the SEs.

We have described how it can be applied to a real and hard case in astronomical images: the automatic detection of low surface brightness galaxies. Our results have been analysed by an astronomer and confirmed that FHMT is suitable for pattern matching at very low SNR. Thereby the field of application of morphological HMT has been extended to very noisy images for which statistical approaches are generally preferred. The process we described can be easily adapted for pattern matching in other domains such as radar imaging. Moreover, in case of noisy multispectral data, the proposed operator should be extended to multivariate mathematical morphology [10].

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