Prior-Based Hierarchical Segmentation Highlighting Structures of Interest

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Plan

Introduction

Hierarchical segmentation

Segmentation : process of partitioning an image into a set of meaningful regions according to some criteria.

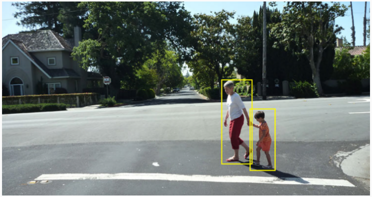
- Segmentation = model
- Simple partition inadequate : number of regions ? Criteria for regions choice ?
- A lot of problems are inherently **multi-scale** : different scales bring different information

Hierarchical segmentation

We can introduce criteria to prioritize the information in the image in order to characterize the image.

(a) Image **(b)** Trivial hierarchy **(c)** Surface-based hierarchy **(d)** Volume-based hierarchy

A growing number of spatial exogenous information sources

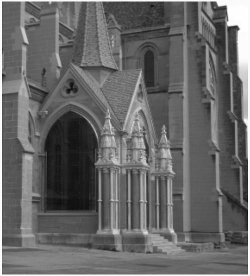


- localization methods adapted to each problem
- different channels

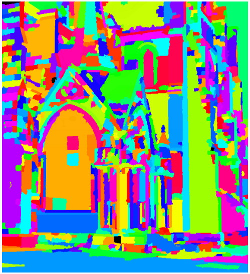
→ **How can we use exogenous information to pilot the hierarchical segmentation process ?**

Fine partition

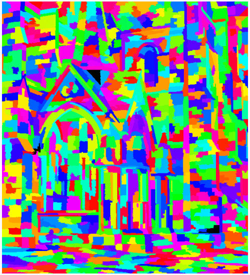
The initial oversegmentation contains all potentially interesting information blocks. Example : superpixels segmentation or watershed segmentation.



(k) Image



(l) Fine partition using watershed



(m) Waterpixels

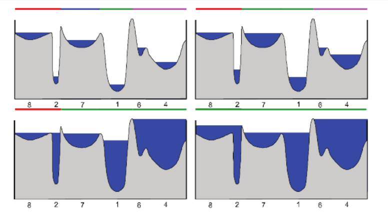
Hierarchical segmentation

(n) Example of hierarchical segmentation

Hierarchy : nested partitions structured by an order relation (predecessor relation).

Watershed hierarchies

To each type of flooding corresponds a hierarchy.

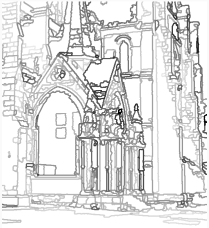


The flooding can be tailored by introducing external criteria :

- markers = flooding sources
- geometric criteria

Ultrametric Contours Maps

Each contour is valued according to its persistence in the hierarchy constructed following a given modality (for example depending on the surfaces of regions it separates)
$\rightarrow$ as many ways of questioning this image



(o) Trivial hierarchy (contrast)

(p) Surface-based hierarchy

(q) Volume-based hierarchy

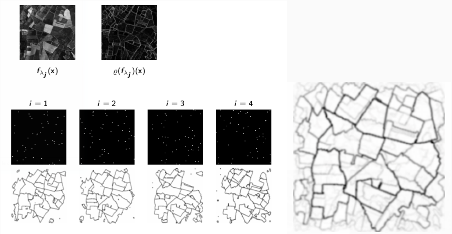
Stochastic Watershed Hierarchies

Stochastic Watershed [1]

N iterations of the following simulation process :

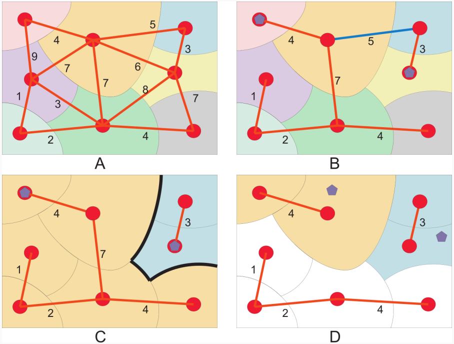
- draw random markers
- compute the corresponding watershed segmentation

Then : mean of the results.
→ non-local estimation of contours strength
→ computationally heavy



1.Angulo, J., & Jeulin, D. (2007, October). Stochastic watershed segmentation. In PROC. of the 8th ISMM (pp. 265-276).

Stochastic Watershed on Graphs [2]



A : a partition represented by an edge-weighed graph ; **B** : a minimum spanning tree of the graph, with 2 markers in blue : the highlighted edge in blue is the highest edge on the path linking the two markers ; **C** : the segmentation obtained when cutting this edge ; **D** blue and orange domain are the domains of variation of the two markers generating the same segmentation.

2.Meyer, F., & Stawiaski, J. (2010). A stochastic evaluation of the contour strength. In Joint Pattern Recognition Symposium (pp. 513-522).

