

# Stochastic watershed segmentation

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ISMM'2007 - Rio de Janeiro, Brazil  
October 10-13, 2007

# Plan

- 1 Introduction
- 2 General methodology
- 3 Probabilistic uniform segmentation
- 4 Probabilistic regionalized segmentation
- 5 Probabilistic uniform-levelled segmentation
- 6 Conclusions and perspectives

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- 2 General methodology
- 3 Probabilistic uniform segmentation
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# Introduction

## Motivation

- watershed-based algorithms for image segmentation: markers, non-parametric pyramids, hierarchies according to morphological criteria, interactive segmentation
- in many applications from natural images: unsupervised segmentation in very few regions

Example: Volumic extinction values to determine the  $R$  most significant regions



$\mathbf{f}$



$\varrho^{LS+H}(\mathbf{f})$



$sg^{R-vol}(\mathbf{f}, 10)$



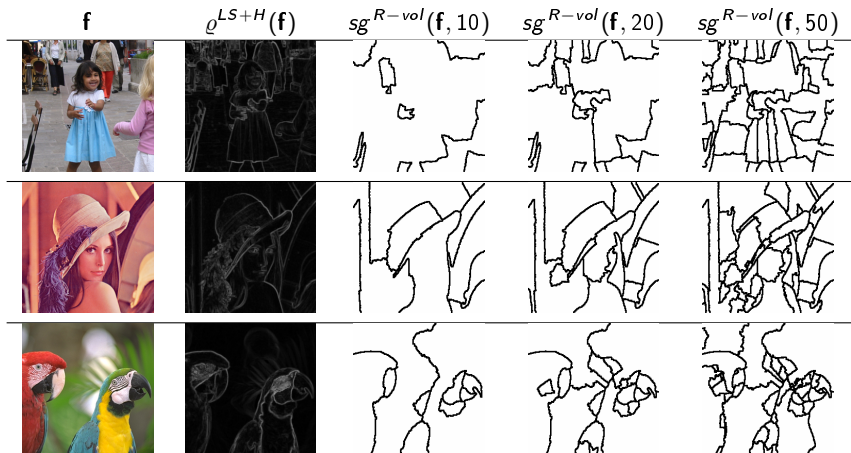
$sg^{R-vol}(\mathbf{f}, 20)$



$sg^{R-vol}(\mathbf{f}, 50)$

# Introduction

More examples:



# Introduction

## Aim

- to improve the watershed-based segmentation in very few regions ( $R \sim 10, 20$ )
- to detect the most significant contours from the gradient: the contours which are robust with respect to variations in the segmentation conditions
- to work in a probabilistic framework in order to build a pdf of contours by Monte-Carlo simulations
- to use the pdf of contours for defining the most significant regions

- 1 Introduction
- 2 General methodology
- 3 Probabilistic uniform segmentation
- 4 Probabilistic regionalized segmentation
- 5 Probabilistic uniform-levelled segmentation
- 6 Conclusions and perspectives

## Main concept

- The classical paradigm of watershed segmentation lays on the appropriate choice of markers: the most intelligent part resides in the development of criteria used to select the required markers
- **Stochastic paradigm**: To select random germs for markers. This arbitrary choice is balanced by the use of a given number of realizations



## Transformations and main operators (1/2)

Colour gradient  $\varrho^{LS+H}(\mathbf{f}(x)) =$   
$$f_S(x) \times \varrho^{\circ}(f_H(x)) + (1 - f_S(x)) \times \varrho(f_L(x)) + \varrho(f_S(x))$$

### Watershed segmentation

- Marker-based segmentation (image of markers  $mrk(x)$ ):  
$$sg^{mrk}(\mathbf{f}(x)) = Wshed(\varrho^{LS+H}(\mathbf{f}(x)), mrk(x))$$
- Volumic-based segmentation in  $R$  regions:  
$$sg^{R-vol}(\mathbf{f}(x)) = Wshed(\varrho^{LS+H}(\mathbf{f}), R)$$

### Markers: Random points

- $N$  Spatially uniform points:  $mrk_i(x) = uniform(N)$
- Regionalized Poisson points of density  $\theta(x)$ :  
$$mrk_i^{\theta}(x) = poisson(\theta)$$
- $M$ : Number of realizations ( $i = 1, 2, \dots, M$ )

## Transformations and main operators (2/2)

Probability density functions of contours (Parzen estimate):

$$pdf(x) = \frac{1}{M} \sum_{i=1}^M k_i(x) = \frac{1}{M} \sum_{i=1}^M sg_i^{mrk}(\mathbf{f}(x)) * G_\sigma$$

