IMAGE SEGMENTATION BY SUPERPIXELS

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deep learning; convolutional neural networks; image segmentation

Abstract:
In this paper, we present an algorithm based upon convolutional neural networks for generating superpixel partitions of images.
By combining an algorithm that generates superpixel partitions through the resolution of the Eikonal equation and ground truth segmentations from the Microsoft Common Objects in Context (COCO) dataset, we were able to generate training examples of superpixel partitions of the images of the dataset. These training examples arise in the form of RGB image where the color is averaged over each superpixel. A convolutional network architecture is then trained on these images. A superpixel algorithm is finally applied to the output of the network to construct the seeked partition.
The algorithm is evaluated on the Berkeley Segmentation Dataset 500. It yields results in terms of boundary adherence that are comparable to the ones obtained with state of the art algorithms including SLIC, while significantly improving on these algorithms in terms of compactness and undersegmentation.

Contents

Todo

-

1 Introduction

1.1 Segmentation

The human eye can easily understand the content of an image, but making a computer interpret the disposition of its pixels is more complex. Segmenting an image is partitioning it into multiple sets of pixels. It transforms the image into something that is easier to analyze, and much more meaningful. It allows one to locate the objects on an image, pointing out their boundaries.

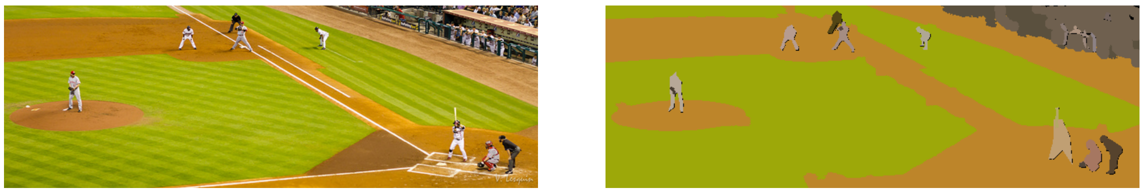


Figure 1: *A segmentation. Left: the original image; right: the segmented image. Both are from the COCO training dataset (REF?).*

Motivation references for segmentation applications

1.2 Superpixels

What it is Superpixel algorithms refer to a class of techniques designed to partition an image into small regions that group perceptually similar pixels. Superpixel representations are generally more meaningful than raw pixel representations and easier to analyze. One of the advantages of using superpixels is notably that their number ismuchsmallerthanthenumberofpixelsintheimage,whichleadstoareductionintheamountofcalculations required for further processing. In addition, thanks to their homogeneity, superpixels constitute subregions of the image on which it is particularly relevant to compute features. As a consequence, superpixel algorithms are commonly employed as a pre-processing step in a number of applications, including depth estimation [26][1], object classification or image segmentation [11][2].

Applications & Motivation démarrer une segmentation
fournir un support sur lequel faire de la classification (couleur/texture moyenne, etc)

1.2.1 Ce qu'est une bonne superpixelsegmentation

pour obtenir metriques des algos, `cnn/results/results.py`

Metrics Defining requirements for a "good" superpixel segmentation algorithm is an ambiguous task [23]. Several criteria are nevertheless commonly retained in the literature to evaluate the quality of a superpixel partition. (article bruno) [3] let $S = S_j{}_{j=1}^{K}$ and $G = G_i$ be partitions of the same image $I : x_n \mapsto I(x_n)$, $1 \leq n \leq N$ S is a segmented image G is the ground truth

- **Boundary Recall.** - most commonly used metric to assess boundary adherence. - intersection entre les frontieres grossies et truth, donc pourcentage de vrais contours deetctes - Let $\mathrm{TP}(G, S)$ be the number of true positive boundary pixels and $\mathrm{FN}(G, S)$ be the number of false negative boudary pixels in the segmented image S.

$$\mathrm{Rec}(G, S) = \frac{\mathrm{TP}(G, S)}{\mathrm{TP}(G, S) + \mathrm{FN}(G, S)}$$

[1][26] CLawrenceZitnickandSingBingKang. Stereoforimage-basedrenderingusingimageover-segmentation. International Journal of Computer Vision, 75(1):49–65, 2007.

[2][11] Brian Fulkerson, Andrea Vedaldi, and Stefano Soatto. Class segmentation and object localization with superpixel neighborhoods. In Computer Vision, 2009 IEEE 12th International Conference on, pages 670–677. IEEE, 2009.

