A deep learning approach to superpixels segmentation

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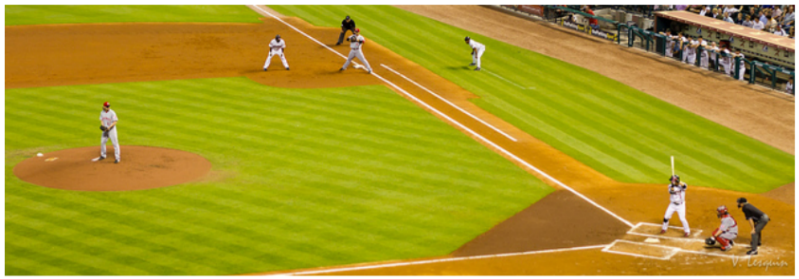

(a) *The original image*

(b) *The segmented image*

Figure: An image (a) and its segmented image (b).

- **context:** image perception
- **idea:** partitioning an image into groups of similar pixels

Figure: Example of a superpixel segmentation. From left to right: original image, original image with its calculated superpixels outlines and resulting superpixel segmentation in average color representation.

- **idea:** over-segmentation of an image
- the superpixels segmentation is *not unique*

- **Boundary recall:** ratio of the number of true positive contour pixels and of the number of contour pixels in the ground truth segmentation, with a tolerance of 2 pixels

- **Compactness:**

$$\text{COMP}(S_i) = \sum_{S_i} \frac{\mid S_i \mid}{N} \frac{4\pi A(S_i)}{P(S_i)^2}$$

- **Undersegmentation error:** Leakage of a superpixel overlapping with a gound truth segment:

$$\text{UE}_{NP}(G, S) = \frac{1}{N} \sum_{G_i} \sum_{S_j \cap G_i \neq \emptyset} \min \{\mid S_j \cap G_i \mid, \mid S_j - S_j \cap G_i \mid\}$$

where S_j is a superpixel and G_i is a ground truth segment.

