



seit 1558

# Difference of Boxes Filters Revisited: Shadow Suppression and Efficient Character Segmentation

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## Introduction

- > Robust character recognition often relies on a good segmentation.
- > Difficulties: dirt, non-uniform illumination, shadow, ...
- > Our method of character segmentation is **simple, efficient and easy to implement**.
- > Algorithm overview:
  1. Shadow suppression using multiple difference of boxes filters
  2. Ternary segmentation using locally estimated thresholds
- > Applications:
  - license plate recognition
  - ID card recognition
  - arbitrary document analysis systems

## Multiple Difference of Boxes

- > Base filter: Difference of Boxes Filter [2]
  - > Simple interpretation of the idea of Vonikakis et al. [3] (hidden in their formulas)
  - > Definition for an one-dimensional signal  $g$  ( $m < M$ )
- $$\text{DoB}_{m,M}(g) = \frac{1}{m} \sum_{i=1}^m g_i - \frac{1}{M} \sum_{l=1}^M g_l = \frac{M-m}{M} \left( \frac{1}{m} \sum_{i=1}^m g_i - \frac{1}{M-m} \sum_{l=m+1}^M g_l \right)$$
- > Approximation of a Difference of Gaussians or Mexican-Hat filter
  - > Runtime independent of filter sizes
  - > Maximum of the result of several DoB filters with different sizes ( $m_i, M_i$ ) leads to the final filter output of a Multiple Difference of Boxes (MDoB) Filter

## Examples



Our character segmentation framework applied to ID cards and license plates

## Local Segmentation

- > Ternary segmentation instead of binary segmentation
  - Object
  - Background
  - Unknown
- > Local binary decision between object and background is not possible for all pixels (e.g. within homogenous regions)
- > Solution: definition of a third label "unknown"
- > Local decision depends on maximum and minimum in a neighborhood around each pixel:  $g_{\max}(\mathbf{x}), g_{\min}(\mathbf{x})$



Original image and ternary local segmentation (white: background, red: object, blue: unknown)

## Local Segmentation (Algorithm)

- 1 Calculate  $g_{\max}$  and  $g_{\min}$
- 2 For each pixel  $\mathbf{x}$ :
  - 2.1 If  $g_{\max}(\mathbf{x}) - g_{\min}(\mathbf{x}) < \gamma$  then
    - 2.2 label point as unknown
  - 2.3 else
    - 2.4  $T = \frac{1}{2}(g_{\max}(\mathbf{x}) + g_{\min}(\mathbf{x}))$
    - 2.5 If  $g(\mathbf{x}) > T$  then label point as object
    - 2.6 else label point as background

## Measuring the Quality of Character Segmentations

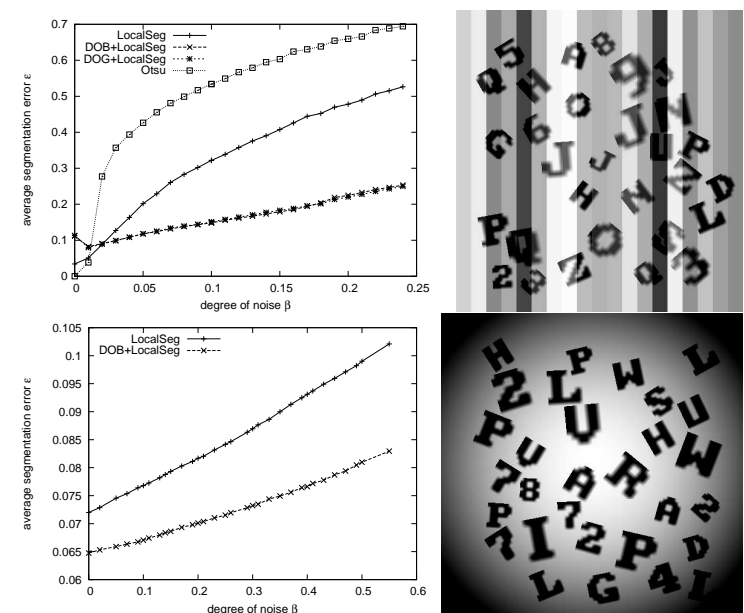
- > Simple measure of segmentation quality as the distance to a given ground truth segmentation
- > Base for parameter optimization and method evaluation
- > Distance between two components  $A$  and  $B$  of segmentations:
 
$$d_{\mathcal{R}}(A, B) = \frac{|A \setminus B| + |B \setminus A|}{|A| + |B|} \quad (1)$$
- > Distance between two segmentations  $\tilde{S}$  ( $p$  components) and  $S$  ( $q$  components)
 
$$d(\tilde{S}, S) = \frac{1}{q} \left( \min_{\pi} \sum_{k=1}^q d_{\mathcal{R}}(\tilde{S}_{\pi(k)}, S_k) \right)$$
- > Optimization over all injective maps  $\pi : \{1, \dots, q\} \rightarrow \{1, \dots, p\}$  can be carried out using the Hungarian method

## Optimal Parameters of the Segmentation Method

- > Given several ground truth segmentations  $S_G^i$ , one can search for optimal parameters maximizing segmentation quality
- > MDoB parameters  $\theta = \{m_1, M_1, \dots\}$ 
  - number of DoB filters used
  - sizes of inner boxes  $m_j$
  - sizes of outer boxes  $M_j$
- > Parameters of our local segmentation method:  $\eta = \{\gamma, \text{size}(U(x))\}$
- > Optimization criteria using our segmentation quality measure:
 
$$\epsilon(\theta, \eta) = \sum_i d(\tilde{S}^i(\theta, \eta), S_G^i)$$
- > Optimization performed by cyclic coordinate search [1]
- > By iteratively adding a new component to the MDoB filter an optimal number of different DoB filters can be estimated.

## Experiments

- > Evaluation within a license plate recognition system
    - 6205 test images, fixed set of single letter training images
    - Segmentation framework used to segment an aligned license plate into character regions
    - Recognition performance measured for whole license plates using the complete license plate recognition system
- |                                   |        |
|-----------------------------------|--------|
| MDoB filters + Local Segmentation | 88.45% |
| Local Segmentation                | 73.47% |
- > Evaluation using synthetic input images
    - random noise simulating shadow influence parameterized with  $\beta$
    - left image: analysis of segmentation error with respect to  $\beta$
    - right image: example of a single synthetic image after applying noise operation



## Conclusions

- > Simple but robust and efficient method for character segmentation
- > Fast computation: combination of basic filter operations
- > Proposed measure for segmentation quality can be used for evaluation and optimization
- > Optimal parameters of our method can be found with an optimization framework

## References

- [1] Jorge Nocedal and Stephen J. Wright. *Numerical Optimization*. Springer, August 1999.
- [2] A. Rosenfeld and M. Thurston. Edge and curve detection for visual scene analysis. *IEEE Transaction on Computers*, 20:562-569, 1971.
- [3] Vassilios Vonikakis, Ioannis Andreadis, Nikos Papamarkos, and Antonios Gasteratos. Adaptive document binarization - a human vision approach. In *Proceedings of the Second International Conference on Computer Vision Theory and Applications (VISAPP)*, Barcelona, Spain, March 8-11, 2007 - Volume 2, pages 104-109, 2007.

We would like to thank ROBOT Visual Systems GmbH for financial support and for providing experimental data for large scale evaluation.