

# **Region and Contour Based Cell Cluster Segmentation Algorithm for In-Situ Microscopy**

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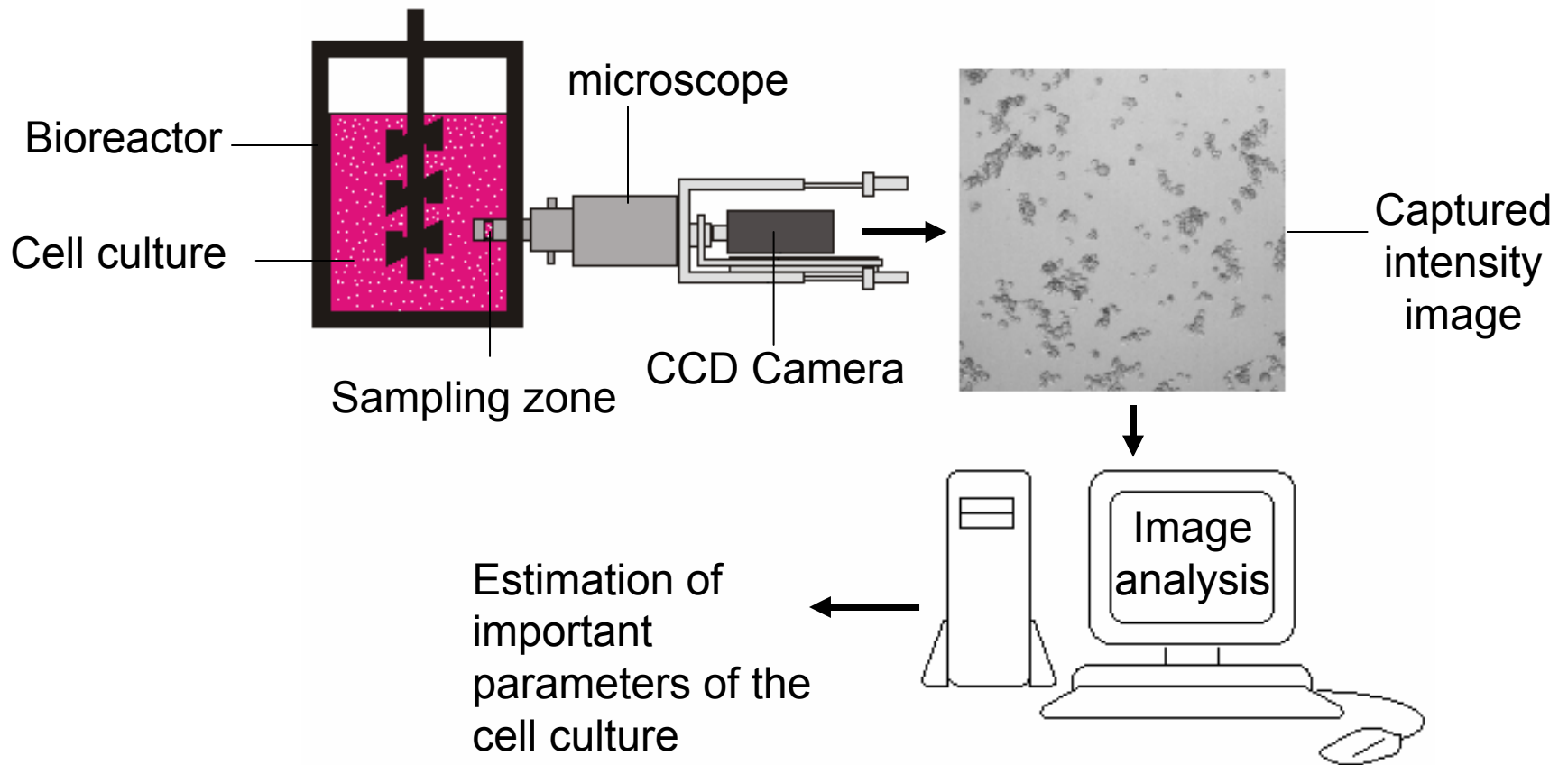
IEEE CCE, Mexico City, Mexico, November 2008

# Topics

- Introduction
- Existing algorithms
- Proposed algorithm
- Experimental results
- Summary and conclusions