[3]cf article https://arxiv.org/pdf/1612.01601.pdf

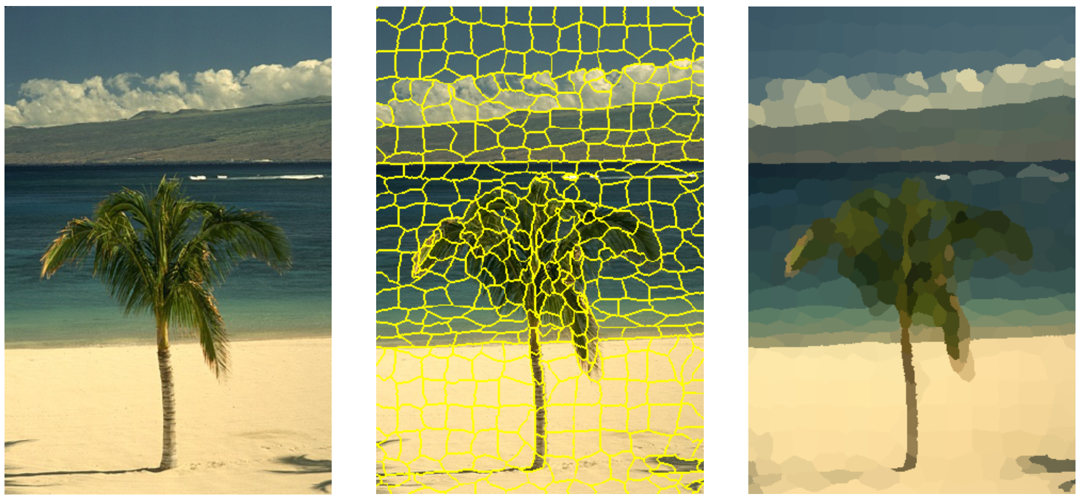


Figure 2: *A superpixel segmentation. From left to right: the original image, the original image with its calculated superpixels outlines and the resulting superpixel segmented image. Each pixel of a superpixel has only one color, the mean color of the original image over the superpixel region.*

- **Undersegmentation Error.**
- **Compactness.** - evaluates the compactness of the superpixels.

$$\mathrm{CO}(G, S) = \frac{1}{N} \sum_{S_j} |S_j| \frac{4\pi A\left(S_j\right)}{P\left(S_j\right)}$$

  - the CO operator computes how close the area $A(S_j)$ of each superpixel S_j is from a circle with same perimeter $P(S_j)$.

Autres algorithmes - SLIC

1.2.2 Motivations/ambitions

Difficultés que l'on cherche à résoudre

Pas de vraie approche DL pour segmentation avec superpixels Most of the aforementioned segmentation methods are based only on color information of pixels in the image. Humans use much more knowledge when performing image segmentation, but implementing this knowledge would cost considerable human engineering and computational time, and would require a huge domain knowledge database which does not currently exist. Trainable segmentation methods, such as neural network segmentation, overcome these issues by modeling the domain knowledge from a dataset of labeled pixels.