$G_\sigma$  is a gaussian filter,

$$sg_i^{mrk}(\mathbf{f}(x)) = Wshed(\varrho^{LS+H}(x), mrk_i(x))$$

Probabilistic segmentation from wshed on pdf In  $R$  volumic regions:

$$sg^{R-vol}(pdf(x)) = Wshed(pdf(x), R)$$

Probabilistic segmentation from wshed on probabilistic gradient

$$\rho(x) = \omega_1 \varrho^{LS+H}(\mathbf{f}(x)) + \omega_2 pdf(x); \quad \omega_1 = (1 - \lambda), \quad \omega_2 = \lambda$$

$$sg^{R-vol}(\rho(x)) = Wshed(\rho(x), R)$$

## Remarks

### Interpretation

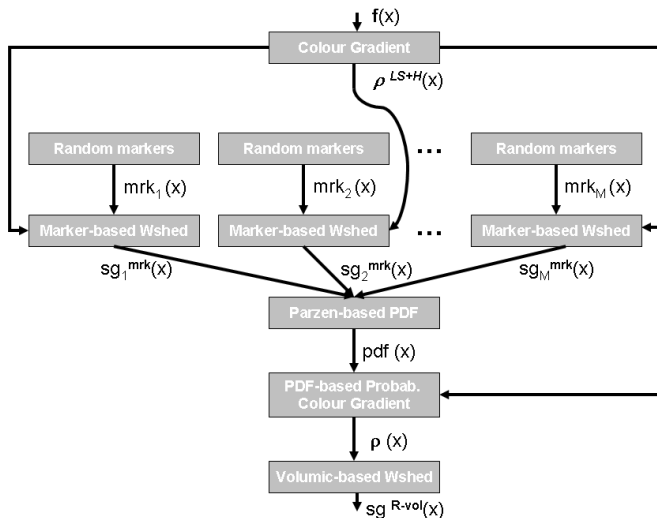
- Each catchment basin (each minima) of  $pdf(x)$  corresponds to one the regions of the sum (or union) of different  $sg_i^{mrk}(x)$ .
- The integral of each catchment basin corresponds to the probability to be region of the segmentation.
- The volumic watershed of  $pdf(x)$  yields the regions according to their probabilities.

### Implementation

- The  $M$  realizations of contours segmentation are obtained from the same function (i.e., colour gradient) using different markers.
- Consequently, working on the neighbourhood graph and its MST, the  $R$  random markers can be considered as  $N$  random nodes of the MST.

- 1 Introduction
- 2 General methodology
- 3 Probabilistic uniform segmentation**
- 4 Probabilistic regionalized segmentation
- 5 Probabilistic uniform-levelled segmentation
- 6 Conclusions and perspectives

# Algorithm



# Uniform random markers and watershed on colour gradient

$mrk_i(x)$   
 $N = 10$

$i = 1$



$sg_i^{mrk}(x)$

# Uniform random markers and watershed on colour gradient

$mrk_i(x)$   
 $N = 10$

$i = 1$



$sg_i^{mrk}(x)$



# Uniform random markers and watershed on colour gradient

$mrk_i(x)$   
 $N = 10$

$i = 1$



$i = 2$



$i = 3$



$i = 4$

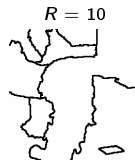


$sg_i^{mrk}(x)$





# pdf estimate and volumic watershed



$N = 10, M = 50$

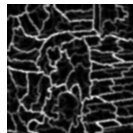
$pdf(x)$



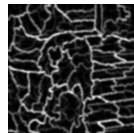
$N = 10, M = 100$



$N = 100, M = 100$



$N = 100, M = 200$

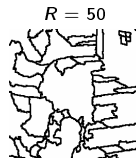
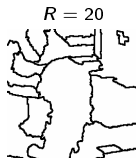


$sg^{R-vol}(x)$

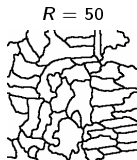
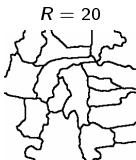
$R = 10$



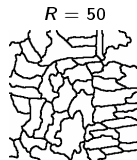
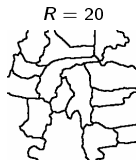
# pdf estimate and volumic watershed