Undersegmentation Error

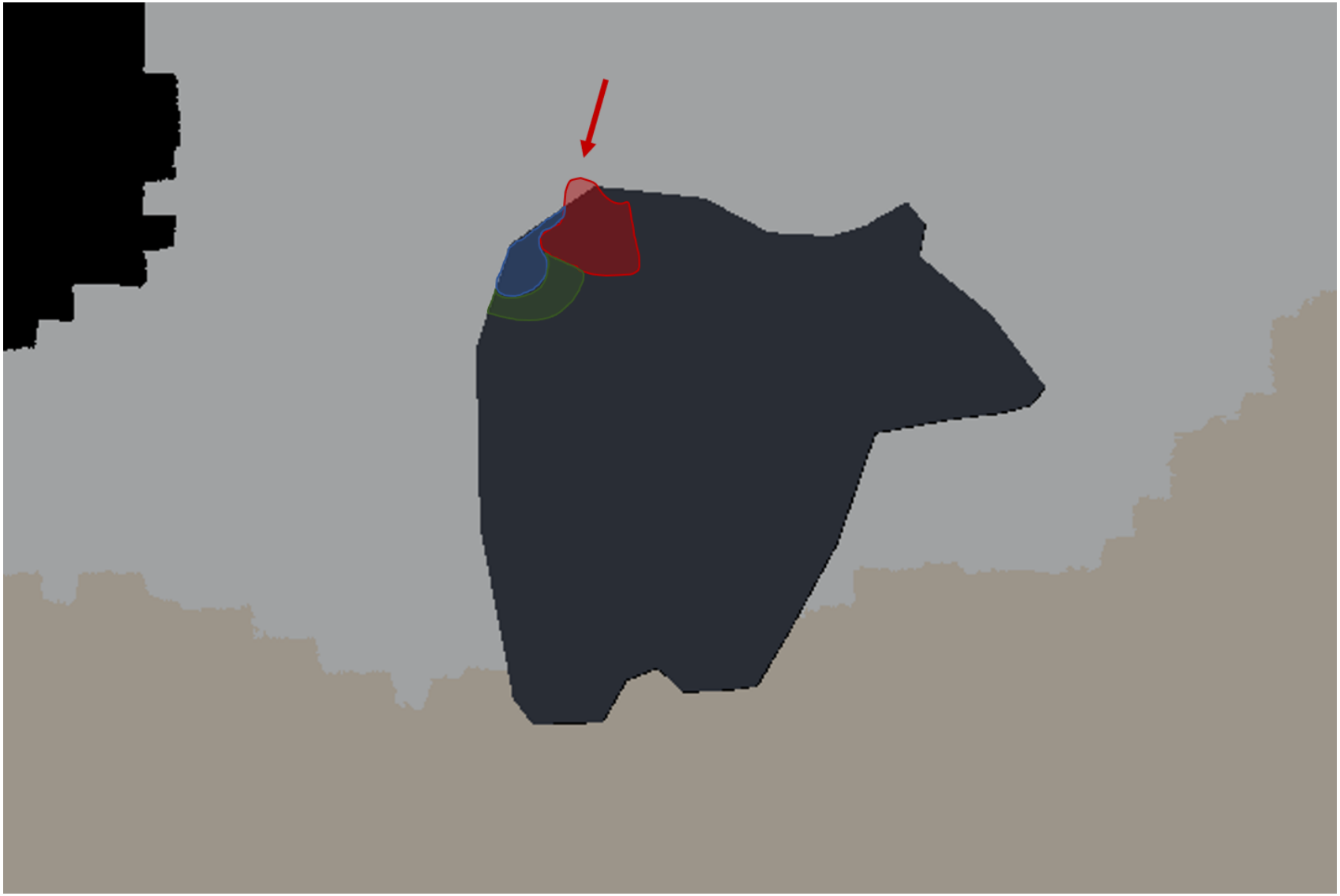

Figure: Undersegmentation illustration.

Ambitions

- interest of deep learning here;
- generating deep learning based over-segmentations? lack of proper training datasets;
- use a CNN to improve SOTA.

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Figure: Eikonal algorithm principle[1].

[1] *cf.* [1], *Fast Marching Based Superpixels Generation*, Kaiwen Chang and Bruno Figliuzzi, 2019.

