Maiwei AI Lab

Machine Learning, Computer Visio

10张图带你认识图像分割的前世今生

汇报人

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迈微AI研习社

Maiwei AI Lab

TERM，TERM POWER

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Machine Learning, Computer Visio

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AI+农业，下一场“工业革命”即将爆发

发展历程

PART ONE

传统分割方法

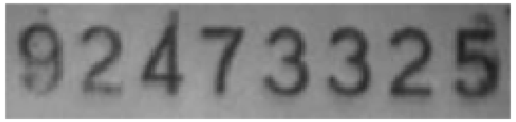


图 4. 原始图像

图 5. 阈值低，对亮区效果好，则暗区差

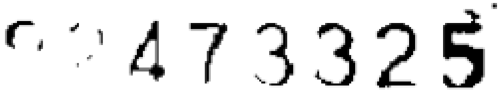
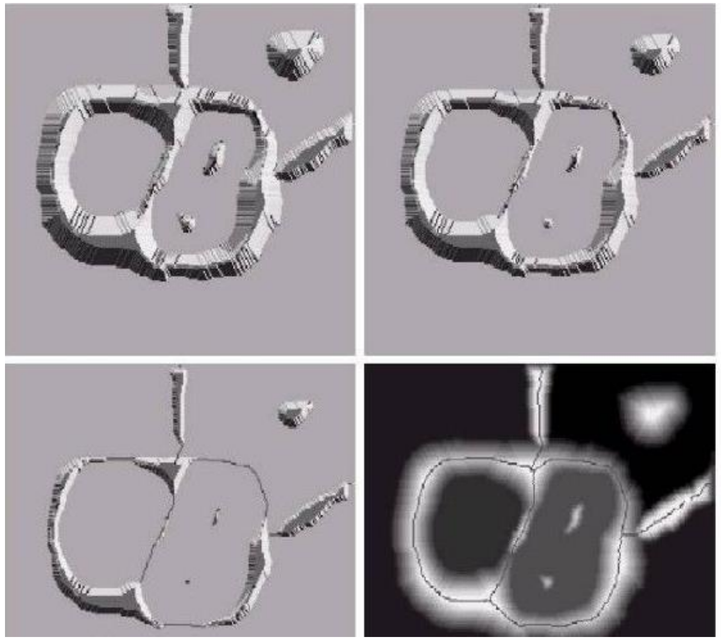


图 6. 阈值高，对暗区效果好，则亮区差



e f
g h

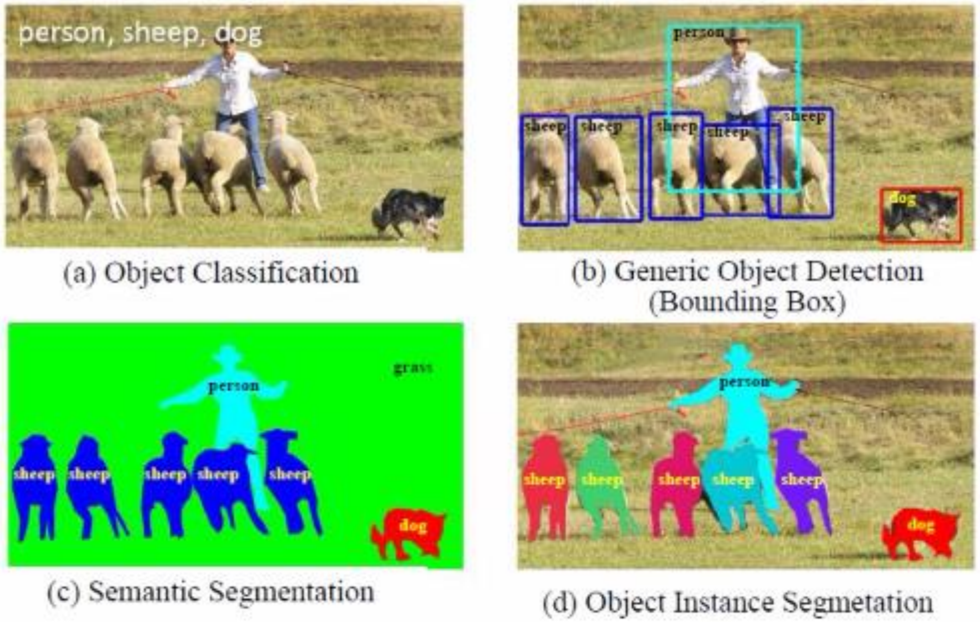
FIGURE 10.44
(Continued)
(e) Result of further flooding. (f) Beginning of merging of water from two catchment basins (a short dam was built between them). (g) Longer dams. (h) Final watershed (segmentation) lines. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