Ambitions améliorer les métriques

2 Dataset generation

2.1 COCO dataset

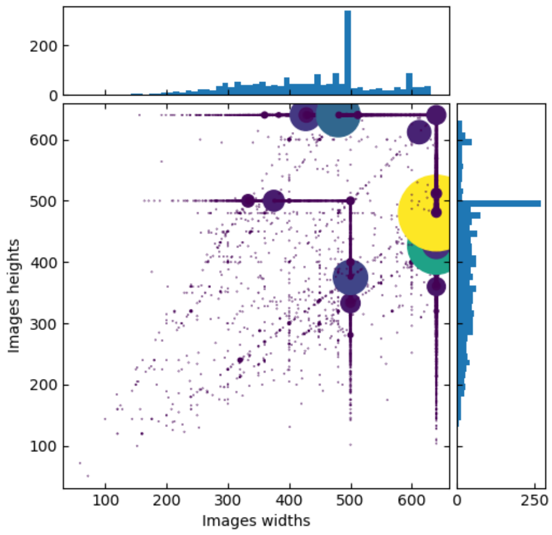
2.1.1 The COCO dataset

COCO dataset[4], nb of images, examples

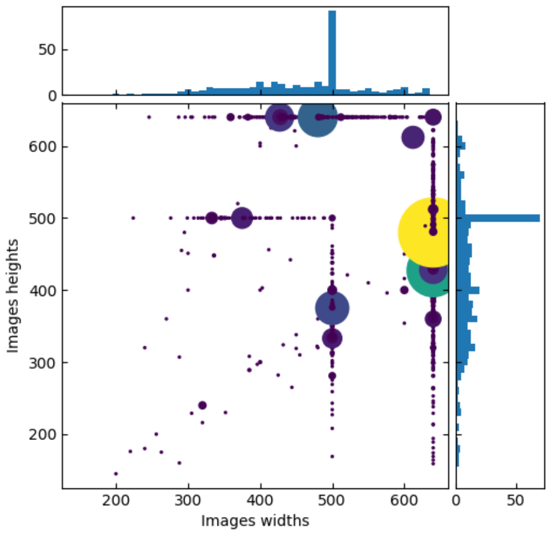
[4]site de COCO

2.1.2 Characteristics

In order to have a better understanding of the dataset, we



(a) *plot*



(b) *plot*

	Training	Height	Width
Images	Min	51	59
118 287	Max	640	640

(c) Tabular

	Validation	Height	Width
Images	Min	145	200
5000	Max	640	640

(d) Tabular

Figure 3: *Training and validation sets characterization*

d'où la nécessité de faire des transformations sur la dataset pour uniformiser les tailles en entrée du réseau.

2.2 Eikonal

2.3 Global approach

en plus réutilisé derrière sur image qui sort du réseau
faire un petit résumé

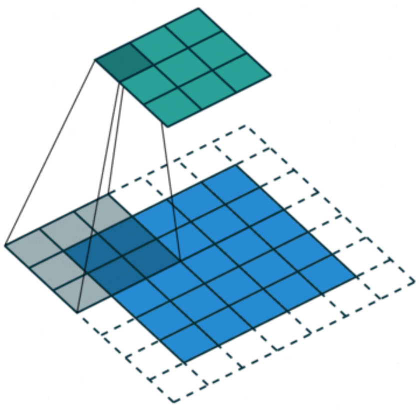
Figure 4: *Title*

3 The model

3.1 Network architecture

3.1.1 Layers definitions

Dilated convolution We consider a layer $L = (L_j)_{j \in [\![1,w]\!]}$, w being the number of feature maps L_j of L. We also consider $K = (K_{i,j})_{i,j}$, each $K_{i,j}$ being a 3×3 convolutional kernel. The dilated convolution operation of $K_{i,j}$ on L_j is denoted by $L_j *_r K_{i,j}$, r being the dilation parameter.


(a) *A simple convolution ($r = 1$)*

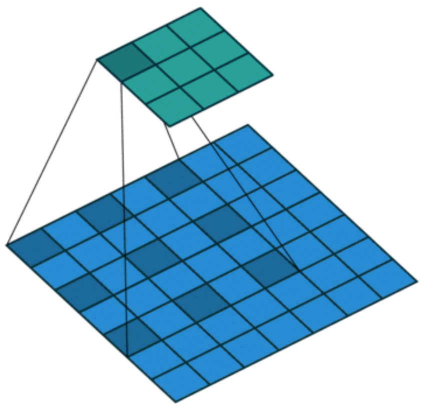

(b) *A dilated convolution ($r = 2$)*

Figure 5: *Illustration of two types of convolutions*

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

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

and we recognize the simple convolution when $r = 1$.
A dilated convolution enables the network getting larger receptive fields while preserving the input resolution[5]

Adaptative Batch Normalization (ABN) As we have seen in (2.1.2), page 5, we need to normalize the data. We define the *adaptative normalization function* Ψ as:

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

where BN is the classic batch normalization[6], defined as:

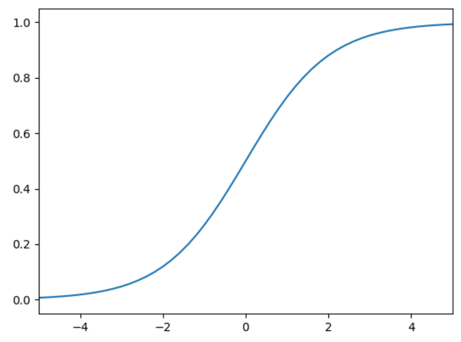
$$BN(x) = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta.$$

As such, Ψ combines identity mapping and batch normalization. a, b, γ and β are learned parameters[7] by backpropagation. It allows the model to adapt to each dataset, choosing whether or not giving a big importance to the identity term and the normalization term.