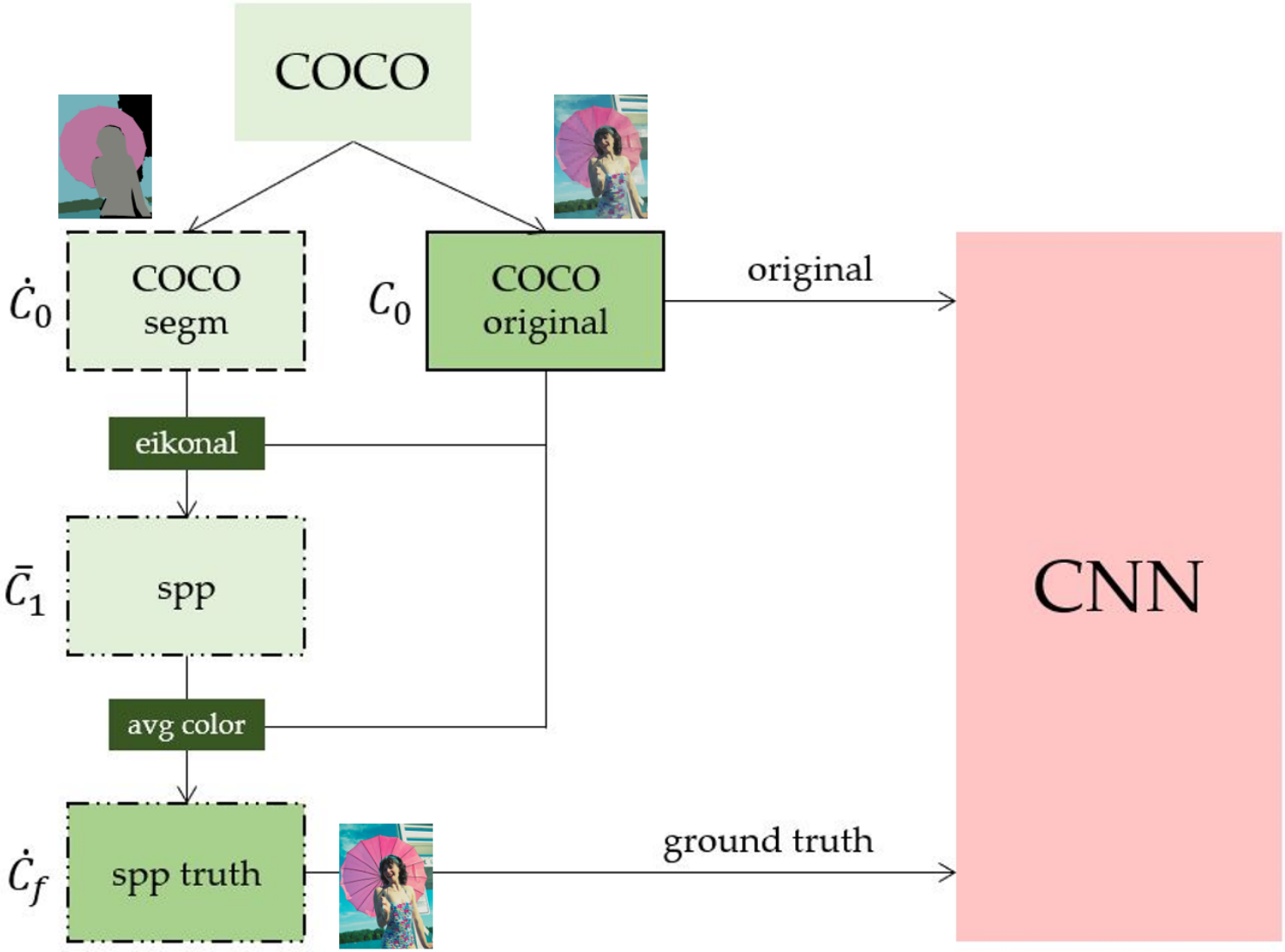

Figure: Training process using the COCO dataset[2].

[2] *cf.* [2], *Microsoft COCO: Common Objects in Context*, `http://cocodataset.org`, 2014.

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Context Aggregation Network (CAN)[3]

	L^1		L^2		$L^d = L^7$	
$m \times n \times 3$	$\longrightarrow$	$m \times n \times 24$	$\longrightarrow$	$\ldots$	$\longrightarrow$	$m \times n \times 3$

Table: *Layers of the network*

For each layer:

1. dilated convolution
2. Adaptative Batch Normalization (ABN)
3. Leaky Rectified Linear Unit (LReLU)

[3] *cf.* [3], *Fast Image Processing with Fully-Convolutional Networks*, Qifeng Chen, Jia Xu and Vladlen Koltun, 2017.