# Introduction

## In-situ microscopy

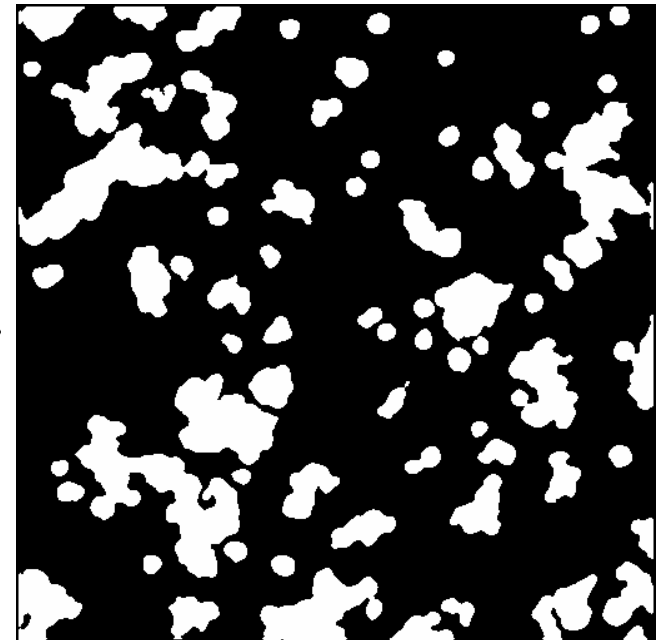
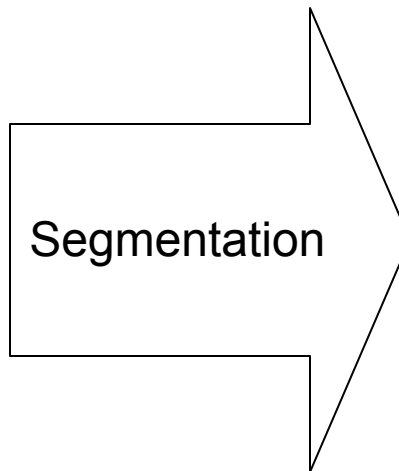


# Introduction

## Cell image segmentation



Intensity image  $I(x,y)$ ,  $x:1..L$ ,  $y:1..M$ , captured by the in-situ microscope



Binary image  $I_B(x,y)$ ,  $x:1..L$ ,  $y:1..M$ , with pixels belonging to the cell clusters in white and pixels belonging to the background in black

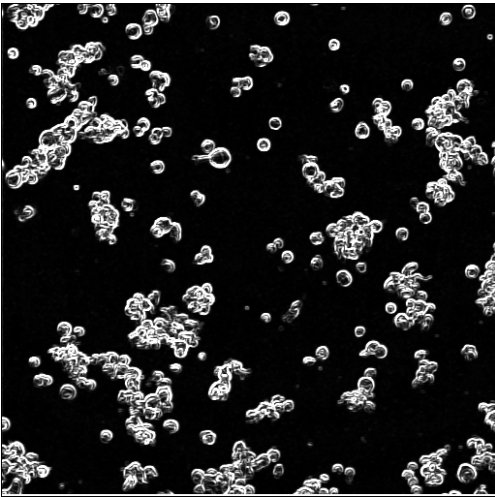
# Existing Algorithms

Cell cluster segmentation algorithms can be roughly divided into 4 main groups:

- Thresholding based segmentation algorithms
  - Espinoza's algorithm: Latest contribution for segmenting BHK cells images captured by an in-situ microscope
- Contour based segmentation algorithms
- Region based segmentation algorithms
- Combinations of the previous

# Espinoza's Algorithm

## 1) Global thresholding of the local variance



- a. Estimate the local variance  $\sigma^2(x,y)$  at each image position  $(x,y)$  using a 3x3 window:

$$\sigma^2(x,y) \cong \frac{1}{50} \cdot \sum_{m=-3}^3 \sum_{n=-3}^3 [I(x+m, y+n) - m(x,y)]^2$$

with:

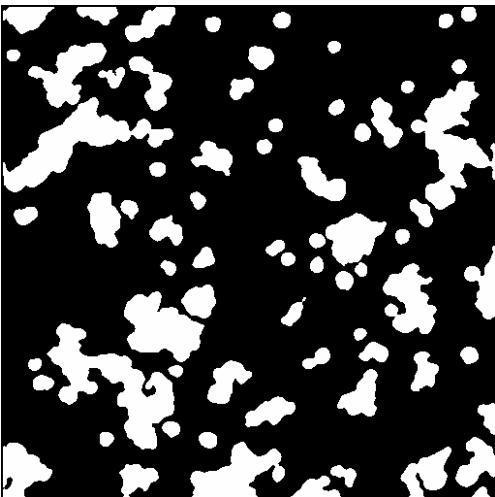
$$m(x,y) \cong \frac{1}{49} \cdot \sum_{m=-3}^3 \sum_{n=-3}^3 I(x+m, y+n)$$

