CELL SEGMENTATION VIA REGION-BASED ELLIPSE FITTING

Costas Panagiotakis[1,2] and Antonis A. Argyros[1,3]

[1] Institute of Computer Science, FORTH, Heraklion, Crete, Greece
[2] Dept. of Business Administration, TEI of Crete, Agios Nikolaos, Greece
[3] Dept. of Computer Science, University of Crete, Greece

GOAL AND MOTIVATION

We present **SEG-SELF**, a region based method for segmenting and splitting images of cells in an automatic and unsupervised manner.

METHOD OVERVIEW

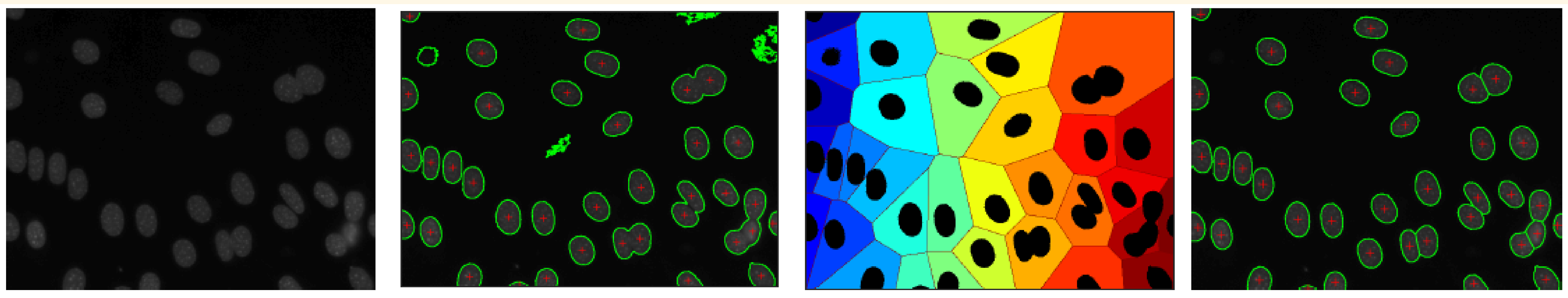

Fig. 1 (a) (b) (c) (d)

(a) Input: A fluorescence microscopy image.
(b) The boundaries of the detected cells according to the Bradleys segmentation [1]. The cell centroids according to the ground truth data are plotted with red "+".
(c) The local backgrounds of the detected cells is given by the Voronoi diagram of their centroids. The detected cells are plotted in black.
(d) Output: Final result of the SEG-SELF method.

CONTRIBUTIONS

- The improvement of Bradleys segmentation [1], taking into account **shape** and **intensity** features and the use of **Voronoi diagram** to compute local background intensity features.
- The use of **DEFA** [2], our previous work on parameter-free ellipse fitting to automatically detect and split touching cells. The proposed method is able to accommodate shape based constraints to automatically **reject spurious splitting solutions**.
- The experimental, quantitative evaluation of the proposed method based on standard datasets which shows that it outperforms existing, state of the art methods.

CELL SEGMENTATION

A drawback of Bradley's method is that segments of the background with locally higher brightness, are erroneously identified as cells (see Fig 1 (b)).
To reduce false positives, we have introduced two shape- and one appearance-based constraints:
1. **Area constraint (shape):** The expected area of each cell should exceed a minimum threshold.
2. **Roundness constraint (shape):** Complex shapes that deviate from circular-like objects are rejected according to Roundness (R).
3. **Intensity constraint (appearance):** The intensity distribution within a cell should be more similar to the distribution within the rest of the cells, rather than to the intensity distribution of the local background. To quantify this, we use the Voronoi diagram (Fig. 1(c)) and **Bhattacharyya distance** (D).

$$R = \frac{4\pi\alpha}{p^2}$$

$$D(q_1, q_2) = \frac{1}{4}\left[ln\left(\frac{\sigma_1^2}{4\sigma_2^2} + \frac{\sigma_2^2}{4\sigma_1^2} + \frac{1}{2}\right) + \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2}\right]$$

REGION SPLITTING

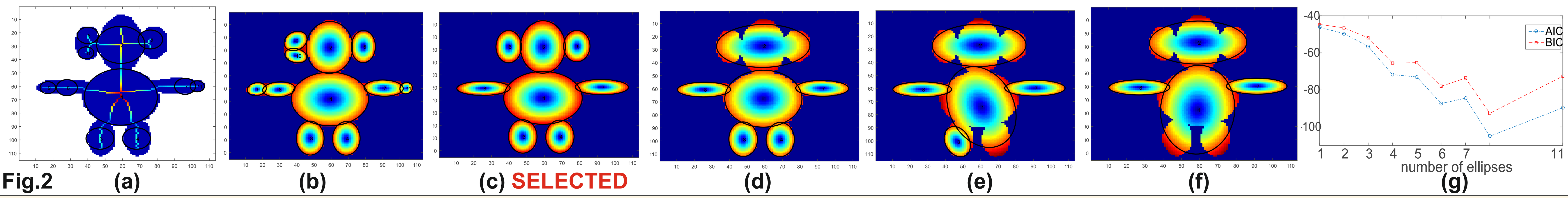

Fig.2 (a) (b) (c) SELECTED (d) (e) (f) (g)