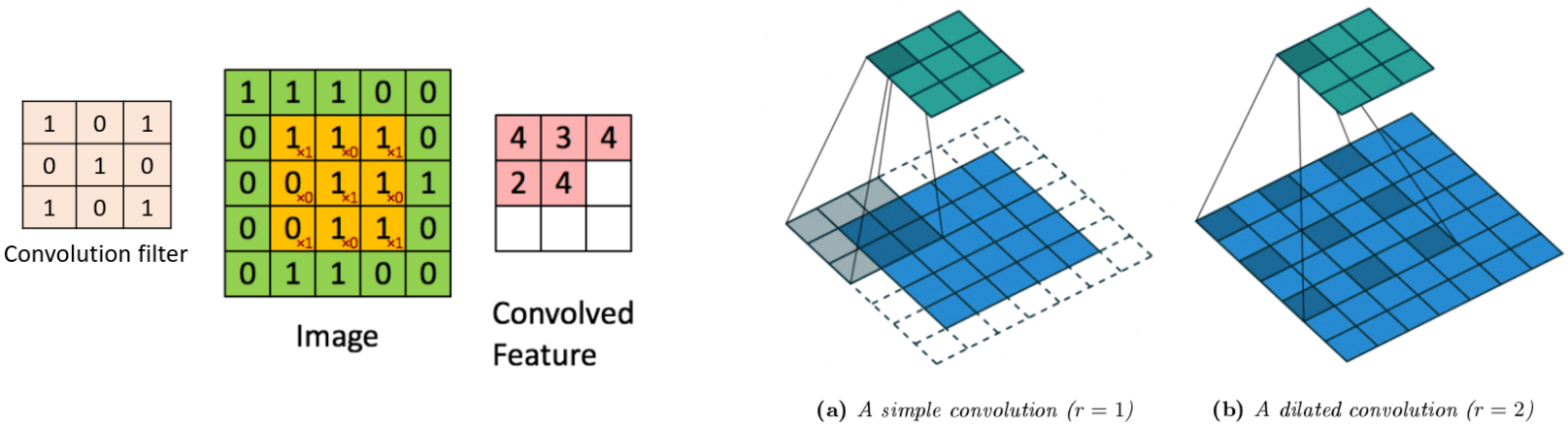


Figure: Simple and dilated convolutions.

- The output $C(x)$ of a pixel x is:

$$\begin{aligned} C(x) :&= (L_j *_r K_{i,j})(x) \\ &= \sum_{a+rb=x} L_j(a) K_{i,j}(b) \\ &= \sum_{b} L_j(x - rb) K_{i,j}(b) \end{aligned}$$

- exponential growth: global information aggregation

ABN

Adaptive normalization function Ψ:

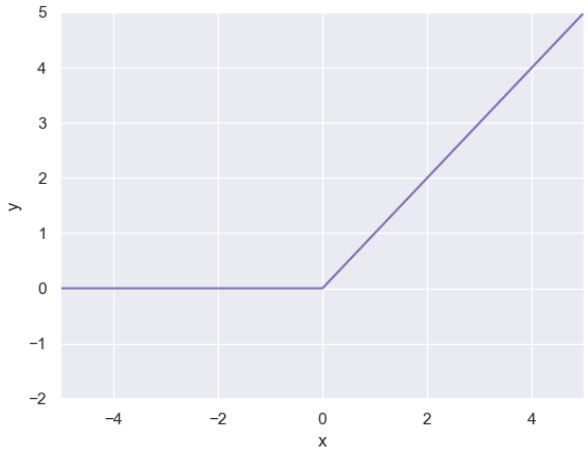
$$\Psi(x) = a\ x + b\ BN(x),$$

where BN is the classic batch normalization, defined as:

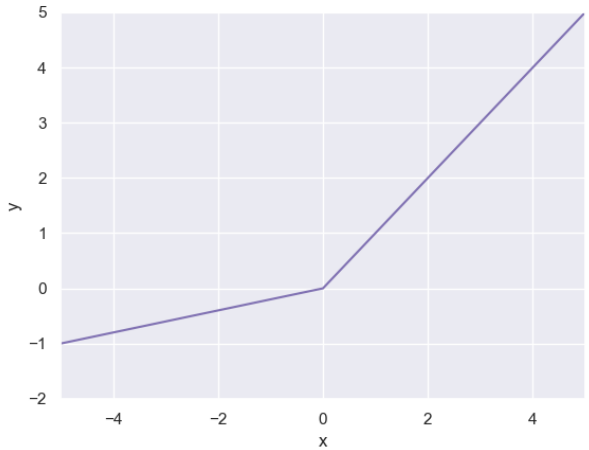
$$BN(x) = \frac{x - \mathrm{E}[\text{batch}]}{\sqrt{\mathrm{Var}[\text{batch}] + \epsilon}} * \gamma + \beta.$$

LReLU

$$\Phi(x) = \max(\alpha x, x), \text{ with } 0 < \alpha < 1.$$



(a) ReLU



(b) LReLU ($\alpha = 0.2$)

$$L_i^s = \Phi\left(\Psi^s\left(b_i^s + \sum_j L_j^{s-1} *_{r_s} K_{i,j}^s\right)\right)$$