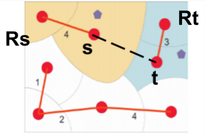
Stochastic Watershed on Graphs

Let denote $\mu(\mathrm{R})$ the number of random markers falling in a region R. We want to attribute to an edge e_{st} the following probability value :

$$\begin{aligned}\tilde{\omega}_{st} &= \mathbb{P}[(\mu(\mathrm{R}_s) \geq 1) \wedge (\mu(\mathrm{R}_t) \geq 1)] \\ &= 1 - \mathbb{P}[(\mu(\mathrm{R}_s) = 0) \vee (\mu(\mathrm{R}_t) = 0)] \\ &= 1 - \mathbb{P}(\mu(\mathrm{R}_s) = 0) - \mathbb{P}(\mu(\mathrm{R}_t) = 0) \\ &+ \mathbb{P}(\mu(\mathrm{R}_s \cup \mathrm{R}_t) = 0)\end{aligned} \tag{1}$$

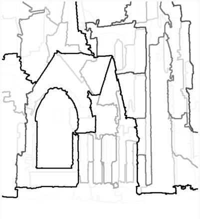
Choices :

- form of markers
- law governing markers distribution



A great versatility

- Choice of the laws governing markers distribution (potentially learned)
- Punctual or non-punctual markers



(a) Erosion with vertical structuring element

(b) Erosion with horizontal structuring element

→ **How to use prior information to obtain a hierarchy suited to a particular problem ?**

Hierarchies highlighting structures of interest using prior information

Markers spread following a Poisson process

For a region R :

$$\mathbb{P}(\mu(R) = 0) = \exp^{-\Lambda(R)}, \tag{2}$$

$\Lambda(R)$ = mean value of the number of markers falling in R.

$$\begin{aligned} \tilde{\omega}_{st} &= \mathbb{P}(\mu(\mathrm{R}_s) \geq 1 \wedge \mu(\mathrm{R}_t) \geq 1) \\ &= 1 - \exp^{-\Lambda(\mathrm{R}_s)} - \exp^{-\Lambda(\mathrm{R}_t)} + \exp^{-\Lambda(\mathrm{R}_s \cup \mathrm{R}_t)} \end{aligned} \tag{3}$$

Choice of density

When the Poisson distribution has an homogeneous density λ :

$$\Lambda(R) = \mathtt{area}(R)\lambda, \tag{4}$$

When the Poisson distribution has a non-uniform density λ :

$$\Lambda(R) = \int_{(x,y)\in R} \lambda(x, y)\, \mathrm{d}x\mathrm{d}y \tag{5}$$

Hierarchy with Regionalized Fineness (HRF)

Exogenous information

- E : object or class of interest
- θ_E : probability density function (PDF) associated with E on the domain D of the image I
- $\mathrm{PM}(\mathbf{I}, \theta_E)$: probabilistic map associated, in which each pixel $p(x, y)$ of $\mathbf{I}$ takes as value $\theta_E(x, y)$ its probability to be part of E

Key idea

$$\tilde{\omega}_{st} = 1 - \exp^{-\Lambda_E(\mathrm{R}_s)} - \exp^{-\Lambda_E(\mathrm{R}_t)} + \exp^{-\Lambda_E(\mathrm{R}_s \cup \mathrm{R}_t)} \tag{6}$$

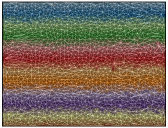
$$\Lambda_E(\mathrm{R}) = \int_{(x,y)\in\mathrm{R}} \theta_E(x, y)\lambda(x, y)\,\mathrm{d}x\mathrm{d}y \tag{7}$$

Methodology

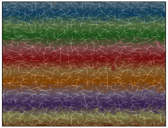
- Compute the fine partition π_0, RAG $\mathcal{G}$, $\mathcal{MST}(\mathcal{G})$

(c) Image

(d) Mosaic



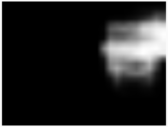
(e) RAG



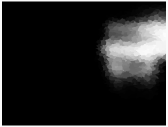
(f) MST

- Compute a probabilistic map $\pi_\mu = \pi_\mu(\pi_0, \mathrm{PM}(\mathbf{I}, \theta_E))$

(g) Image



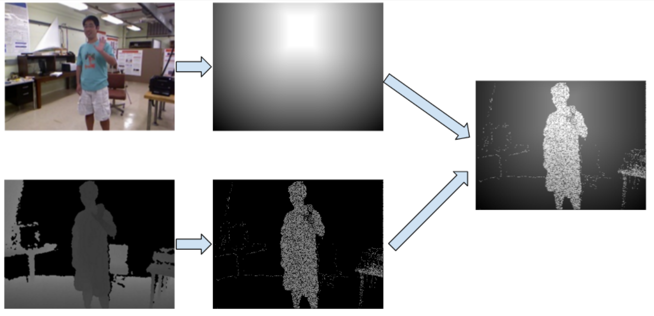
(h) Probabilistic Map associated with “Bike" class



(i) π_μ

- compute new values of edges using previous formulas

Multiple sources

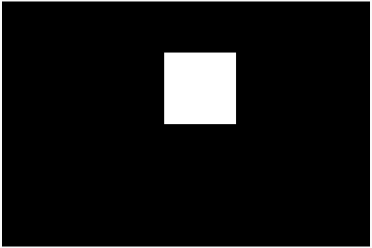


$$\theta_{E_1}, \theta_{E_2} \rightarrow \frac{(\theta_{E_1} + \theta_{E_2})}{2}\lambda$$

Applications

Application 1 : hierarchical segmentation (prior : face detection)