- b. Globally threshold the local variance:

$$I_B(x,y) = \begin{cases} 0, & \text{if } \sigma^2(x,y) \leq th_g \\ 1, & \text{if } \sigma^2(x,y) > th_g \end{cases}$$

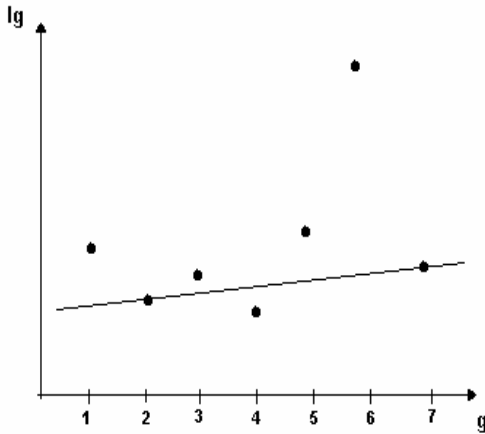
$th_g$  is estimated applying a maximum likelihood algorithm (Kittler & Illingworth)

- c. Apply a 5x5 median filter to  $I_B$  and eliminate small regions (<0.5%)



# Espinoza's Algorithm

## 2) Local thresholding of the intensity

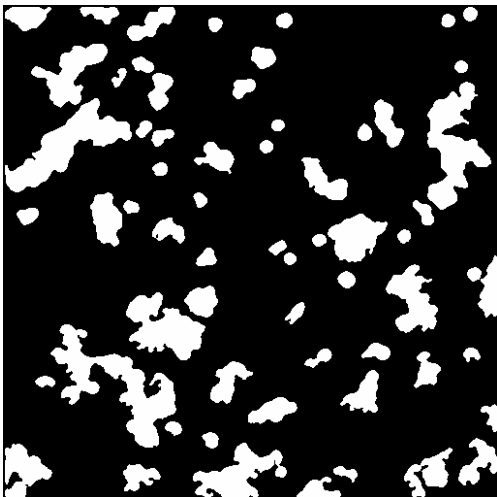


- a. Find for each segmented region  $r$  all the border pixels  $I_g^{(r)}$ ,  $g:0...G^{(r)}$ .
- b. Select from all the border pixels  $I_g^{(r)}$  only those border pixels  $I_h^{(r)}$ ,  $j:0...H^{(r)}$  that have an intensity value similar to the background intensity value by applying a RANSAC algorithm
- c. Locally threshold the intensity in each region  $r$ :

$$I_B(x, y) = \begin{cases} 1, & \text{if } I(x, y) \leq th^{(r)} \\ 0, & \text{if } I(x, y) > th^{(r)} \end{cases}, \quad \forall (x, y) \in r$$

$$\text{with: } th_l^{(r)} = \frac{1}{H^{(r)}} \sum_{h=1}^{H^{(r)}} I_h^{(r)}$$

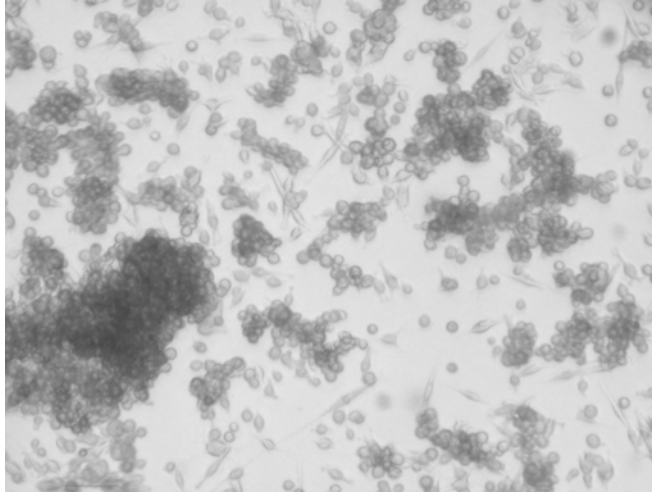
- d. Apply a 5x5 median filter to  $I_B$  and eliminate small regions ( $<0.5\%$ )