Layer L_s		1	2	3	4	5	6	7
Conv	Input w_s	3	24	24	24	24	24	24
	Output w_{s+1}	24	24	24	24	24	24	3
	Receptive field	3×3	3×3	3×3	3×3	3×3	3×3	1×1
	Dilation r_s	1	2	4	8	16	1	1
	Padding	1	2	4	8	16	1	0
ABN		Yes	Yes	Yes	Yes	Yes	Yes	Yes
LReLU		0.2	0.2	0.2	0.2	0.2	0.2	No

Table: Our Context Aggregation Network

L_2 Loss

$$L = \frac{1}{N} \sum_{i=1}^{N} |\hat{f}(I)_i - f(I)_i|^2$$

Figure: A segmented image. Many regions have a gradient equal to 0.

Total Variation (TV) Loss

$$L_{TV} = \frac{1}{N} \sum_{i=1}^{N} |\hat{f}(I)_i - f(I)_i|^2 + \alpha_{TV} \frac{1}{N} \sum_{i=1}^{N} |(\nabla f(I))_i|^2$$

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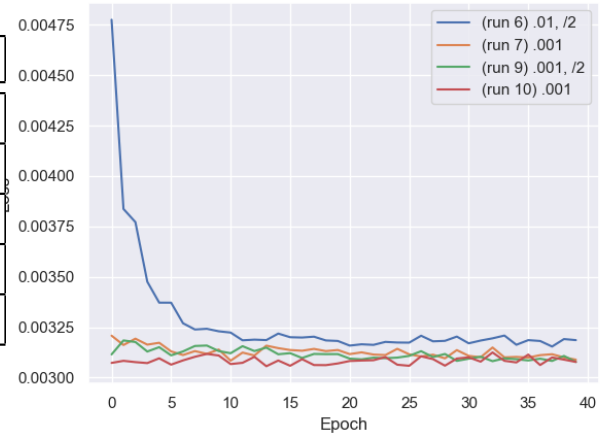
id	lr_0	decay	thresh.	start from
6	10^{-2}	$\times.5$ ev. 2 ep.	10^{-4}	run 0 ep.5
7	10^{-3}	No		run 0 ep.40
8	10^{-2}	No		run 0 ep.40
9	10^{-3}	$\times.5$ ev. 2 ep.	10^{-4}	run 0 ep. 40
10	10^{-3}	No		run 9 ep.40

(a) Runs for learning rate tuning, with $d = 7$



(b) Runs 6, 7, 9 and 10

Figure: Tuning of learning rate: validation loss for different runs.

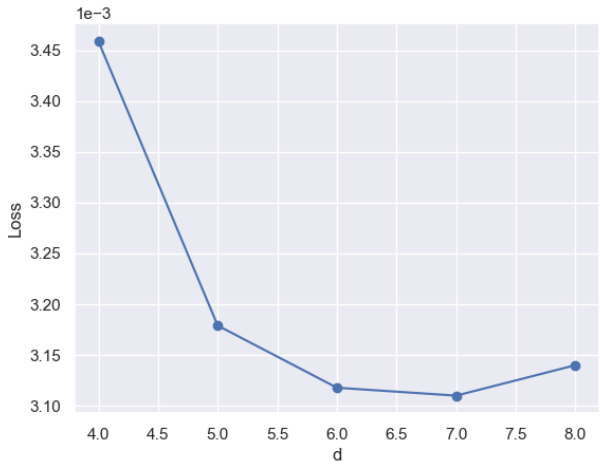
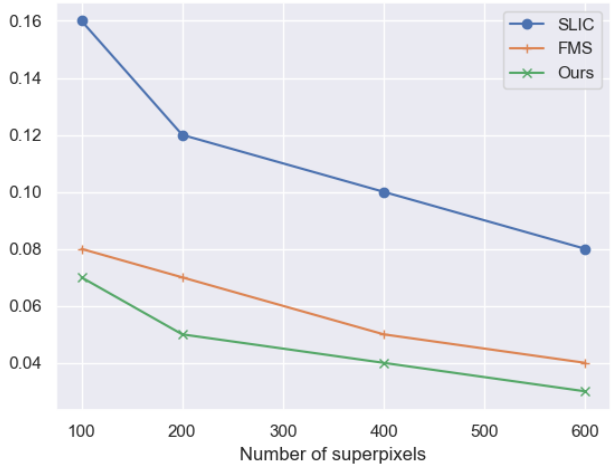