(j) Image



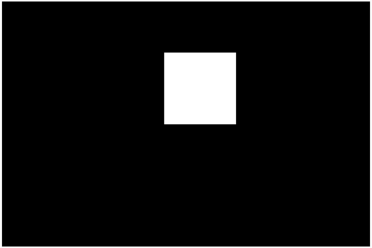
(k) Face detection

Face detection using Haar wavelets

Source : `https://gist.github.com/dannguyen/cfa2fb49b28c82a1068f`

Application 1 : hierarchical segmentation (prior : face detection)

Obtention of a probability map using a morphological distance function



(a) Face detection

(b) Associated probability map

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(c) Non homogeneous law

(d) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 200 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 175 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

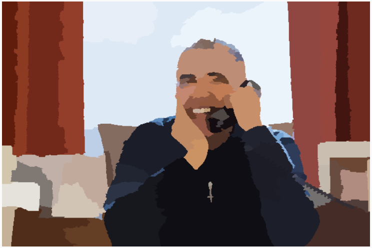
(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 150 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law



(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 125 regions

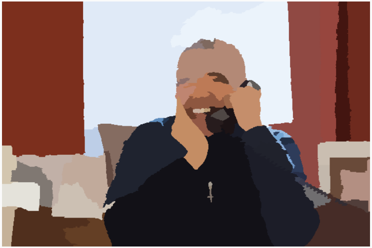
Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law **(b)** Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 100 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law

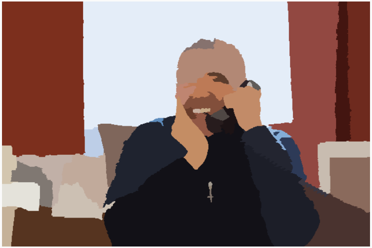


(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 75 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law



(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 50 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 25 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 20 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law **(b)** Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 15 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 10 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

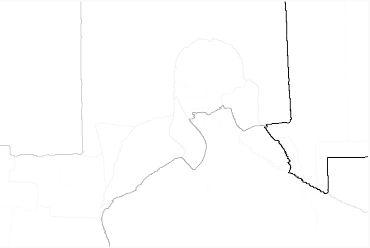
(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 5 regions

Application 1 : hierarchical segmentation (prior : face detection) - volume-based hierarchy

(a) Non homogeneous law



(b) Homogeneous law

Saliency images

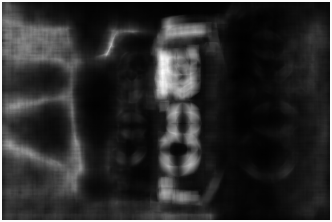
Application 2 : hierarchical segmentation (prior : blur detection)

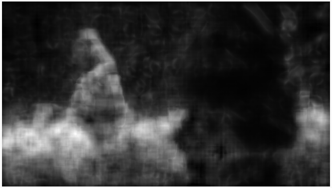
(a) Image

(b) Image

Images

Application 2 : hierarchical segmentation (prior : blur detection)





Probability maps of non-blur zones

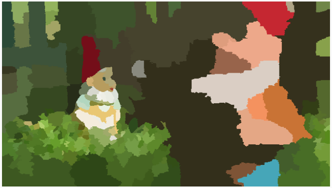
Su, B., Lu, S., & Tan, C. L. (2011, November). Blurred image region detection and classification. In Proceedings of the 19th ACM international conference on Multimedia (pp. 1397-1400). ACM.

Application 2 : hierarchical segmentation (prior : blur detection)

Image and associated probability map

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy

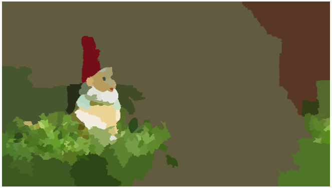
(a) Non homogeneous law



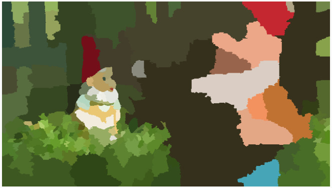
(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 200 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



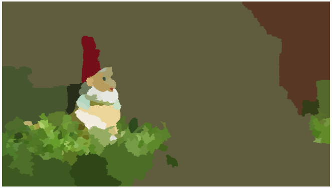
(a) Non homogeneous law



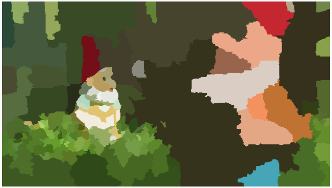
(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 175 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



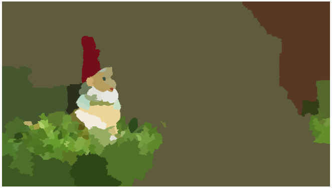
(a) Non homogeneous law



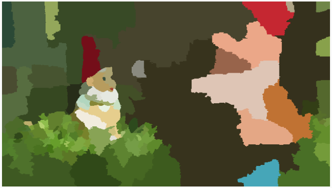
(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 150 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



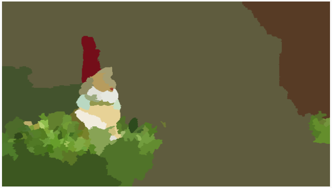
(a) Non homogeneous law



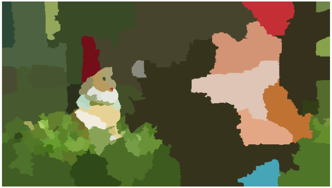
(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 125 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