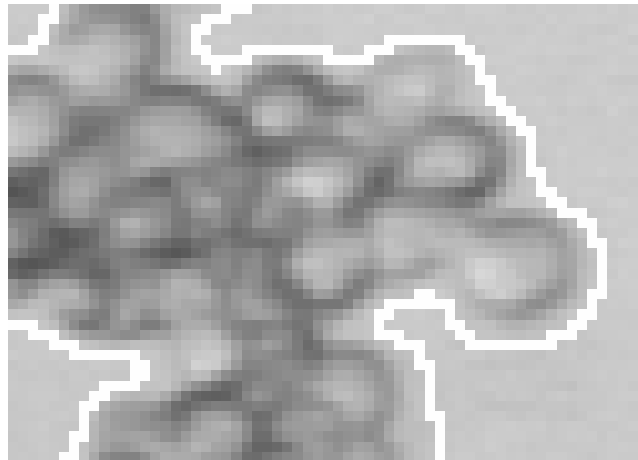
# Espinoza's Algorithm

## Problems

Low  
reliability in  
low contrast  
images:

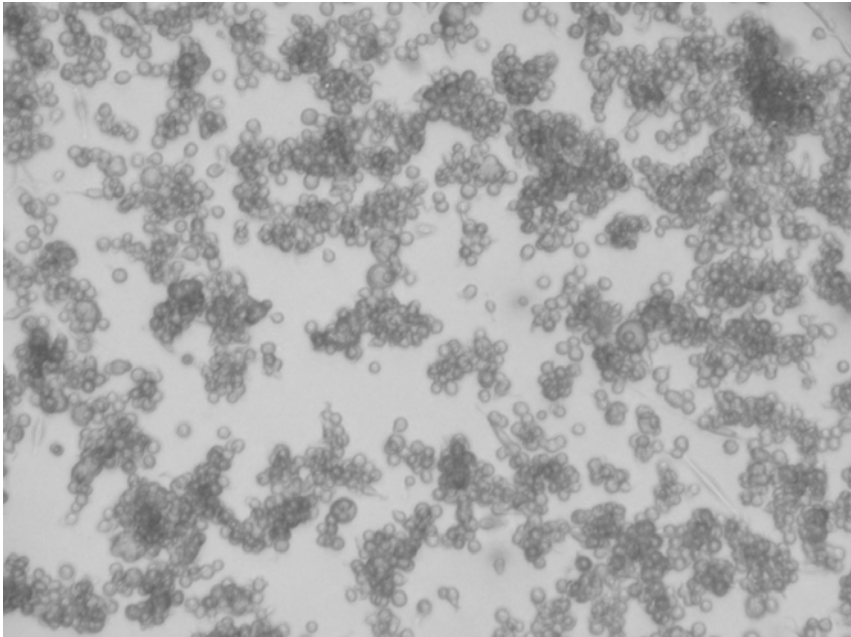


Low  
precision:





# Proposed Algorithm



Because:

1. The background is homogeneous
2. The cell clusters are non homogeneous with darker intensity values and well defined contours

we propose:

To segment the background using a region and contour based approach and then to invert the resulting binary image to get the cell cluster regions

# Proposed Algorithm

## 1) Seed selection

- a. Select as background seed candidates those pixels that meet the following rules:

$$I(x, y) > m_2 - \sigma_2$$

$$\sigma^2(x, y) < 0.20 \cdot \sigma_2^2$$

where,  $m_2$  and  $\sigma_2$  are the mean and standard deviation of the pixels' intensity values in the background

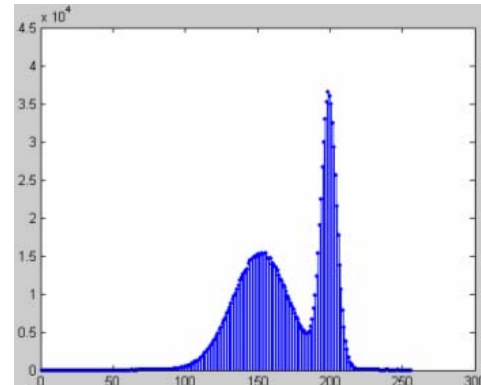
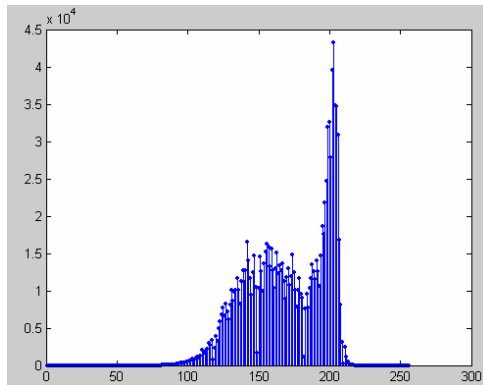
# Proposed Algorithm

