MULTI-SCALE SPOT SEGMENTATION WITH SELECTION OF IMAGE SCALES

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Introduction

- Spot detection is involved in many image processing applications.
- Selecting the right scale is required to correctly detect spots of interest and counteract noise and spurious elements.

Elements of interest can exhibit different sizes or scales, thus an automated selection of meaningful scales is needed with the associated multiscale segmentation paradigm.

Scale-space representation of an image

Let f be an image containing spots of various sizes, corrupted by Gaussian noise.

- We predefine a set of scales $\mathcal{S} = \{s_0 r^n, n \in [0, \nu]\}$.
- With a Laplacian of Gaussian (LoG) transform, we build a 3-dimensional map H_f where each slice corresponds to the LoG filtered image for a given scale $\mathbf{s} \in \mathcal{S}$.
- The response of a bright spot of radius ς located at point p, to the multiscale LoG transform should be minimum at scale $\mathbf{s} \in \mathcal{S}$, where s is the closest value to ς^2.
- A local minimum in H_f is called a blob.

A contrario selection of multiple scales

Let us take as H_0 hypothesis, the situation where no spots are present, i.e., only uncorrelated Gaussian noise. Let Ω be the image domain.

- The probability of a pixel to be a blob at scale s is binomial of mean ν_s.
- If N_s is the random variable representing the number of spots at scale s in the random image, N_s is Poisson-distributed of mean $\lambda_s = \nu_s |\Omega|$.
- We generate $\mathcal{G} = \{g_i, 1 \leq i \leq M\}$, a set of M standard normal noise images, and $n_s(g_i)$ is the computed number of blobs in g_i at scale $\mathbf{s}$.
- We estimate λ_s as $\hat{\lambda}_s = \frac{1}{M}\sum_{i=1}^{M} n_s(g_i)$.
- We count the number $n_s(f)$ of blobs in H_f at every scale $\mathbf{s} \in \mathcal{S}$.
- We evaluate the probability that $n_s(f)$ blobs may occur under "no-spots" H_0 hypothesis, referred to as the probability of false alarm $\mathrm{PFA}(\mathbf{s}, f)$:

$$\mathrm{PFA}(\mathbf{s}, f) = \mathbb{P}(N_s \geq n_s(f)) \simeq 1 - \Phi_{\hat{\lambda}_s}(n_s(f)) \quad (1)$$

where $\Phi_{\hat{\lambda}_s}$ is the cumulative density function (CDF) of the Poisson distribution of mean $\hat{\lambda}_s$. Meaningful scales should correspond to very low PFA values, it cannot happen "by chance".
- Thus, the subset of ϵ-meaningful scales $\mathcal{S}^\star \subset \mathcal{S}$ is given by:

$$\mathcal{S}^\star = \{s \in \mathcal{S} | \mathrm{PFA}(\mathbf{s}, f) < \epsilon\}. \quad (2)$$

Spot detection at a given scale

A spot detection binary map $\mathbf{\Delta}_s$ is computed at each scale s by thresholding the lowest values of LoG map $H_f(\cdot, \mathbf{s})$, $s \in \mathcal{S}^\star$ (for bright spots).

- For every point $p \in \Omega$, we estimate the local mean $\mu_s(p)$ and variance $\sigma_s^2(p)$ over a Gaussian window $W_s(p)$ in $H_f(\cdot, \mathbf{s})$.
- The likelihood $\mathcal{L}_s$ of belonging to the background of the LoG map in the vicinity of p at scale $s \in \mathcal{S}^\star$ is then defined by:

$$\mathcal{L}(p) = \varphi((H_f(p, \mathbf{s}) - \mu_s(p))/\sigma_s(p)), \quad (3)$$

where φ denotes the density function of the standard normal distribution.
- Given a p-value α, the local threshold value τ_s is then automatically inferred as $\tau_s(p) = \sigma_s(p)\varphi^{-1}(\alpha) + \mu_s(p)$.
- A point p is detected as belonging to a (bright) spot if

$$H_f(p, \mathbf{s}) < \tau_s(p).$$

Multiscale spot segmentation

To combine results of spot detection at different scales we adopt a coarse-to-fine nested approach. The set of meaningful scales, $\mathcal{S}^\star = \{s_l, l = 1, \eta\}$ is ranked in decreasing order.

- At each scale $\mathbf{s}_l \in \mathcal{S}^\star$, we compute the filtered image $\psi(p, s_l)$:

$$\psi(p, s_l) = H_f(p, \mathbf{s}_l)\mathbf{\Delta}_{\mathbf{s}_{l-1}}(p) \quad (4)$$

where $\mathbf{\Delta}_{\mathbf{s}_{l-1}}(p)$ is the spot detection binary map obtained at scale $\mathbf{s}_{l-1}$.
- For $l = 1$, corresponding to the coarsest scale or level, we take $\mathbf{\Delta}_{\mathbf{s}_0}(p) = 1, \forall p \in \Omega$.
- The spot detection binary map at a given scale operates as a mask for spot segmentation at the subsequent finer scale.
- The final spot segmentation map is given by $\mathbf{\Delta}_{\mathbf{s}_\eta}$.

Experimental results

We compare our multiscale method to other multiscale methods: MSSEF [2], MS-VST [1], and the variant AS-MSSEF, a combination of our method and the coarse-to-fine framework of [2]. Parameter values for all experiments: $s_0 = 1$, $r = 1.2$ and $\epsilon = 0.1$.