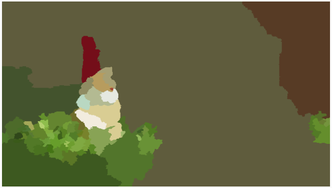
(a) Non homogeneous law



(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 100 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy

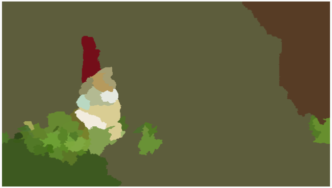


(a) Non homogeneous law

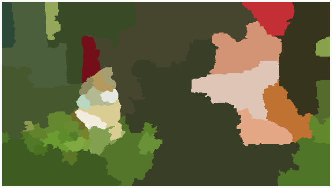
(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 75 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



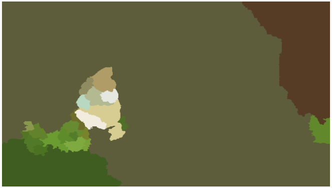
(a) Non homogeneous law



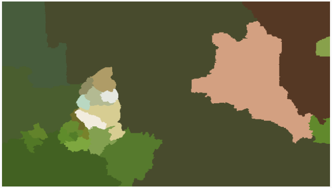
(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 50 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



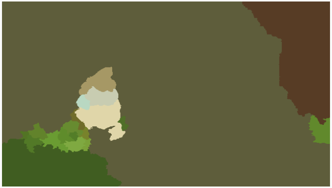
(a) Non homogeneous law



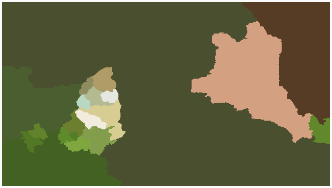
(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 25 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



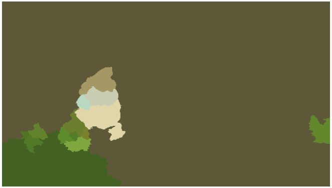
(a) Non homogeneous law



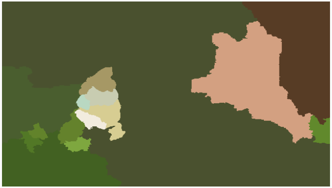
(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 20 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



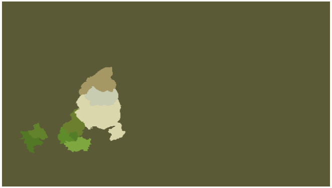
(a) Non homogeneous law



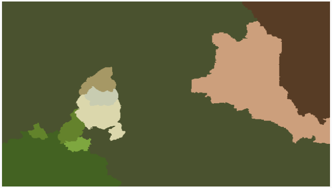
(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 15 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



(a) Non homogeneous law

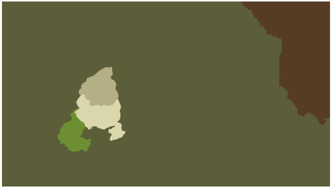


(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 10 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy

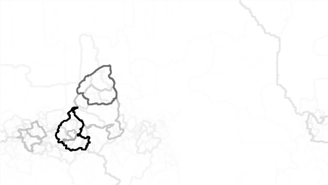
(a) Non homogeneous law



(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 5 regions

Application 2 : hierarchical segmentation (prior : blur detection) - volume-based hierarchy



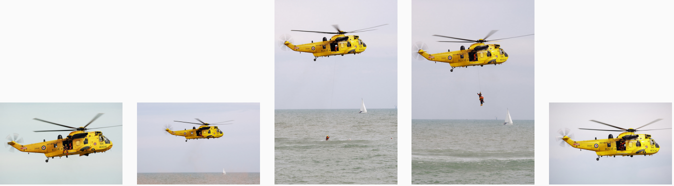
(a) Non homogeneous law

(b) Homogeneous law

Saliency images

Application 3 : hierarchical cosegmentation (prior : matching between objects)

Images from iCoSeg database (`http://chenlab.ece.cornell.edu/projects/touch-coseg/`).

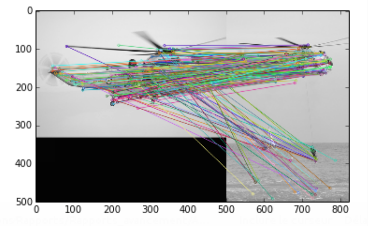


(a) **(b)** **(c)** **(d)** **(e)**

Images to co-segment

Application 3 : hierarchical cosegmentation (prior : matching between objects)

Matching of interest points SIFT/SURF/ORB between the image to segment and all other images of the class.
We keep on an image all matched points.



(a)

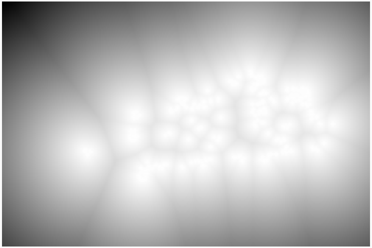
(b)

Example of matching ; *prior* result of the matching with all other images of the class

Application 3 : hierarchical cosegmentation (prior : matching between objects)

$\rightarrow$ We use a morphological distance function to attribute to each point a probability of being part of the object depending on its distance to the interest points.