$N = 50, M = 100$



$N = 100, M = 200$



# pdf estimate and volumic watershed



$R = 20$



$R = 50$



$N = 50, M = 100$

$R = 20$



$R = 50$



$N = 100, M = 200$

$R = 20$



$R = 50$



## pdf estimate and volumic watershed



$R = 10$



$R = 20$



$R = 50$



$N = 10, M = 100$

$R = 10$



$R = 10$



$N = 100, M = 200$

$R = 20$



$R = 50$



# pdf estimate and volumic watershed



$R = 10$



$R = 20$



$R = 50$



$N = 10, M = 100$

$R = 10$



$R = 10$



$N = 100, M = 200$

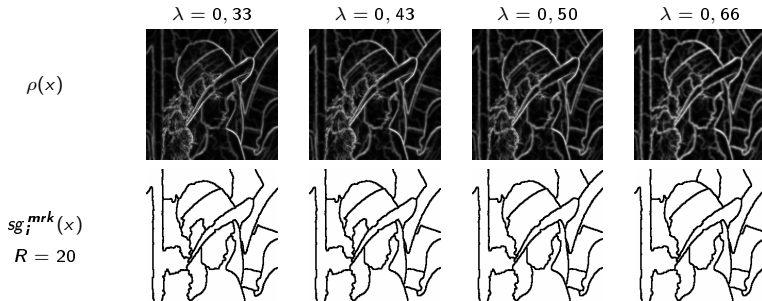
$R = 20$



$R = 50$

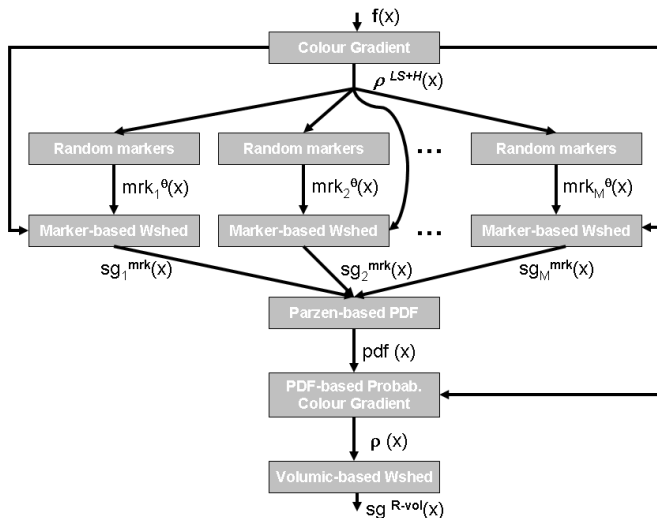


# Probabilistic gradient and volumic watershed



- 1 Introduction
- 2 General methodology
- 3 Probabilistic uniform segmentation
- 4 Probabilistic regionalized segmentation**
- 5 Probabilistic uniform-levelled segmentation
- 6 Conclusions and perspectives

# Algorithm





# Function of regionalization to define random markers

$f_L$



$\varrho^{LS+H}(\mathbf{f})$



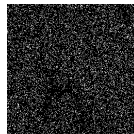
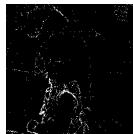
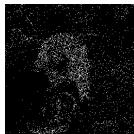
$\theta = f_L$

$\theta = \overline{f_L}$

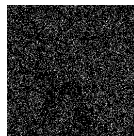
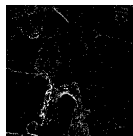
$\theta = \varrho^{LS+H}$

$\theta = \overline{\varrho^{LS+H}}$

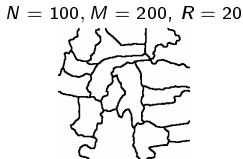
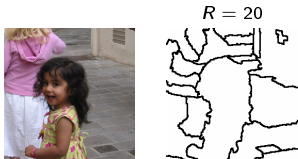
$mrk_1^\theta(x)$



$mrk_2^\theta(x)$

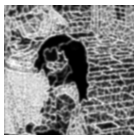


# Regionalized random markers, pdf estimate and volumic watershed

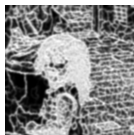


$\theta = f_L, M = 100$

$pdf(x)$



$\theta = \overline{f_L}, M = 100$



$\theta = \varrho^{LS+H}, M = 100$



$\theta = \overline{\varrho^{LS+H}}, M = 100$



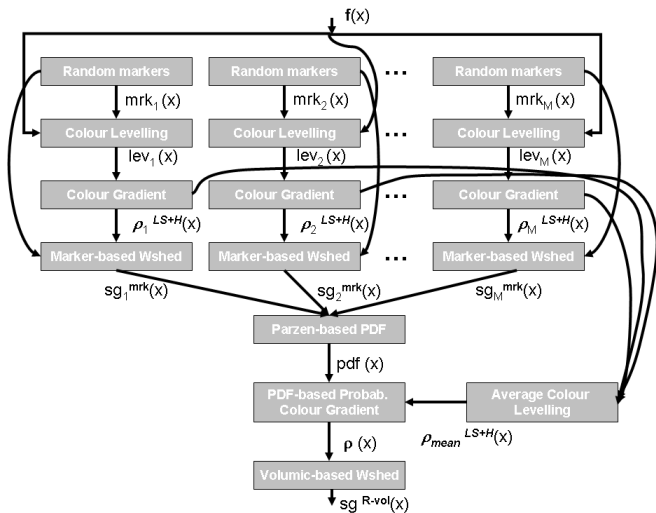
$sg^{R-vol}(x)$

$R = 20$



- 1 Introduction
- 2 General methodology
- 3 Probabilistic uniform segmentation
- 4 Probabilistic regionalized segmentation
- 5 Probabilistic uniform-levelled segmentation**
- 6 Conclusions and perspectives

