SPADE: A Small Particle Detection Method Using A Dictionary Of Shapes Within The Marked Point Process Framework

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Highlights

- High-throughput biological imaging techniques are now common.
- Detecting and characterizing structures only a few pixels wide is a classical task of biological image processing.
- Marked point process (MPP) detectors have proven to be efficient in similar tasks but are not suited for objects of this size.
- We introduce SPADE, a discretized MPP detector where objects are described by a dictionary of shapes instead of parametrically.

Marked Point Process

In this framework the objects are defined in a low dimensionality space $O \subset \mathbb{R}^p$. The configuration space is defined as $\Omega = \cup_n \Omega_n$ where $\Omega_n = (K \times O)^n$ is the set of n objects sets. $K\ in\ \mathbb{R}^2$ is a compact set embedding the discrete image lattice. Denote π the Poisson process, with intensity 1 for normalizing, on K and consider a measure, for example the Lebesgue measure λ, on O. We define a marked point process by a density as follows:

$$\forall \omega = \{((k_i, o_i)i = 1, \ldots, n\} \in \Omega,$$
$$dp(\omega) = h(\omega) d\pi(k) \prod_{i=1}^{n} d\lambda(o_i)$$

where the density h is written as follows: $h(\omega) \exp -U(\omega)$, U being the energy function:

$$U(\omega_1, \omega_2, \ldots, \omega_n) = \sum_{i=1}^{n} u_1(\omega_i) + \sum_{i,j} u_2(\omega_i, \omega_j)$$

where n is the unknown number of objects in the image, ω_i is the ith unknown object configuration, $u_1(\omega_i)$ is the data term value and the prior u_2 is a pairwise constraint defined as:

$$u_2(\omega_i, \omega_j) = \begin{cases} 0 & \text{if } \omega_i \cap \omega_j = \emptyset \\ \infty & \text{otherwise} \end{cases}$$

Dictionary of Shapes

The shapes we used all fit in a 5×5 pixels grid and were generated using a heuristic.

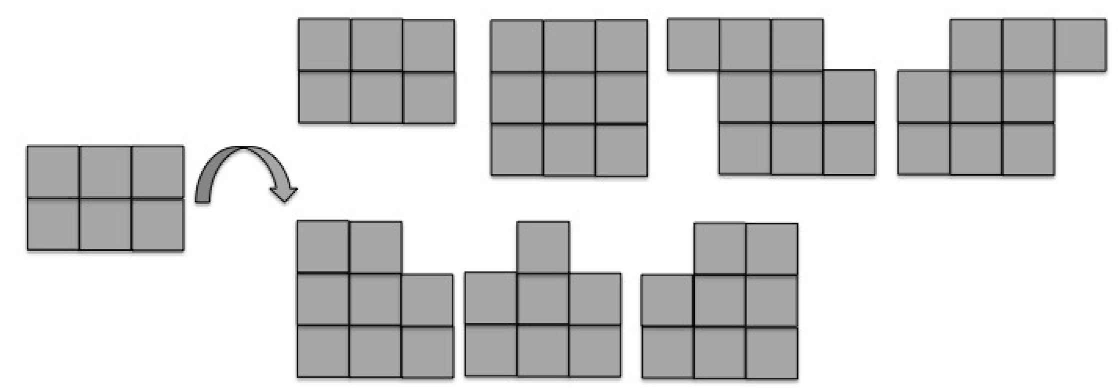

Figure 1: **Construction of the dictionary** A given shape and the new shapes obatined by adding a segment on the top line.

Implementation

- Consider each of the 5% brightest pixels in the image as potential positions of an object configuration.
- For a given potential position, center each shape of the dictionary and compute the corresponding data fidelity term. Retain the one shape that has the minimum term value.
- List the candidates from lowest to highest data fidelity term values.
- Keep the candidates that do not intersect previously listed ones.

Use, study, improve and share the code!