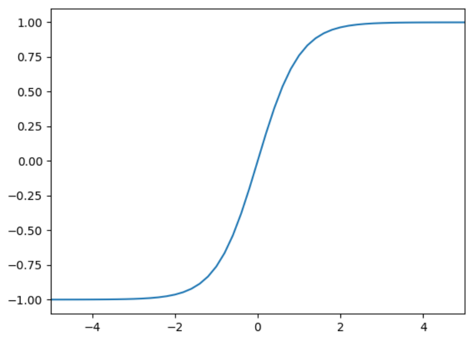
Leaky rectifier (LReLU) In order to let our neural network model complex patterns in the data, we have to add a non-linear property to the model. It often is an activation function, such as a sigmoid or a tanh (Figure 6).

these activation functions are often used but they are bounded and their gradient is very low on the edges. Because we are going to manipulate high scalar values, we have to use an unbounded activation function, such as ReLU, $\Phi(x) = \max(0, x)$ (Figure 7a). But the issue with ReLU is that all the negative

[5]ref ?
[6]reference ?
[7]ref : `https://pytorch.org/docs/stable/_modules/torch/nn/modules/batchnorm.html`



(a) *Sigmoid*

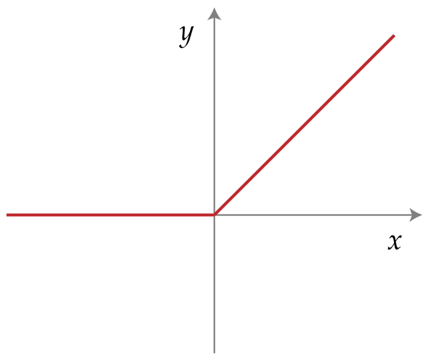


(b) *tanh*

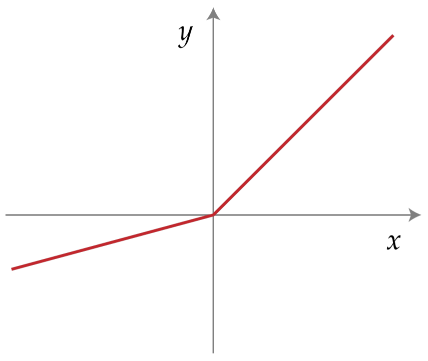
Figure 6: *Illustration of two bounded rectifiers*

values become zero immediately, which decreases the ability of our model to train from the data. Hence the implementation of a *leaky rectifier*, LReLU (7b):

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



(a) *ReLU*



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

Figure 7: *Illustration of two unbounded rectifiers*

By implementing a Leaky Rectifier, we are able to take into account the negative valued pixels.

3.1.2 Chen

Context Aggregation Network (CAN) [8] blabla sur le RGB en entrée, RGB en sortie I -> f(I)

input I	$\longrightarrow$	L^1	$\longrightarrow$	$\cdots$	$\longrightarrow$	L^s	$\longrightarrow$	$\cdots$	$\longrightarrow$	output (L^d)
$m \times n \times 3$		$m \times n \times w_1$				$m \times n \times w_s$				$m \times n \times 3$

Table 1: *Layers*

Architecture of a block Each block L_s is made of 3 layers:

1. *A dilated convolution*, $r_s = 2^s$

[8] reference

2. *An adaptative batch normalization*
3. *A leaky rectifier (ReLU)*

so that the content of an intermediate layer L^s can be computed from the content of the previous layer L^{s-1}:

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

where ... is ...
and

$$L_j^{s-1} *_{r_s} K_{i,j}^s = \sum_{a+r_s b=x} L_j^{s-1}(a) K_{i,j}^s(b) \tag{2}$$

because of 3.1.1, page 5.

Layer	1	2	3	4	5	6	7
Convolution	3×3						
Dilation	1						
Batch Normalization	Yes						
LReLU	Yes						

Table 2: *Chen*

3.1.3 UNet

3.1.4 Chen + UNet

3.2 Total Variation (TV) Loss

3.2.1 MSE

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

3.2.2 TV

[9]

Why In such a search for well-segmented images, 2 criteria have to be fulfilled. The output needs to be as close as possible to the ground truth image; but we also need the segmented image to present a lot of zones where the color gradient $\nabla f(I)$ is equal to 0. Thus, we want to implement a train loss function that could help us satisfy these two criteria. In order to do so, we use the Total Variation (TV) loss, defined below.