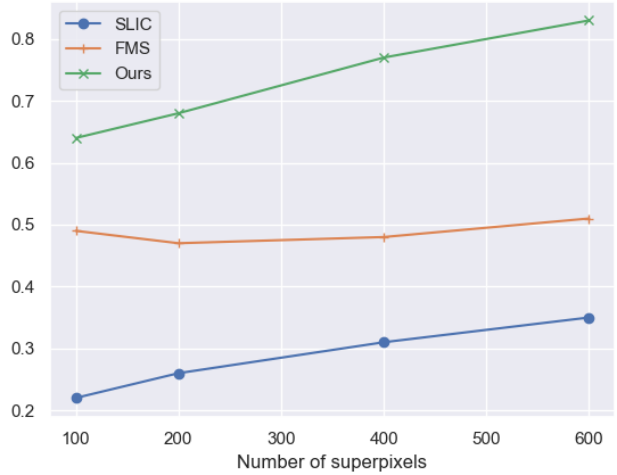
Figure: Tuning of network size: loss values on the validation set.

batch_size	epochs	d	lr_0	decay for lr_0	α_{TV}
32	80	7	10^{-2}	10^{-3} after 10 ep.	0

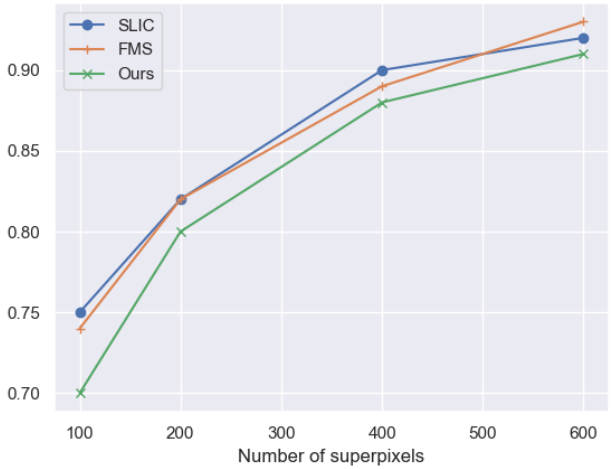
Table: Hyperparameter values



(a) Undersegmentation Error



(b) Compactness



(c) Boundary Recall

Figure: Comparisons of metrics on the BSDS500 dataset[4]

[4] https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/resources.html.

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- CNN can achieve good performance on superpixel segmentation
- discussion on TV-loss

- U-Net
- COCO dataset lacks quality
  1. train on COCO and finetune on BSD?
  2. add gaussians to each superpixel?
  3. pre-process image with grid?

- application in research in grainy materials imaging, with indicator of the center of the particules

Essential References

[1], *Fast Marching Based Superpixels Generation*, Kaiwen Chang and Bruno Figliuzzi, 2019

[2], *Microsoft COCO: Common Objects in Context*, `http://cocodataset.org`, 2014

[3], *Fast Image Processing with Fully-Convolutional Networks*, Qifeng Chen, Jia Xu and Vladlen Koltun, 2017

...

Code: `github.com/theodumont/superpixels-segmentation`

Thank you very much to M. Bruno Figliuzzi.