1. The skeleton of the 2D shape is computed for initilization (Fig 2. (a)).
2. In order to identify the proper number of ellipses the employed method (DEFA [2]) evaluates different alternatives based on an AIC criterion (Fig 2. (b)-(f)). Solutions involving different numbers of ellipses are evaluated based on this AIC criterion (Fig 2. (g)).
3. To reduce the over-segmentation, DEFA rejects spurious solutions (e.g. small ellipses).

EXPERIMENTAL RESULTS

Table 1. Segmentation results on the **U20S** dataset.

Methods	Jaccard	MAD	Hausdorff	DiceFP	DiceFN
Otsu	83.5	4.5	11.5	3.0	16.7
Three-step	88.4	4.7	13.4	5.3	5.2
LSBR	83.2	5.8	19.8	11.8	9.1
LLBWIP	**91.6**	3.5	12.7	**4.7**	**3.9**
SEG-SELF	89.3	**3.0**	**8.3**	**4.7**	6.8

Table 2. Segmentation results on the **NIH3T3** dataset.

Methods	Jaccard	MAD	Hausdorff	DiceFP	DiceFN
Otsu	56.9	6.2	12.9	24.2	35.4
Three-step	70.8	5.7	16.4	15.5	19.7
LSBR	64.2	7.2	19.8	21.2	20.4
LLBWIP	75.9	4.1	14.3	**12.7**	12.2
SEG-SELF	**80.8**	**3.7**	**8.8**	**12.7**	**9.0**

Table 3. Splitting results on the **U20S** and **NIH3T3** datasets.

Methods	U20S		NIH3T3	
	FP	FN	FP	FN
Three-step	0.5	3.9	1.7	11.3
LLBWIP	**0.3**	2.7	1.5	5.0
SEG-SELF	2.7	**0.3**	**0.7**	**0.8**

Employed datasets [3]:
1. U20S dataset: A collection of 48 images (1349x1030 pixels) that include 1,831 cells.
2. NIH3T3 dataset: A collection of 49 images (1344x1024 pixels) that include 2,178 cells.

SEG-SELF is compared with **Three-step** [4], the **LSBR** [5], the **LLBWIP** [6]) and the **Otsu** methods [7].

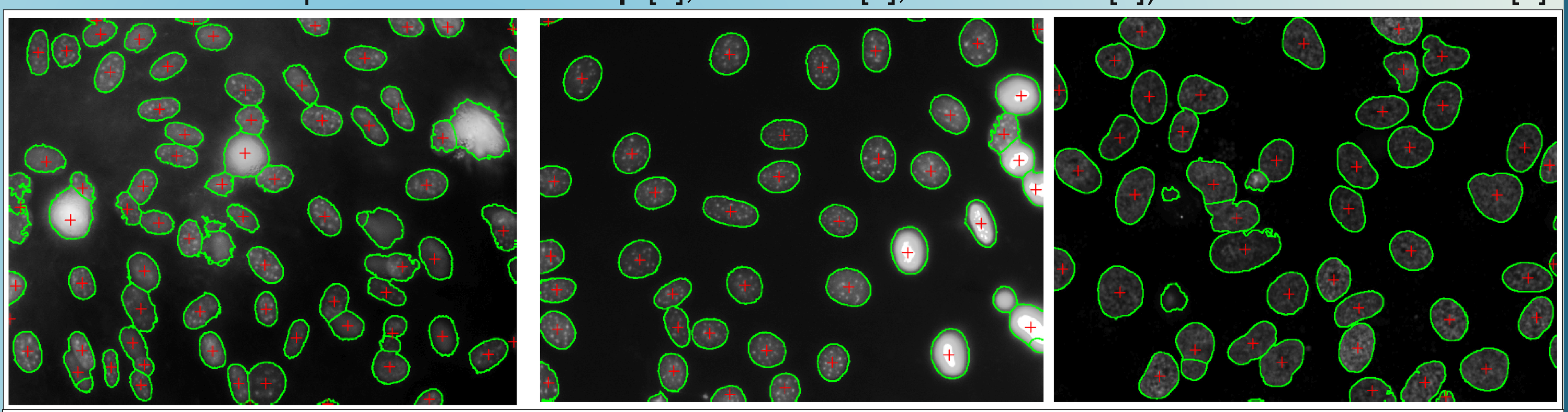

Fig. 3. Representative results of the SEG-SELF method. The ground truth centroid is shown with a red plus. The boundaries detected by the proposed method are plotted in green color. SEG-SELF successfully recognizes and correctly splits the cells, even if there exist important variations on cell shape and intensity.

REFERENCES

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