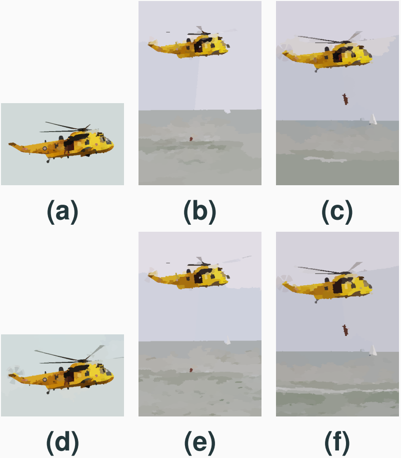
(a)



(b)

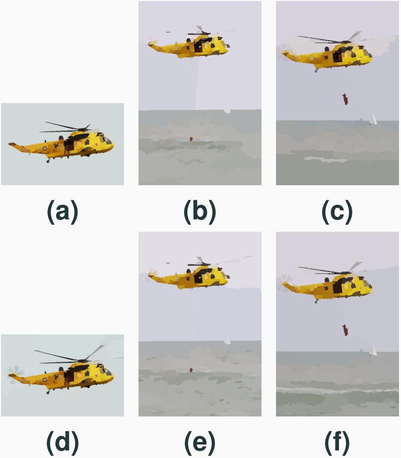
prior and associated probability map

Application 3 : hierarchical cosegmentation (prior : matching between objects)



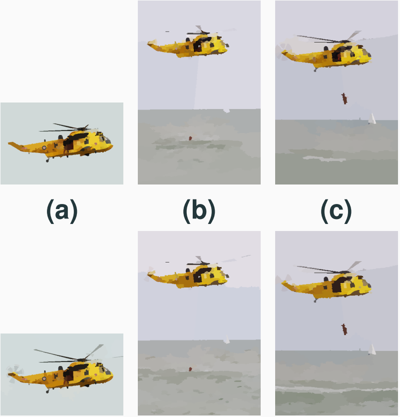
Comparison between HRF and hierarchy with homogeneous law - 200 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)



Comparison between HRF and hierarchy with homogeneous law - 200 regions

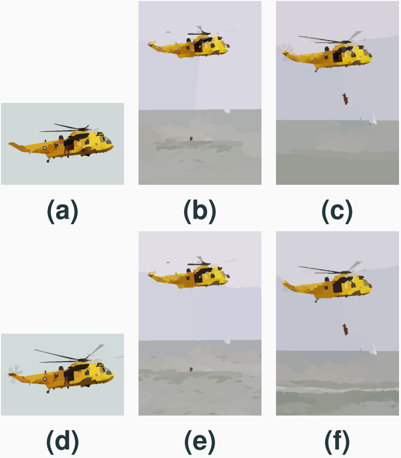
Application 3 : hierarchical cosegmentation (prior : matching between objects)



(a) (b) (c) (d) (e) (f)

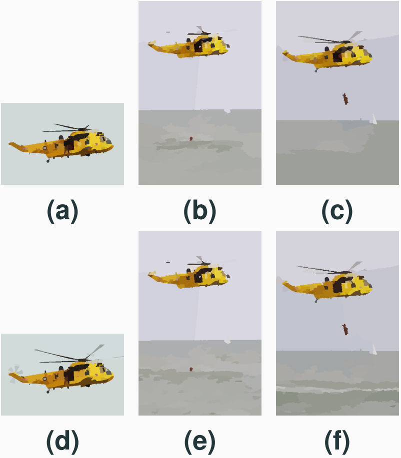
Comparison between HRF and hierarchy with homogeneous law - 175 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)



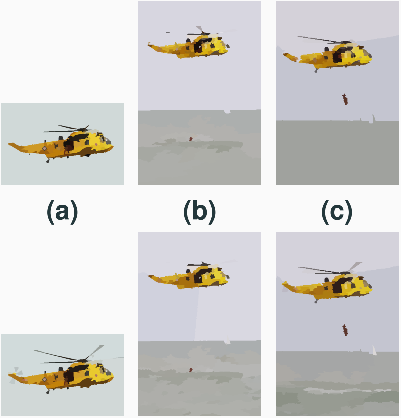
Comparison between HRF and hierarchy with homogeneous law - 150 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)



Comparison between HRF and hierarchy with homogeneous law - 125 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)

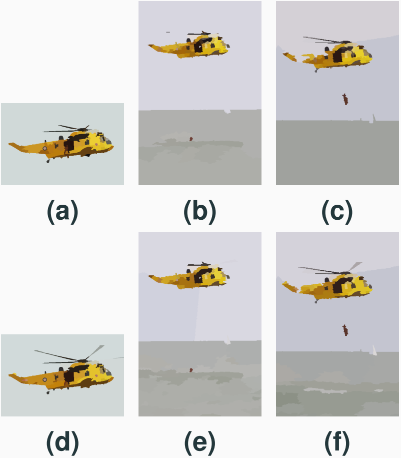


(a) (b) (c)

(d) (e) (f)

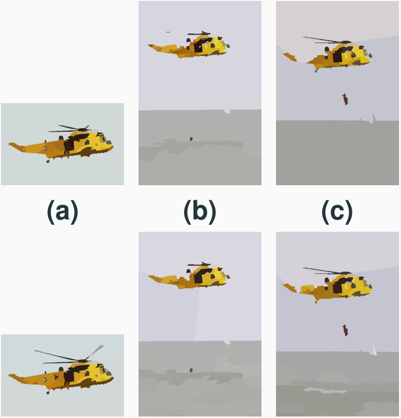
Comparison between HRF and hierarchy with homogeneous law - 100 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)