Appendix

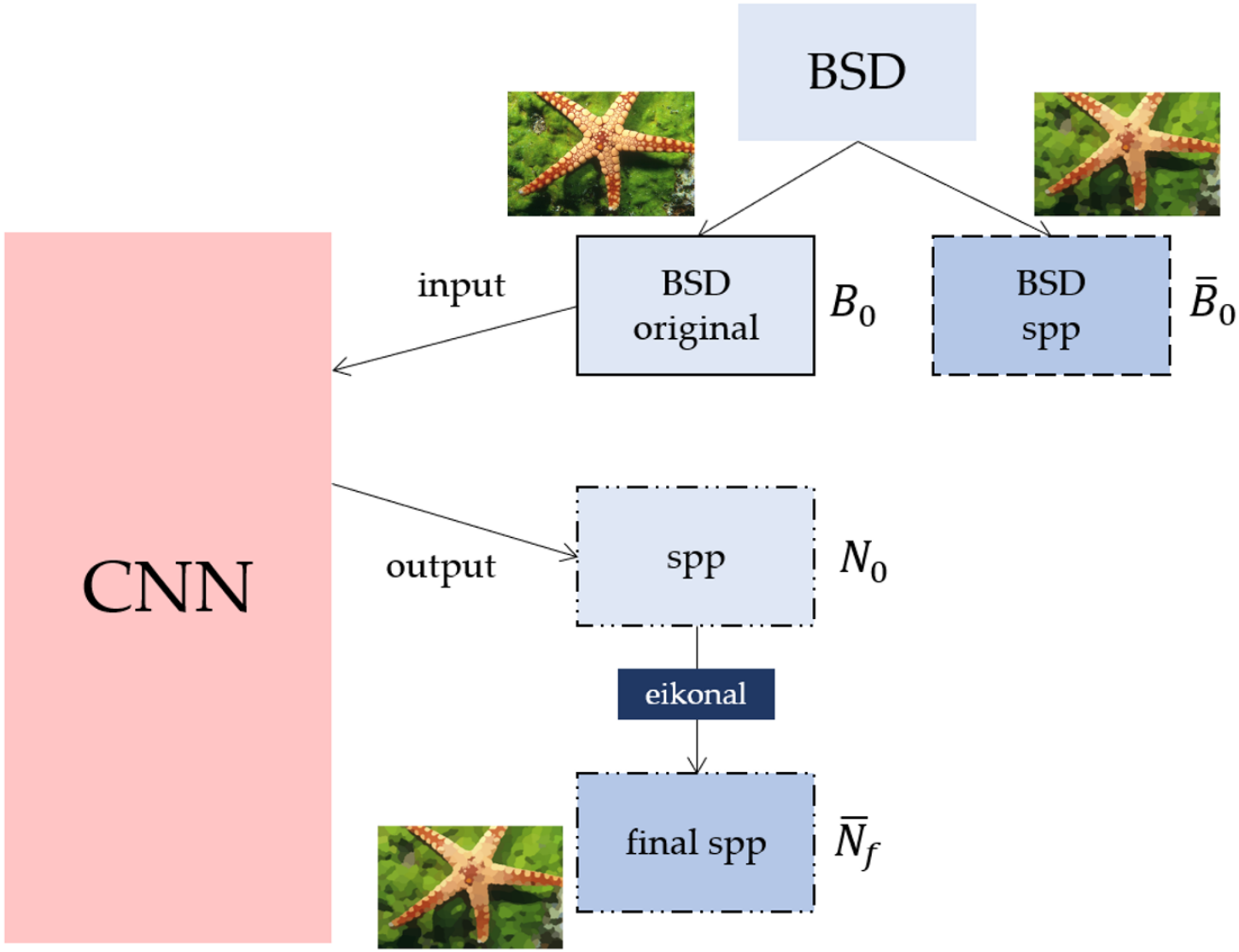


Figure: Testing process.