传统分割方法

(a) 梯度算法处理的结果　(b) Roberts 算法　(c) Sobel 算法

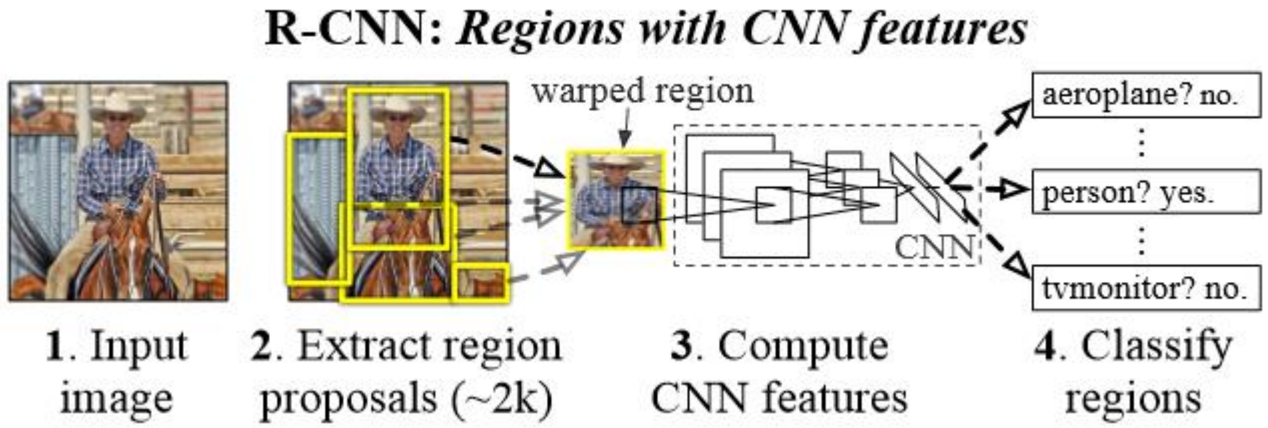
(d) Prewitt 算法　(e) Kirsch 算法　(f) Laplacian 算法

概念区分

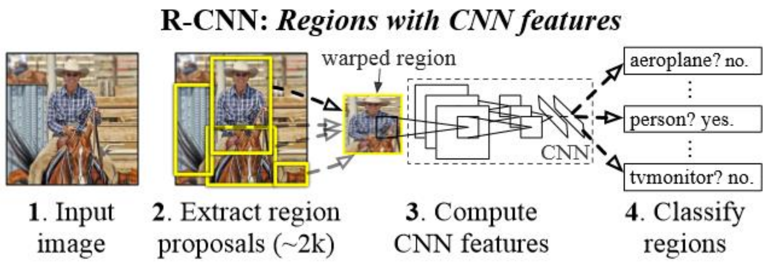

person, sheep, dog
(a) Object Classification
(b) Generic Object Detection (Bounding Box)
(c) Semantic Segmentation
(d) Object Instance Segmetation

研究现状
PART TWO

传统分割方法


R-CNN: Regions with CNN features
warped region
aeroplane? no.
person? yes.
tvmonitor? no.
CNN
1. Input image
2. Extract region proposals (~2k)
3. Compute CNN features
4. Classify regions