Comparison between HRF and hierarchy with homogeneous law - 75 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)

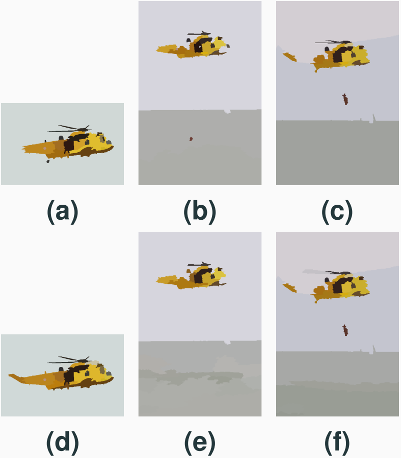


(a) (b) (c)

(d) (e) (f)

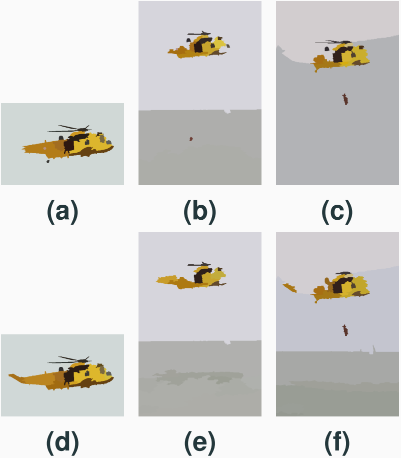
Comparison between HRF and hierarchy with homogeneous law - 50 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)



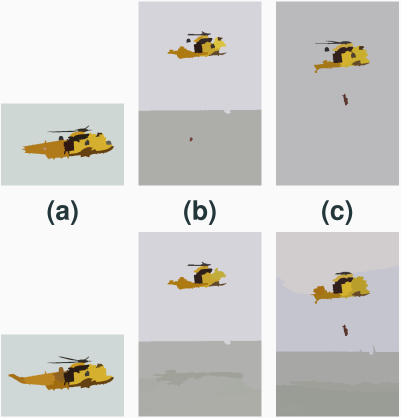
Comparison between HRF and hierarchy with homogeneous law - 25 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)



Comparison between HRF and hierarchy with homogeneous law - 20 regions

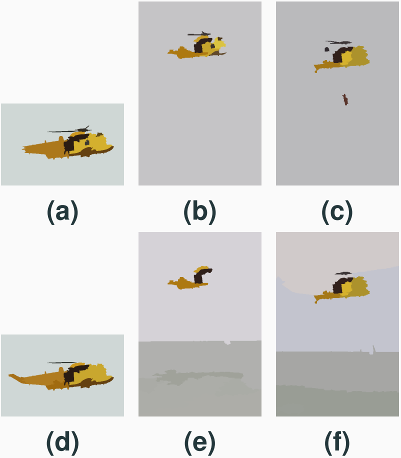
Application 3 : hierarchical cosegmentation (prior : matching between objects)



(a) (b) (c) (d) (e) (f)

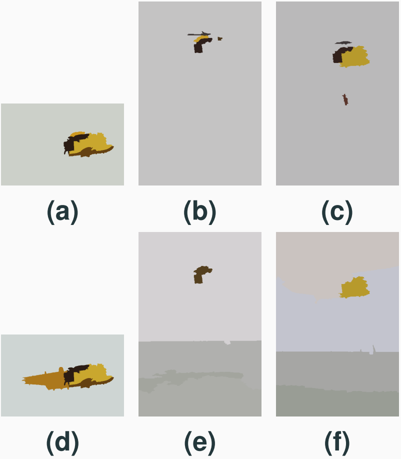
Comparison between HRF and hierarchy with homogeneous law - 15 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)



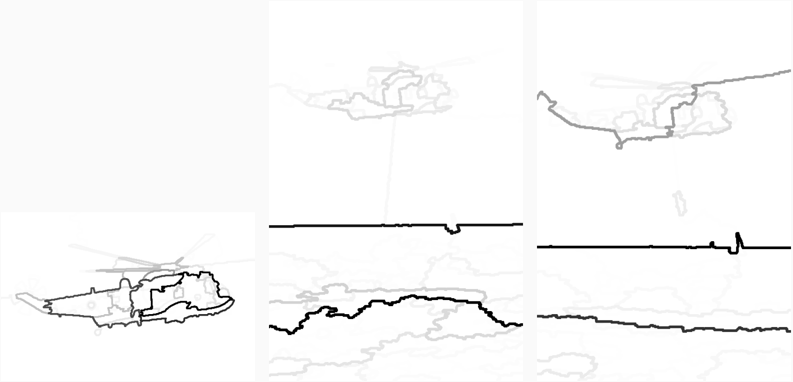
Comparison between HRF and hierarchy with homogeneous law - 10 regions

Application 3 : hierarchical cosegmentation (prior : matching between objects)



Comparison between HRF and hierarchy with homogeneous law - 5 regions

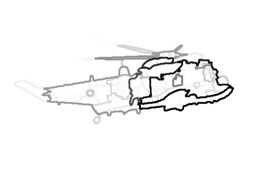
Application 3 : hierarchical cosegmentation (prior : matching between objects)



(a) (b) (c)

Saliency images for homogeneous process

Application 3 : hierarchical cosegmentation (prior : matching between objects)



(a)

(b)

(c)

Saliency images for non-homogeneous process

Application 4 : Hierarchical co-segmentation of RGB+D images

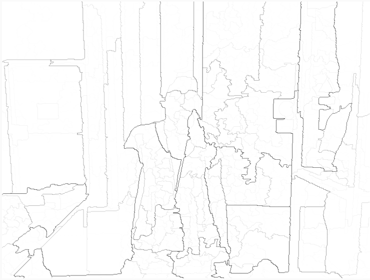
→ We use the Depth information to segment the RGB image. So that we can privilege objects at a given distance and draw markers accordingly.