$m_2$  and  $\sigma_2$ , as well as the mean  $m_1$  and standard deviation  $\sigma_1$  of the pixels' intensity values in the cell clusters are estimated modeling the probability density function of the intensity values  $p(I)$  as a sum of two weighted Gaussian density functions:

$$\begin{aligned} c_1 &= \sum_{I=0}^k \frac{h(I)}{N} & m_1 &= \frac{1}{c_1(k)} \cdot \sum_{I=0}^k I \cdot \frac{h(I)}{N} & \sigma_1^2 &= \frac{1}{c_1(k)} \cdot \sum_{I=0}^k (I - m_1)^2 \cdot \frac{h(I)}{N} \\ c_2 &= \sum_{I=k+1}^{255} \frac{h(I)}{N} & m_2 &= \frac{1}{c_2(k)} \cdot \sum_{I=k+1}^{255} I \cdot \frac{h(I)}{N} & \sigma_2^2 &= \frac{1}{c_2(k)} \cdot \sum_{I=k+1}^{255} (I - m_2)^2 \cdot \frac{h(I)}{N} \end{aligned}$$

where  $N$  is the total number of pixels,  $h(I)$  is the number of pixels with intensity  $I$  and  $k$  is selected maximizing the following likelihood function:

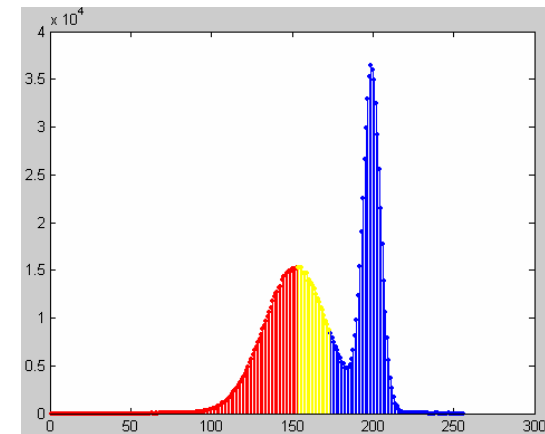
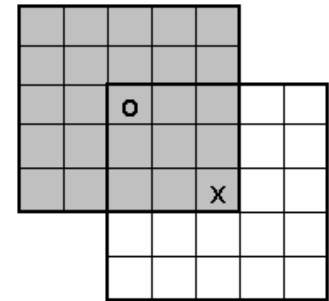
$$L_1(k) = N \cdot \sum_{j=1}^2 c_j(k) \cdot \log(c_j(k)) - \frac{N}{2} \cdot \log(2\pi) - \frac{N}{2} \cdot \sum_{j=1}^2 c_j(k) \cdot \log(\sigma_j^2(k)) - \frac{N}{2}$$