传统分割方法


R-CNN: Regions with CNN features
warped region
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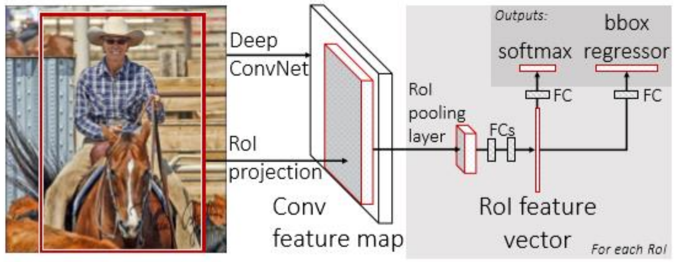
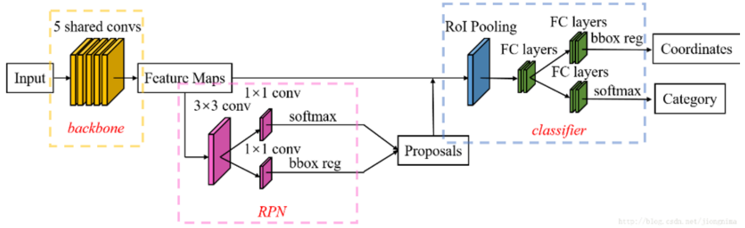
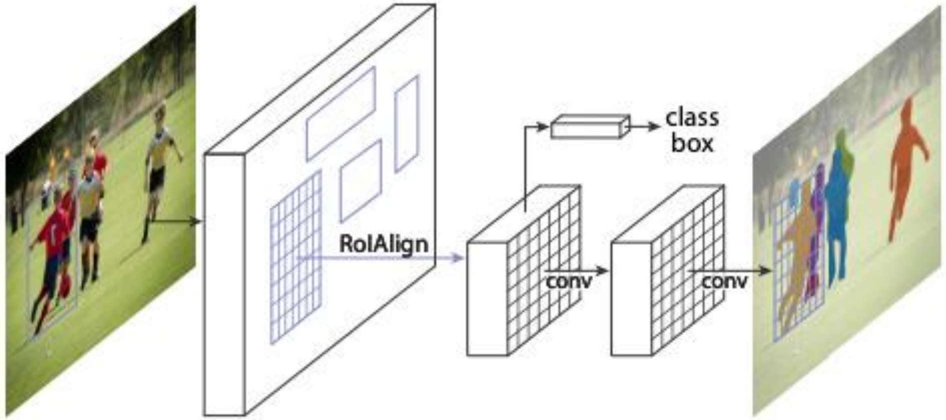
person? yes.
tvmonitor? no.
CNN
1. Input image
2. Extract region proposals (~2k)
3. Compute CNN features
4. Classify regions

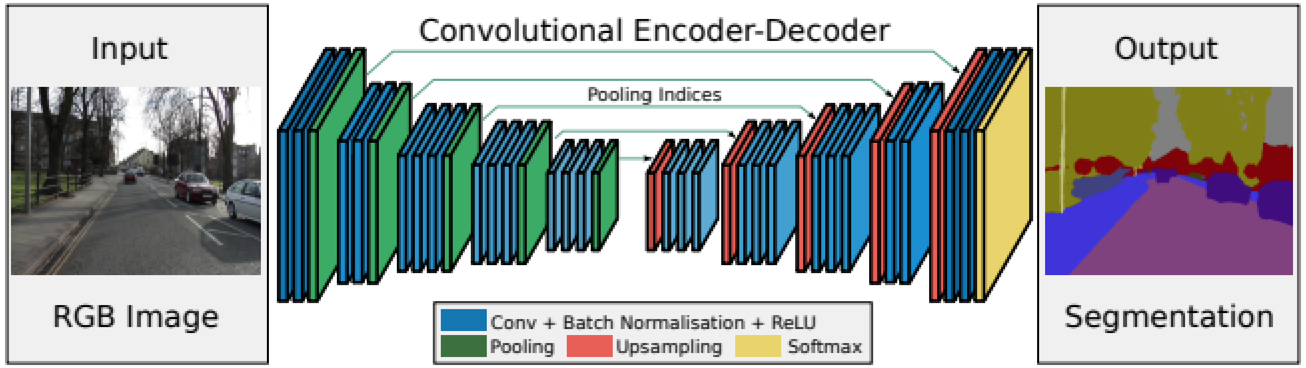

Deep ConvNet
RoI projection
Conv feature map
RoI pooling layer
FCs
Outputs:
softmax
bbox regressor
FC
FC
RoI feature vector
For each RoI