SPADE is released under a GPL-compatible license.
It can be easily installed using the standard python package manager `pip`:

```
$ pip install small-particle-detection
```

Its source code is available at `https://gitlab.inria.fr/ncedilni/spade`.

Comparison on Synthetic Images

Using synthetic images of increasing blur, we showed that, on certain images, SPADE can outperform widely used methods in this classical task of biological image processing. We also show that the data fidelity term must be adapted to the nature of the images in order to get the best results.

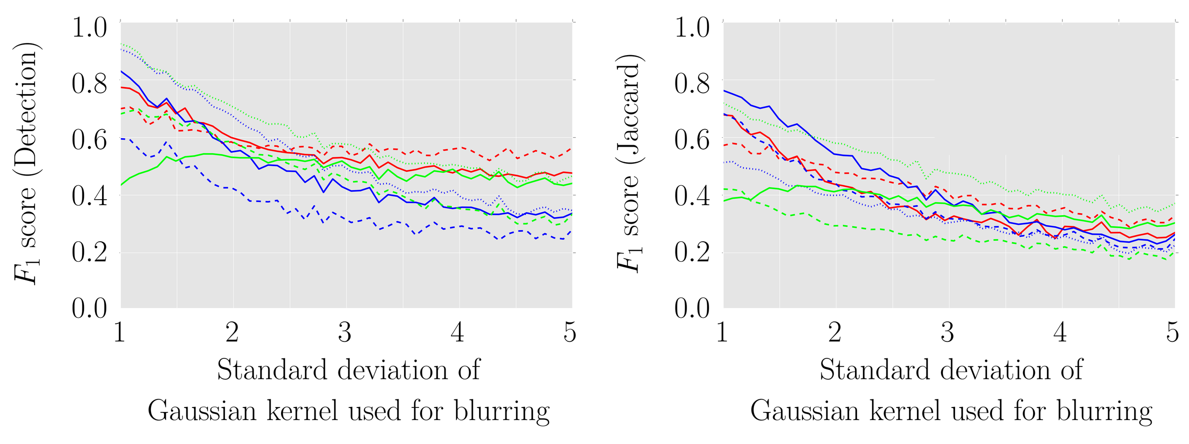

Figure 2: Evaluation of SPADE (using different data fidelity terms, blue and green) against a wavelet-based detector (- - -) and simple intensity thresholding (——) on synthetic images

Results on Real Images

SPADE is now used by biologists in our team on images obtained from different devices.