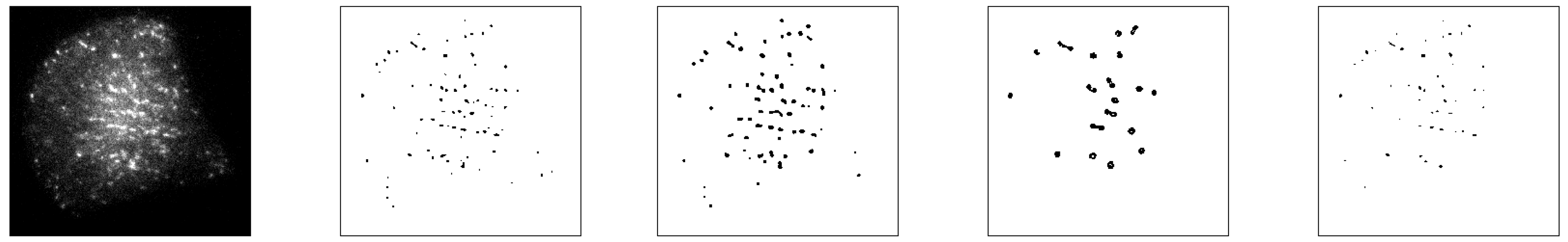
▶ Simulated data

We generated two sets of 20 simulated images each. 150 Gaussian spots, of three equally distributed sizes ς (resp. $\{\sqrt{2.6}, 2, \sqrt{6}\}$, and $\{\sqrt{3}, \sqrt{5}, \sqrt{7}\}$ for the two sets), were randomly sampled in each simulated image over a uniform zero-valued background and added Gaussian noise.

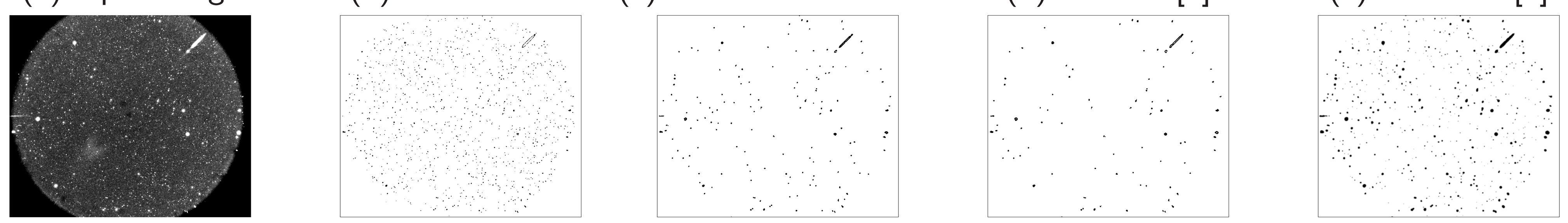
	Our method		AS-MSSEF		MSSEF		MS-VST	
	F-m.	Jacc.	F-m.	Jacc.	F-m.	Jacc.	F-m.	Jacc.
Mean	**0.982**	**0.724**	0.978	0.664	0.937	0.645	0.961	0.357
Std	**0.008**	0.052	0.009	0.068	0.037	0.048	0.015	**0.019**
Min	**0.966**	**0.641**	0.955	0.565	0.866	0.589	0.926	0.331
Max	**0.995**	**0.790**	**0.995**	0.745	0.989	0.708	0.989	0.386

Table: Statistics over the 40 simulated images of the two experiments, on the F-measures and Jaccard index, for the four methods.

▶ Real data

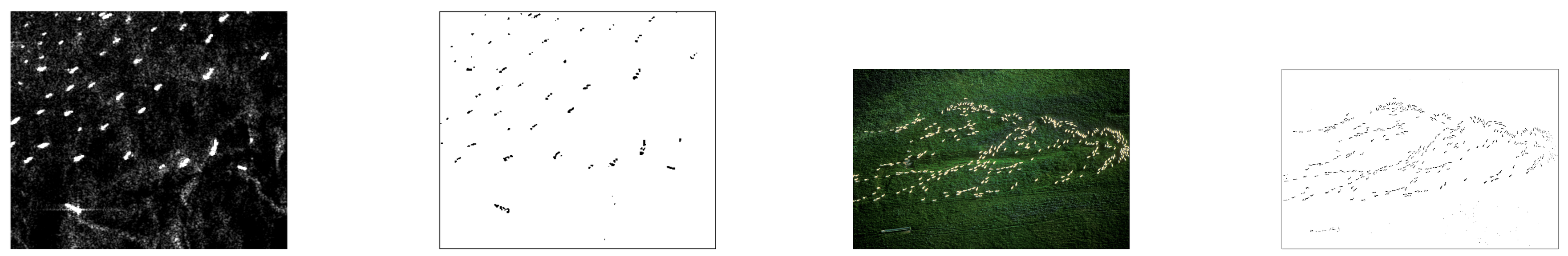


(a) Input image (b) Our method (c) Variant AS-MSSEF (d) MSSEF [2] (e) MS-VST [1]



(a) Input image (b) Our method (c) Variant AS-MSSEF (d) MSSEF [2] (e) MS-VST [1]

Figure 1: Spots segmented (in black) by the four methods on a real light microscopy cell image (top row, by courtesy of Institut Curie), and on a real astronomy image (bottom row, from NASA webpage).



(a) Input image (b) Our method (c) Input image (d) Our method

Figure 2: Spots segmented (in black) by our method on a SAR satellite image including ships (a) and an aerial color image depicting a sheep herd in a meadow (c).

References

[1] B. Zhang, et al. Multiscale variance-stabilizing transform for mixed Poisson-Gaussian processes and its applications in bioimaging. *ICIP'2007*.

[2] A. Jaiswal, et al. Tracking virus particles in fluorescence microscopy images using multi-scale detection and multi-frame association. *IEEE T-IP, 2015*.