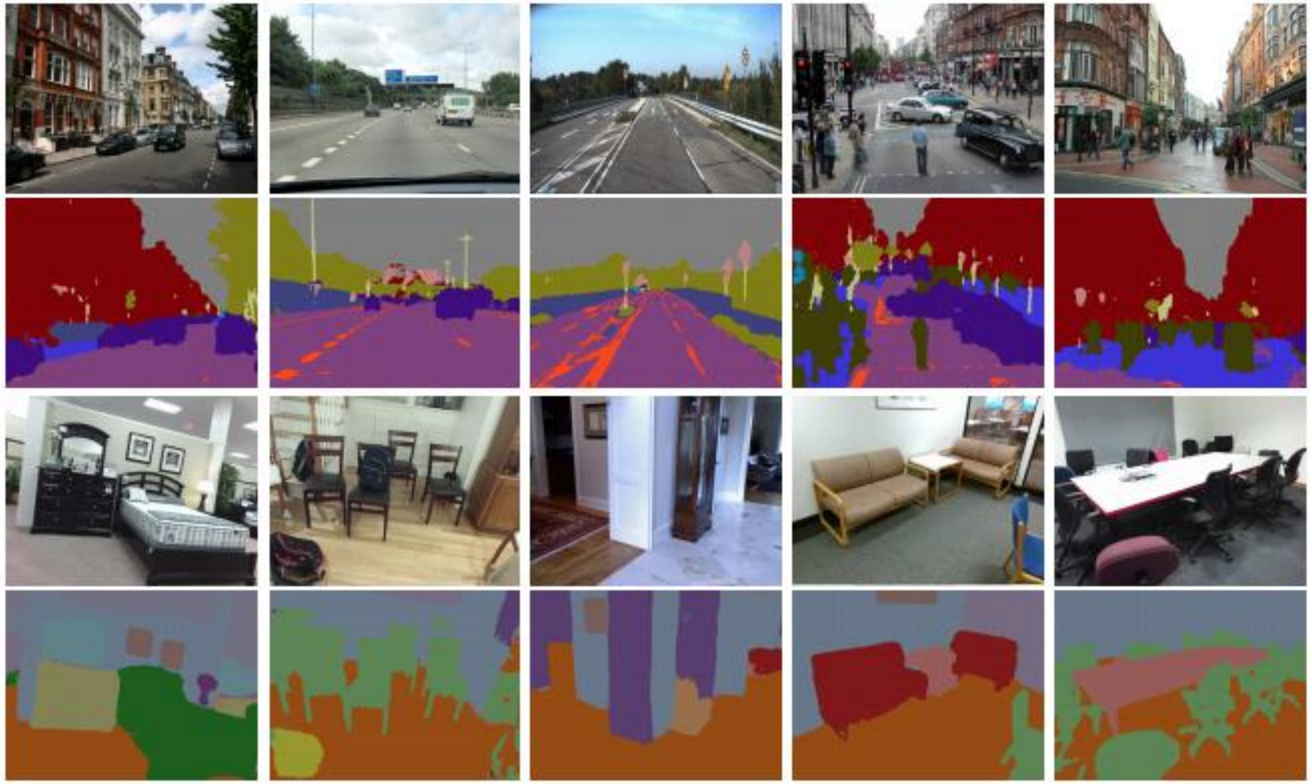

Input
5 shared convs
backbone
Feature Maps
3×3 conv
1×1 conv
softmax
1×1 conv
bbox reg
RPN
Proposals
RoI Pooling
FC layers
FC layers
bbox reg
FC layers
softmax
classifier
Coordinates
Category