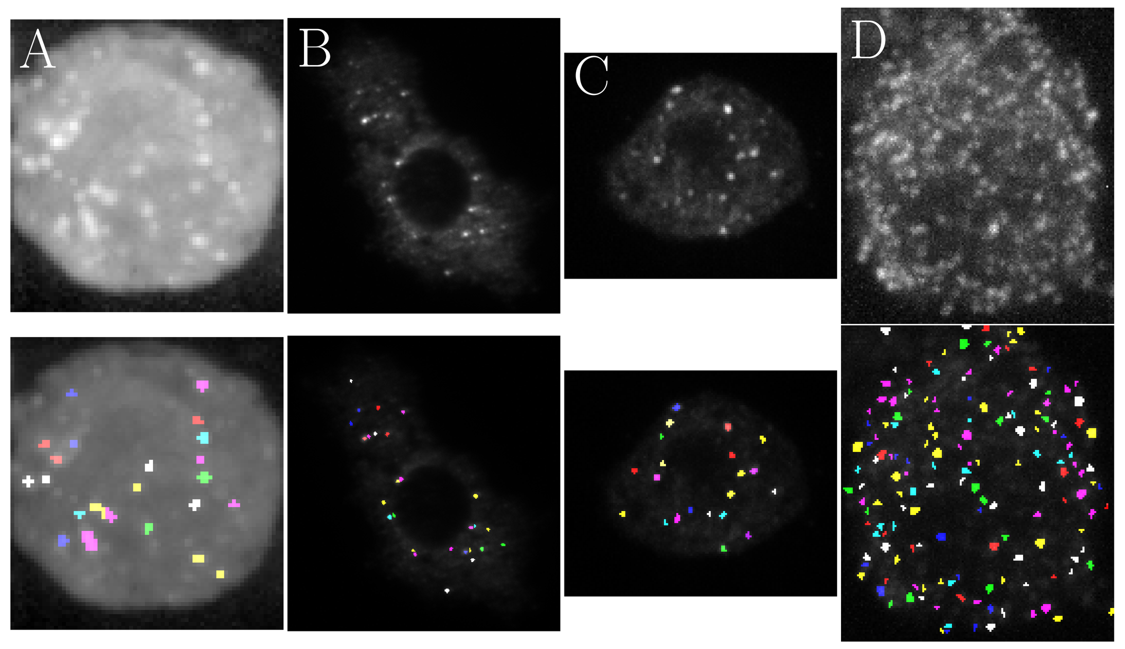

Figure 3: Examples of real images (top) and the corresponding SPADE detections (bottom) Particles are fusion proteins (Green fluorescent protein-Imp), except (D): in situ hybridization with quasar 570-marked oligonucleotidic probes.

Conclusion

SPADE is a promising tool that met our detection requirements. It has proven to be beneficial against other reference methods for similar tasks in terms of detection quality, although it was computationally more expensive. It extends the marked point processes framework to objects only a few pixels wide. We believe that the versatility provided by the choice of different data fidelity terms and dictionaries of shapes is one of its major strengths.
Our future work will focus on integrating it into a fully automated pipeline including cytoplasms segmentations on fluorescence microscopy images.

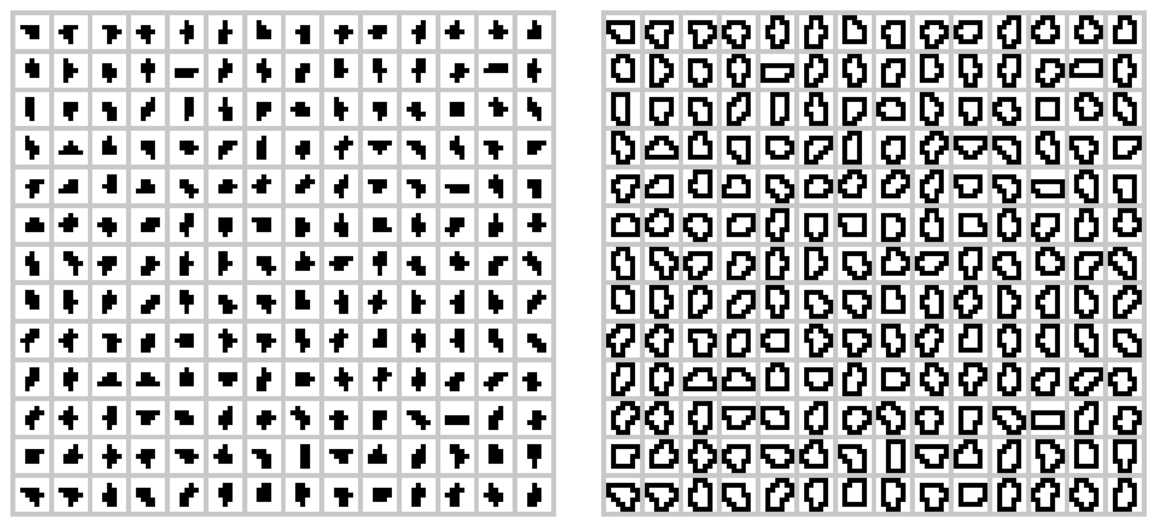

Figure 4: Part of SPADE default dictionary of shapes and their contours

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Cells detection using segmentation competition.
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