# Proposed Algorithm

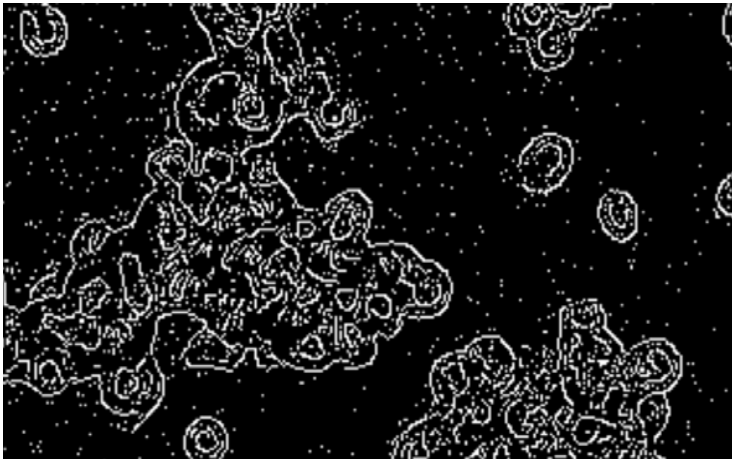
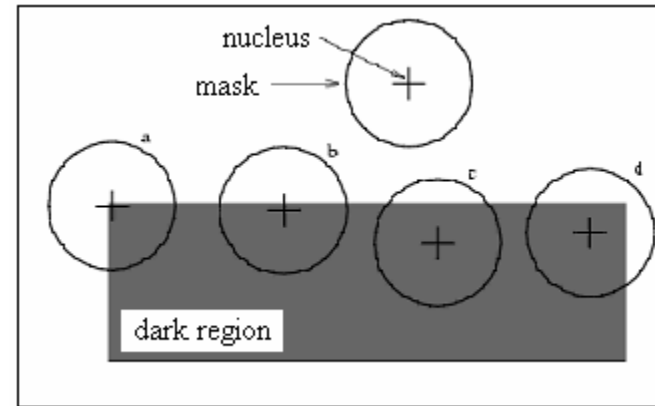
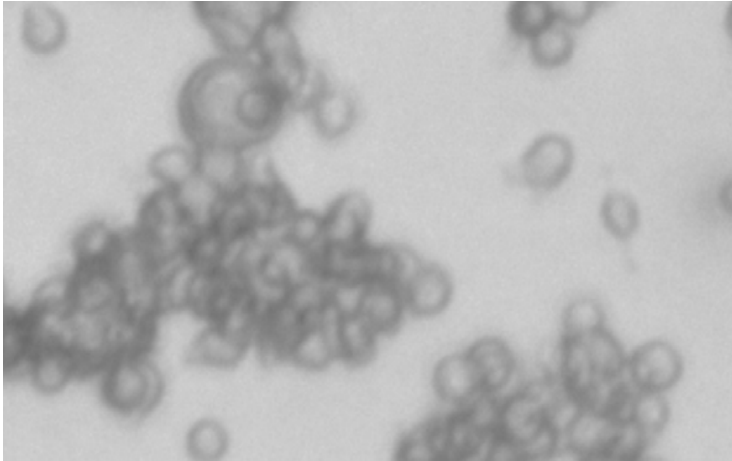
b. Reject those seed candidates that meet at least one of the following rules:

- One of its neighbors is a contour pixel
- One of its neighbors has  $I(x, y) < m_1$  and also has a neighboring contour pixel
- One of its neighbors has  $m_1 < I(x, y) < m_1 + \sigma_1$ ,  $\sigma^2(x, y) > \sigma_2^2$  and a neighboring contour pixel



# Proposed Algorithm

The contours in the image are obtained with the SUSAN algorithm:



The intensity values inside a circular mask are compared with the intensity value in the center (nucleus). If there is a low amount of pixels inside the mask with an intensity value similar to the intensity value of the nucleus, then the nucleus is a contour pixel.

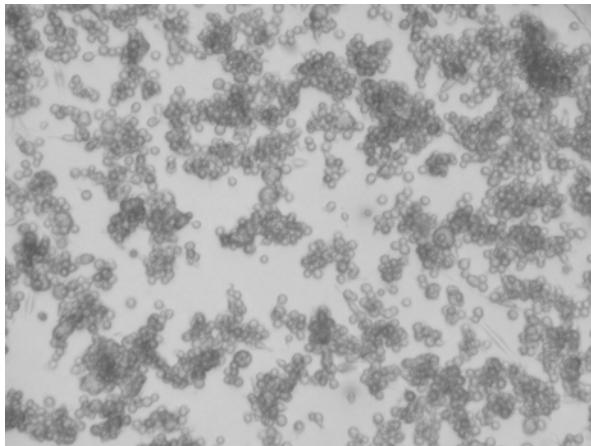
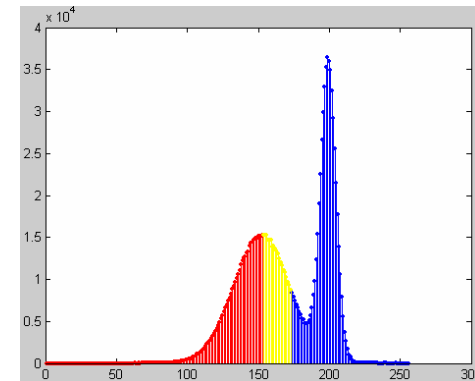
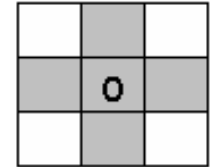
# Proposed Algorithm