(a) **(b)** **(c)**

RGB+D images and markers associated with a given depth

Note : images are not realigned, holes in depth image

Application 4 : Hierarchical co-segmentation of RGB+D images



(a) Non homogeneous law

(b) Non homogeneous law

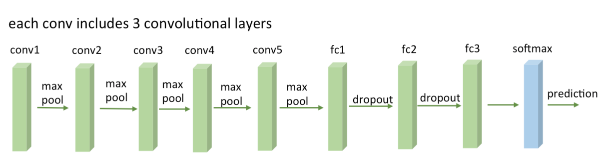
Saliency images

Application 5 : Hierarchical segmentation (prior : rough localization provided by CNN-based method)

We make use of a reference CNN classifier, trained on ImageNet [3] called VGG16.

Input : image in 224×224 pixels

Output = 1000 long vector with a probability of apparition of each class in this image.



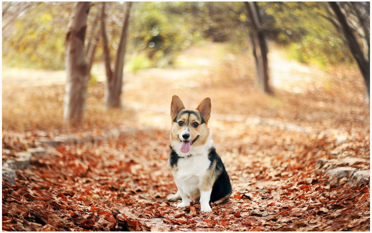
[4]

VGG16 Network Architecture (by Zhicheng Yan et al.)

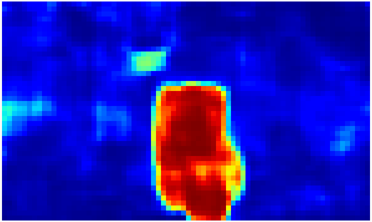
3.http ://image-net.org/

4.http://www.robots.ox.ac.uk/~vgg/research/very_deep/

Application 5 : Hierarchical segmentation (prior : rough localization provided by CNN-based method)



(a) Image


[5]

(b) Heatmap output by CNN-based method

Generation of probability maps using CNN-based method

M. Oquab, L. Bottou, I. Laptev, J. Sivic ; "Is Object Localization for Free ? - Weakly-Supervised Learning With Convolutional Neural Networks", in CVPR, 2015, pp. 685-694

5. https://github.com/heuritech/convnets-keras

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Image **(b)** Waterpixels **(c)** Prior : main class localization

Image, fine partition and localization image

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 95 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 90 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 85 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 80 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 75 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 70 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 65 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 60 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 55 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 50 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 45 regions

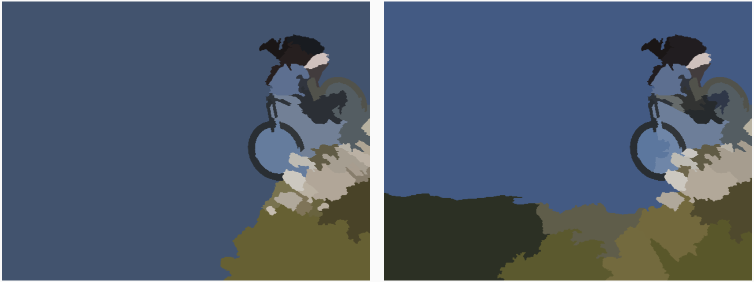
Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 40 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)



(a) Non homogeneous law **(b)** Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 35 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 30 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 25 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 20 regions

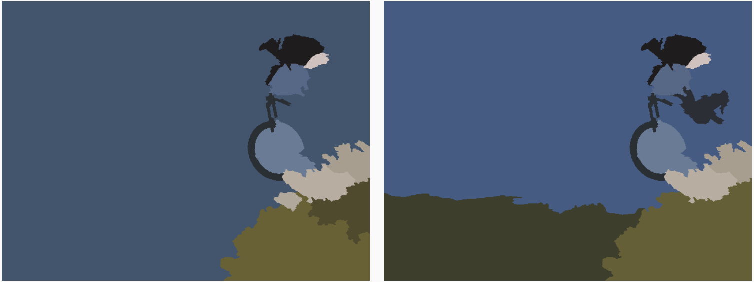
Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 15 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)



(a) Non homogeneous law **(b)** Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 10 regions

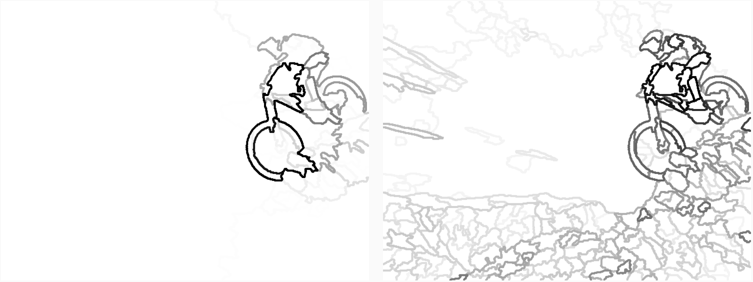
Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

(a) Non homogeneous law

(b) Homogeneous law

Comparison between HRF and hierarchy with homogeneous law - 5 regions

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)



(a) Non homogeneous law **(b)** Homogeneous law

Saliency images

Modulating the HRF depending on regions features

Key idea

Take into account features extracted from **pairs** of regions.