# Algorithm



# Uniform random markers, levelled colour images



$mrk_i(x)$   
 $N = 10$

$i = 1$



$i = 2$



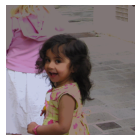
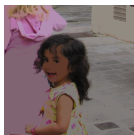
$i = 3$



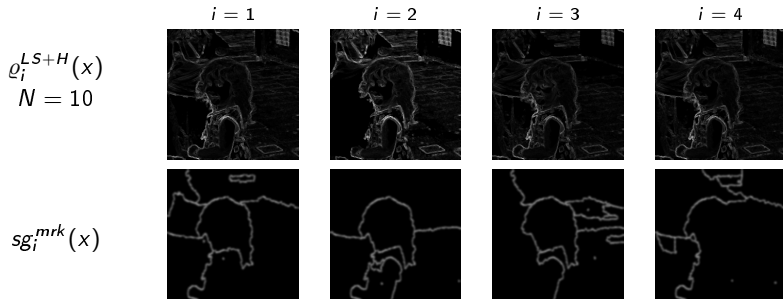
$i = 4$



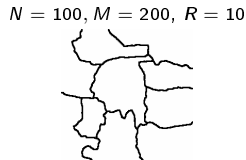
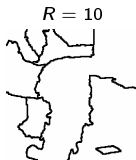
$lev_i(x)$



# Uniform random markers, levelled-based colour gradients



# pdf estimate and volumic watershed



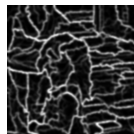
$pdf^{Lev}(x)$



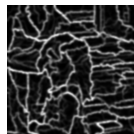
$N = 10, M = 100$



$N = 100, M = 100$



$N = 100, M = 200$



$sg^{R-vol}(x)$

$R = 10$



## pdf estimate and volumic watershed

 $R = 20$  $R = 50$  $N = 100, M = 200$  $R = 20$  $N = 100, M = 200$  $R = 50$  $N = 50, M = 100$  $R = 20$  $R = 50$  $N = 100, M = 200$  $R = 20$  $R = 50$ 



# Averaged probabilistic gradient and volumic watershed

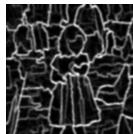
$N = 100, M = 200$



$g^{LS+H}(c)$



$pdf^{lev}(x)$



$N = 100, M = 200$

$\rho(x)$

$\lambda = 0.5$

$R = 10$



$R = 20$



$R = 50$



$N = 100, M = 200$

$\rho^{lev}(x)$

$\lambda = 0.5$

$R = 10$



$R = 20$



$R = 50$



- 1 Introduction
- 2 General methodology
- 3 Probabilistic uniform segmentation
- 4 Probabilistic regionalized segmentation
- 5 Probabilistic uniform-levelled segmentation
- 6 Conclusions and perspectives

# Conclusions

- Complex images segmented in a few regions: both (uniform and regionalized) probabilistic approaches outperform the standard watershed segmentation.
- Images presenting specific objects on an homogeneous background: the improvement is less important.
- Uniform segmentation is mainly depending on parameter  $N$  (number of random points) which is related to  $R$  (number of regions to be determined):  $N \gg R$ .
- Regionalized segmentation depends on parameter  $S$  (spacing for Poisson density function) and the properties of colour gradient.
- Probabilistic approaches working on the same gradient can be adapted to a graph-based framework to obtain an optimized algorithm. The approach using random marker levellings has a huge computational load (time of computation).

## Perspectives

- Other variants:
  - Evolved random point simulations (structural grids, conditional models, etc. )
  - Multi-scale framework (working on image pyramids)
- To study the relation with other techniques such as random walks, Galton-Watson processus, etc.
- Probabilistic approaches combining colour gradients and texture information

### Two types of contours associated to watershed

- 1st order contours: corresponding to “significant” regions and relatively independent from markers.
- 2nd order contours: corresponding to “small”, “low contrasted” or “textured” regions and depend strongly on the place of markers.

It is possible to determine the type of each contour without using a probabilistic approach?