传统分割方法

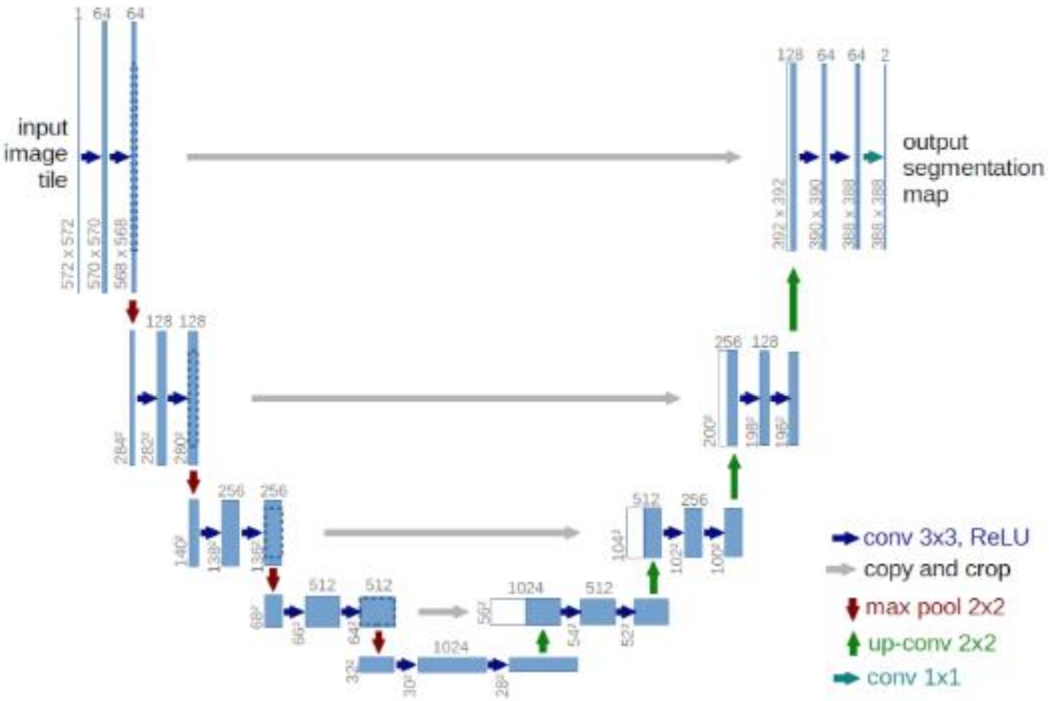


传统分割方法

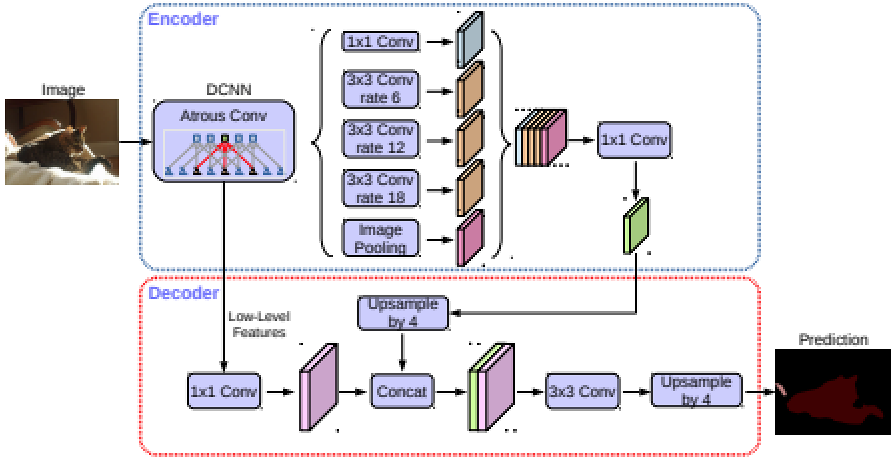

Input
RGB Image
Convolutional Encoder-Decoder
Pooling Indices
Conv + Batch Normalisation + ReLU
Pooling
Upsampling
Softmax
Output
Segmentation