Example : volume-based SWS

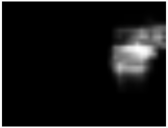
$\chi(\mathrm{R}_s, \mathrm{R}_t)\lambda$, with $\chi(\mathrm{R}_s, \mathrm{R}_t) = \omega_{st}$

$\rightarrow$ Can we use any prior information in a similar way ?

Highlighting transitions between background and foreground

Idea : have more precision where the limit between foreground and background is actually unclear.

(a) Image



(b) Rough localization

$$\begin{cases} \tilde{\lambda} = \chi\lambda \\ \chi(\mathrm{R}_s, \mathrm{R}_t) = \frac{\max(m(\mathrm{R}_s), m(\mathrm{R}_t))(1 - \min(m(\mathrm{R}_s), m(\mathrm{R}_t)))}{0.01 + \sigma(\mathrm{R}_s)\sigma(\mathrm{R}_t)}, \end{cases} \tag{8}$$

With $m(\mathrm{R}_s)$ and $\sigma(\mathrm{R})$ the normalized mean and normalized variance of region R.

Highlighting transitions between background and foreground

(c) Image

(d) Face detection

Highlighting transitions between background and foreground

(e) Homogeneous

(f) HFR

(g) Pairs-dependent HFR

Comparison - 25 regions

Highlighting transitions between background and foreground

(a) Homogeneous

(b) HFR

(c) Pairs-dependent HFR

Comparison - 10 regions

Highlighting transitions between background and foreground

(a) Homogeneous **(b)** HFR **(c)** Pairs-dependent HFR

Comparison - 4 regions

Highlighting transitions between background and foreground

(a) Image

(b) Homogeneous

(c) HFR

(d) Pairs-dependent HFR

Saliency images.

Conclusion

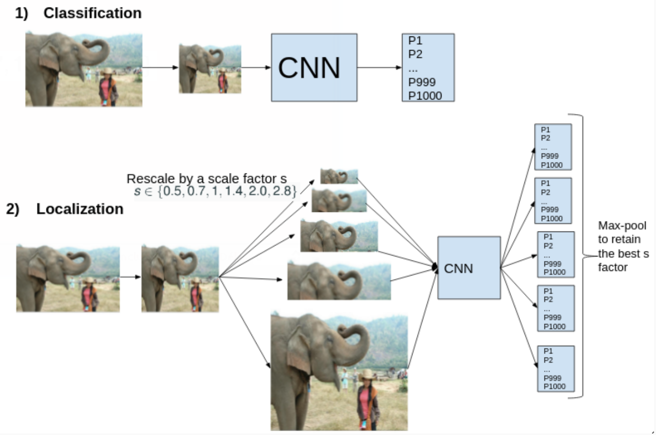
- Fast process for obtaining hierarchies
- Possibility to incorporate exogenous information while preserving the important structures in the image
- Very versatile : takes a probability map as input, returns a hierarchy (multi-scale information) as output

Perspectives :

- Extend this work to videos
- Semantic segmentation : use HRF to refine contours of the main objects in image and enhance semantic segmentation algorithms output

Thank you for your attention.

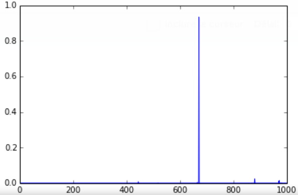
Supplementary Material



M. Oquab, L. Bottou, I. Laptev, J. Sivic ; "Is Object Localization for Free ? - Weakly-Supervised Learning With Convolutional Neural Networks", in CVPR, 2015, pp. 685-694

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)

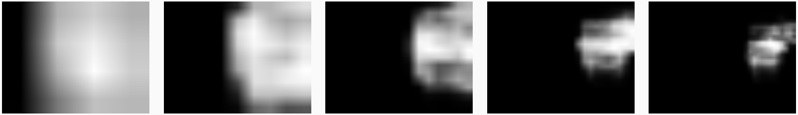
```
(1, 1000)
Class: 671 Prob:0.932747066021
['n03792782', 'mountain', 'bike,', 'all-terrain', 'bike,', 'off-roader\n']
Class: 880 Prob:0.0228912923485
['n04509417', 'unicycle,', 'monocycle\n']
Class: 972 Prob:0.0139717785642
['n09246464', 'cliff,', 'drop,', 'drop-off\n']
Class: 970 Prob:0.00960946921259
['n09193705', 'alp\n']
Class: 444 Prob:0.00769259082153
['n02835271', 'bicycle-built-for-two,', 'tandem', 'bicycle,', 'tandem\n']
Researched classes in ImageNet :
[671]
```



(a) Classification results

More important classes in the image $\rightarrow$ we look for classes with a probability superior to *thresh* $= 0.1$

Application 5 : Hierarchical segmentation (prior : rough localization provided by a CNN)



(a) Prior for s=0.7 **(b)** Prior for s=1.0 **(c)** Prior for s=1.4 **(d)** Prior for s=2.0 **(e)** Prior for s=2.8

Comparison between priors for different scale parameters

$\rightarrow$ Here we select s=2.0 by max-pooling