

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

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Top-Down and Bottom-up Cues for Scene Text Recognition

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Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

Introduction

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

- Robust methods have allowed recognizing letters efficiently recently (OCR).
- Scene text recognition has been a center of interest in computer vision for those few last years.
- We decided to implement a paper by A. Mishra, K. Alahari, C. V. Jawahar, *Top-down and Bottom-up Cues for Scene Text Recognition* [1]

Sommaire

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

**Learning
preliminaries**

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

1 Learning preliminaries

- Learning characters
- Learning words

2 Character detection

3 Recognizing words

4 Implementation and first results

Learning characters

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

We need to build classifiers to recognize characters in a natural picture:

- 1 Use a database to identify characters: ICDAR 2003 [2], Chars74K [3];
- 2 extract features: Histogram Of Gradient (HOG) [4]¹;
- 3 build K SVMs (K is the number of classes, 62) with RBF Kernel, Fig.(1):

$$\exp(-\gamma|x - x'|^2), \gamma > 0 \quad (1)$$

method one-versus-all, we used a Python library scikit-learn [5]: two parameters γ and regularization C optimized by cross-validation -> test error without optimization 25%, with optimization 16%.

¹N. Dalal, B. Triggs, Histogram of oriented gradients for human detection

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

**Learning
characters**
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

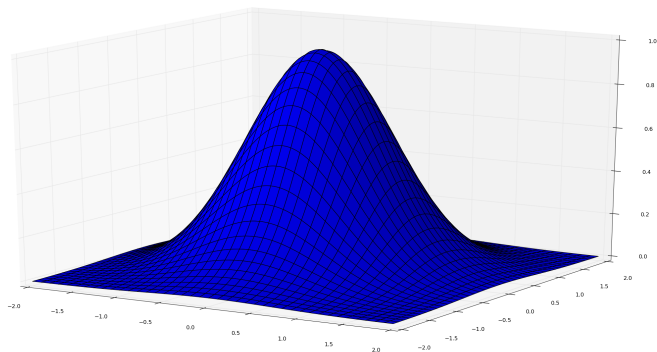


Figure: RBF Kernel

Learning words

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

We have to build a prior lexicon that contains how characters interact to create words.

- 1 Load a database of words $[6]^2$;
- 2 count for each pair of characters (c_i, c_j) their frequency of occurrence $p(c_i, c_j)$ in the database (bi-gram model);
- 3 will be used as an energy term to be minimized afterwards.

²<http://algoval.essex.ac.uk/icdar/Datasets.html>

Sommaire

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

1 Learning preliminaries

2 Character detection

3 Recognizing words

4 Implementation and first results

Sliding window and pruning

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

- Characters retrieved by sliding windows of different scales scanning the image;
- for each window l_i , compute the features ϕ_i of HOG with 12 orientations;
- run the 62 SVMs on ϕ_i and compute the goodness score:

$$GS(l_i) = \max_c p(c|\phi_i) \exp \left(-\frac{(a_i - \mu_{a_j})^2}{2\sigma_{a_j}^2} \right) \quad (2)$$

where a is the aspect ratio and j is the class that reaches the maximum *i.e.* the index of the character that has the highest probability of being in this window.

Sliding window and pruning

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

- if $GS(I_i) > 0.1$ then we keep the window *and* all the probabilities of each character.
- apply Non-Maximum Suppression algorithm (NMS) to merge windows that overlap:

- ① find the window with maximum confidence, say I_i .
- ② for all others I_j compute:

$$\text{criterion} = \frac{I_i \cap I_j}{I_i \cup I_j} \quad (3)$$

- ③ if $\text{criterion} > \text{threshold}$ then merge the windows.
- ④ the ending merged window has the highest confidence and is located at the barycenter of all the windows merged.

Sommaire

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

1 Learning preliminaries

2 Character detection

3 Recognizing words

4 Implementation and first results

Graph construction

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

This part of the paper is implemented for the course of PGM, we will be brief!

Suppose we are given a set of n windows with possible characters inside.

- ① for each sliding window assign a node that takes values in \mathcal{K}_ϵ^n (add ϵ void label);
- ② build edges if the windows are 'close enough';
- ③ assign unary energy to each node, and pairwise energy for edges composed of a term of overlapping and lexicon prior;
- ④ minimize the discrete energy on the graph (NP-hard) with TRW-S algorithm [7].

Sommaire

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results

1 Learning preliminaries

2 Character detection

3 Recognizing words

4 Implementation and first results

Implementation and first results

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results



Figure: Image for testing the algorithm

Implementation and first results

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementation
and first
results



Figure: Word retrieved: 'P E '

References

Top-Down
and
Bottom-up
Cues for
Scene Text
Recognition

Vincent
BODIN &
Thomas
MOREAU

Introduction

Learning
preliminaries

Learning
characters
Learning
words

Character
detection

Recognizing
words

Implementatio
and first
results



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