## 2) Region growing

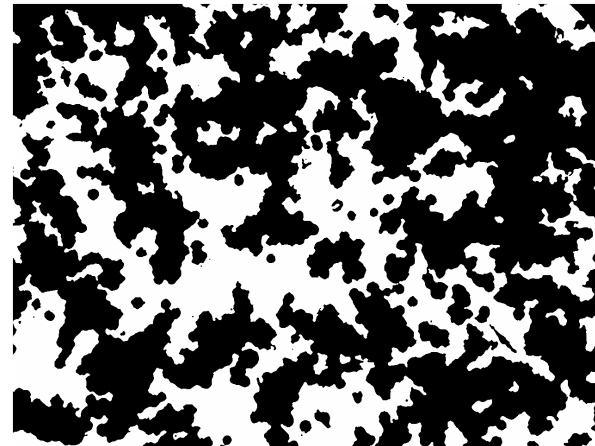
- a. Add a pixel to a seed unless it meets at least one of the following rules:

- It is a contour pixel.
- It has  $I(x, y) < m_1$  and a neighboring contour pixel.
- It has  $m_1 < I(x, y) < m_1 + \sigma_1$ ,  $\sigma^2(x, y) > \sigma_2^2$  and a neighboring contour pixel

- b. Repeat step a. until no more pixels can be added to the background region



Intensity image

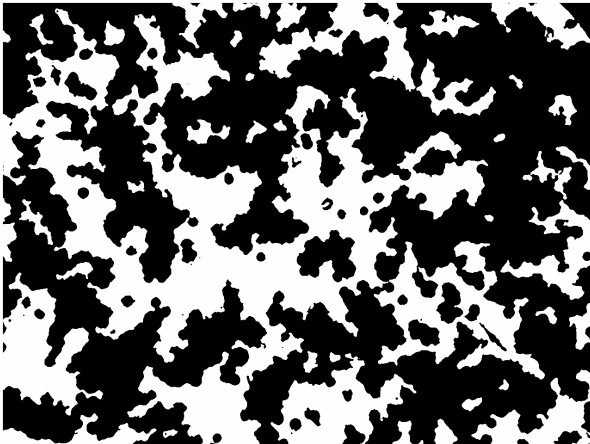


Binary image with segmented background

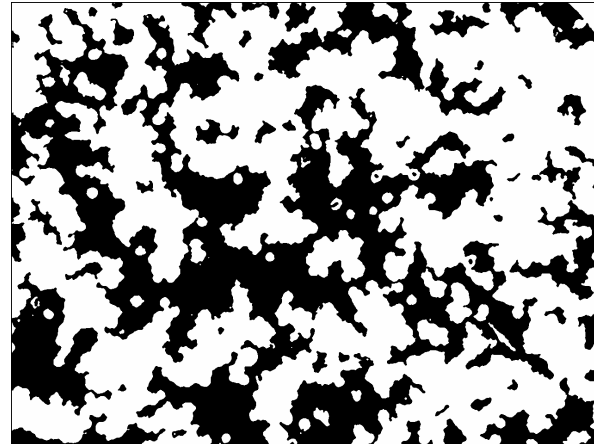
# Proposed Algorithm

## 3) Invert the binary image

- a. Invert the binary image with the segmented background.



Binary image with  
segmented background



Inverted binary image

- b. Apply a 5x5 median filter to the inverted binary image.