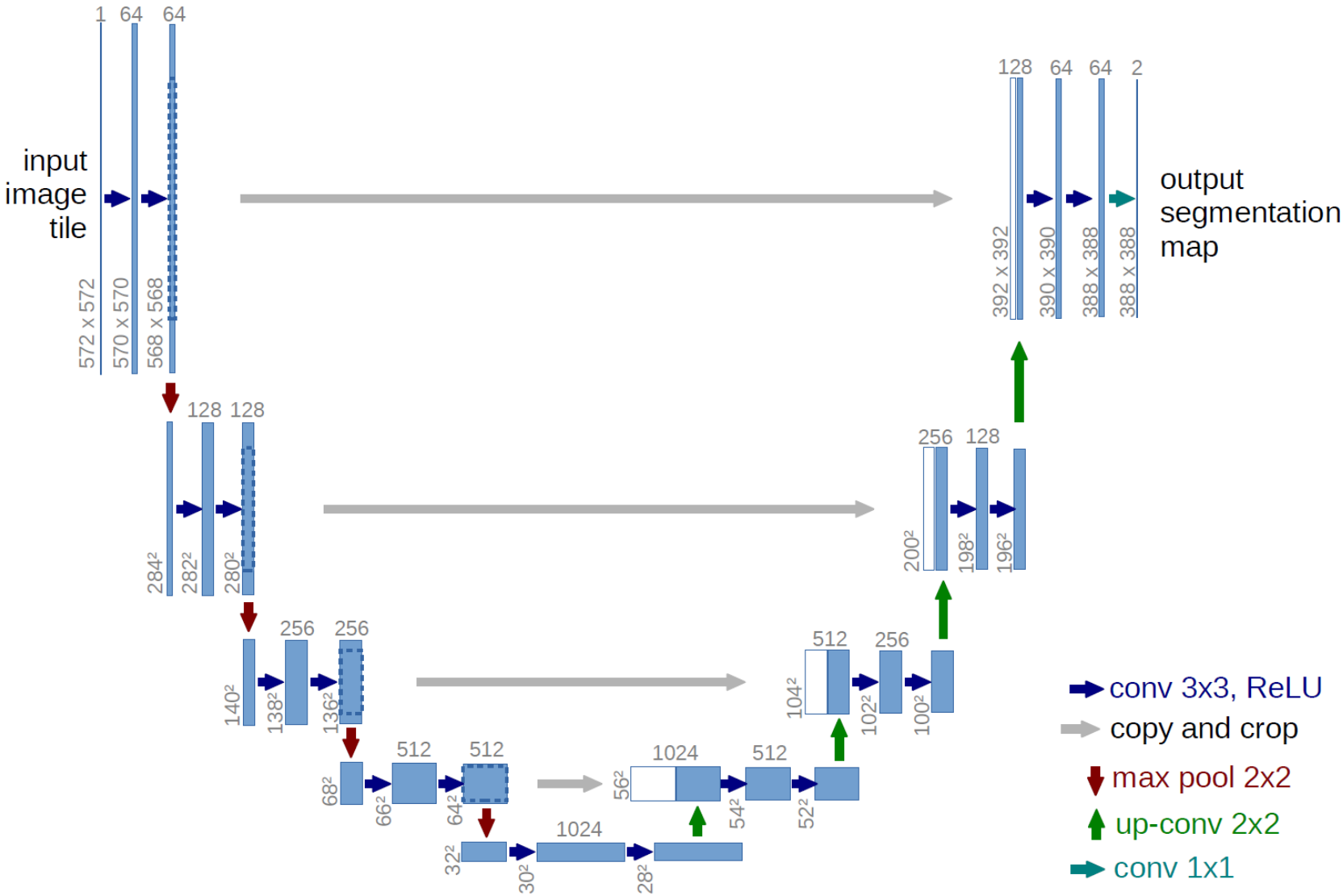
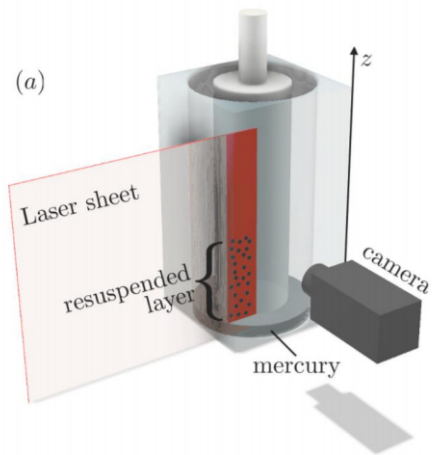


Figure: U-Net architecture.

Traitement d'image par algorithme de machine learning



Dispositif expérimental

Image expérimentale

Partie de l'image original

Image segmentée (centres et surfaces)

Particule segmentation (2/2)