Formula

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

granting an improvement in the output image smoothness.

[9] ref

3.3 Implementation

The network was implemented with PyTorch[10] and we used GPU acceleration [...] (pytorch), se renseigner (section assez courante) GPU acceleraation code sur github

4 Expérience et résultats

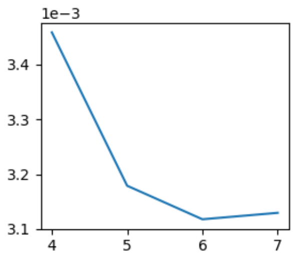
4.1 Hyperparameters

petit bilan des valeurs choisies évolution des paramètres a et b ?

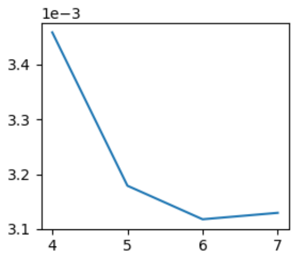
4.1.1 Learning rate

lr_0	decay?	saturation?	d	TV?
0.001	No	No	7	No
0.01	No	No	7	No
0.01	$\times 0.5$ every 2 epochs	10^{-4}	7	No
0.001	$\times 0.5$ every 2 epochs	10^{-4}	7	No

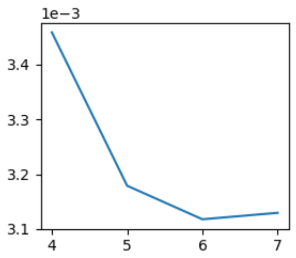
Table 3: Runs for learning rate tuning



(a) *Graph*



(b) *Graph*



(c) *Graph*

Figure 8: *Tuning of learning rate*

Constant value entrainement (lr, alpha) -> courbes de loss, et loss qui sature (cluster) d'où changement de lr au cours des epochs

Non constant value

4.1.2 Network size d

- Learning rate initialisé à 0.01, divisé par 2 toutes les 2 époques, saturation à 1e-4 - Pas de régularisation TV CONCLUSION des run 3 à 5: Il est préférable de laisser d=7. Entre d=6 et d=7, l'amélioration semble relativement faible. bon intermédiaire entre temps de calcul et performances

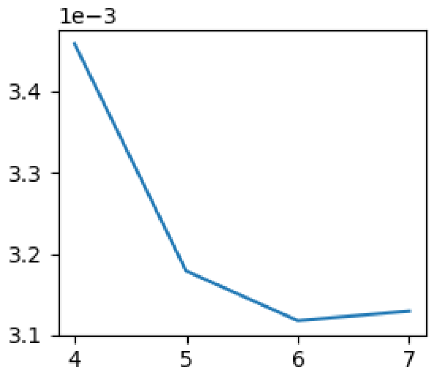
4.1.3 Number of epochs

nb epochs: on le sélectionne en prenant le minimum de la validation loss

[10] Repository can be found at `https://github.com/theodumont/superpixels-segmentation`.

d	4	5	6	7	8
loss$\times 10^3$	3.46	3.18	3.12	3.13	???

(a) *Loss values on validation set*



(b) *Graph*

Figure 9: *Tuning of network size*

4.1.4 TV regularization

4.1.5 Runs

tableaux et graphes

4.2 Results on dataset

image originale -> CNN -> résultat du filtre dans eikonal -> superpixels sans couleurs + couleur moyenne pour chaque spp de l'image originale cf results/images

4.2.1 The dataset

BSD dataset, BSD fait a la main et pas a l'arrache comme COCO

4.2.2 Results

metrics Here are the previously defined metrics of some well-known superpixel segmentation algorithms.

Algorithm		BR	UE	CO
image analysis	EI [11]			
	EIT [12]			
	WS [13]			
neural networks	ref [14]	0.8995	0.0473	0.5409
	Ours	0.8781[15]	0.0388	0.7682

Table 4: Comparisons of metrics on the BSD dataset for different superpixel segmentation algorithms

We use the ?? alorithm as a reference to evaluate the performances of our model. pas très grave parce que la compacité est pourrie du coup comme les contours oscillent ils intersectent plus de contours de l'image

5 Conclusion/Discussion

On a présenté un nouveau...
On a prouvé...
Il reste à faire...

relire tous les mails pour avoir toutes les infos sur performances etc

Special thanks

Sources

[1] [1] C. Smith, J.C. Green, Titre de l'article, Titre du journal, 10 (2009) 55-72
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