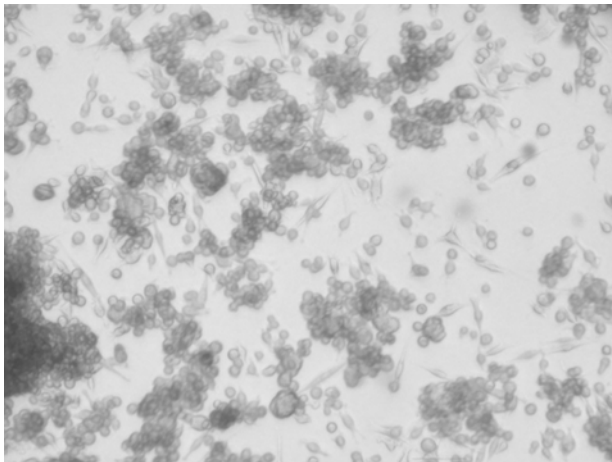
# Experimental Results

## Reliability

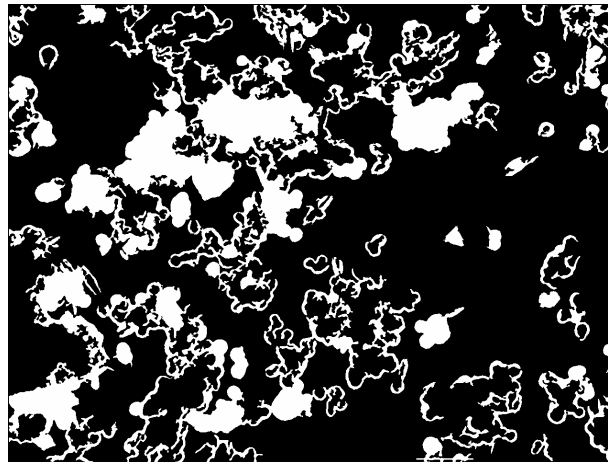
Experiments in 30 different BHK cell images:

\*BHK: Baby Hamster Kidney cells

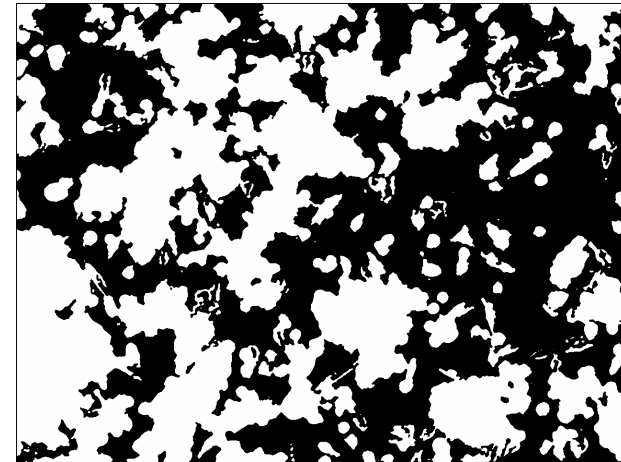
Algorithm	# images with most cell clusters correctly segmented	Percentage of images with most cell clusters correctly segmented
Espinoza's algorithm	20	66%
Proposed algorithm	30	100%



Low contrast intensity image



Espinoza's algorithm segmentation result



Proposed algorithm segmentation result



# Experimental Results

## Precision

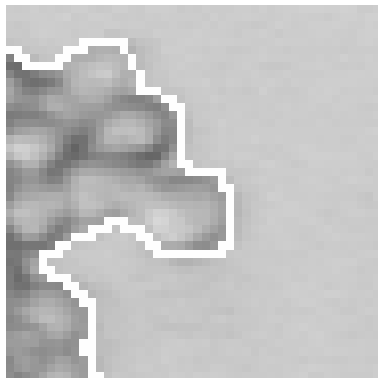
Distance from each boundary pixel  $i$ ,  $i:1...n$ , of the automatically segmented regions to the closest boundary pixel of the manually segmented regions:

$$d_i^2 = (\Delta x_i)^2 + (\Delta y_i)^2$$

Mean square position error of the boundaries:

$$MSE = \frac{\sum_{i=1}^n d_i^2}{n}$$

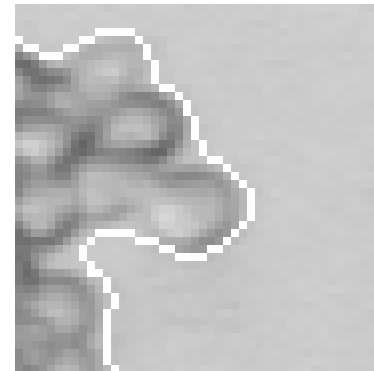
Average MSE for Espinoza's algorithm	Average MSE for the proposed algorithm	Improvement
4,02 pixel <sup>2</sup>	1,8 pixel <sup>2</sup>	55,10%



Manual segmentation



Espinoza's algorithm segmentation result



Proposed algorithm segmentation result

# Conclusions

The proposed segmentation algorithm is

- 33% more reliable
- 55% more accurate

than the Espinoza's algorithm in low contrast images

Thank you very much for your attention