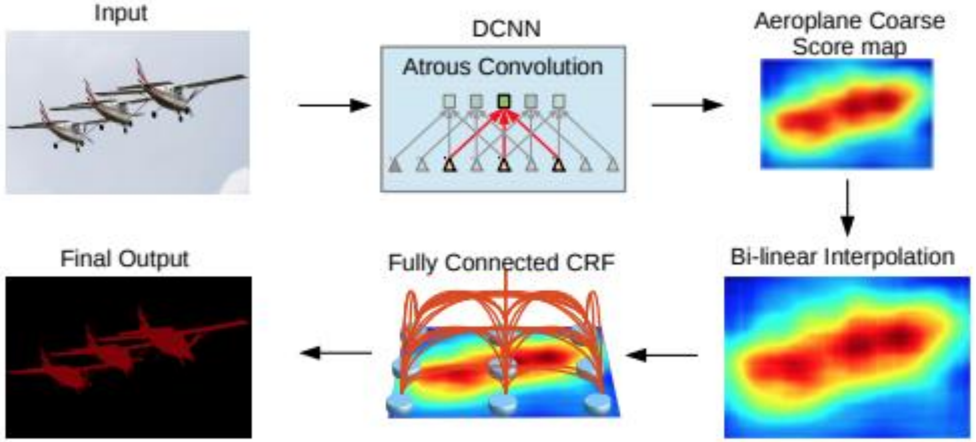


传统分割方法

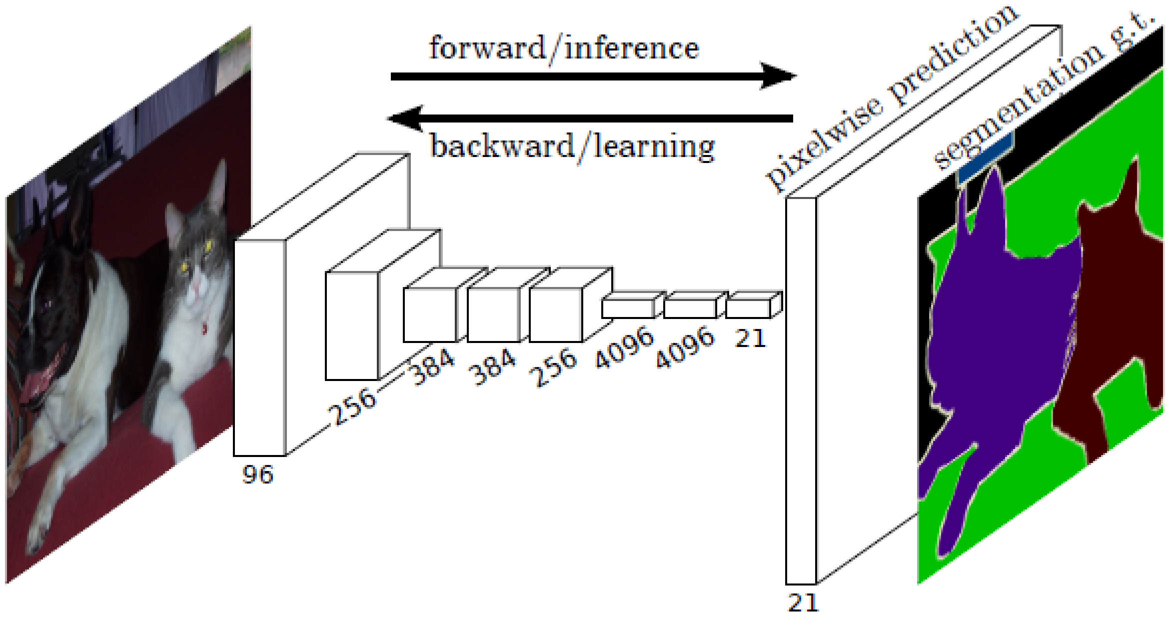

input
image
tile
output
segmentation
map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

传统分割方法


Encoder
Image
DCNN
Atrous Conv
1x1 Conv
3x3 Conv rate 6
3x3 Conv rate 12
3x3 Conv rate 18
Image Pooling
1x1 Conv
Decoder
Low-Level Features
Upsample by 4
1x1 Conv
Concat
3x3 Conv
Upsample by 4
Prediction


Input
DCNN
Atrous Convolution
Aeroplane Coarse Score map
Bi-linear Interpolation
Fully Connected CRF
Final Output

传统分割方法



* J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in CVPR, pp. 3431–3440, 2015.

传统分割方法

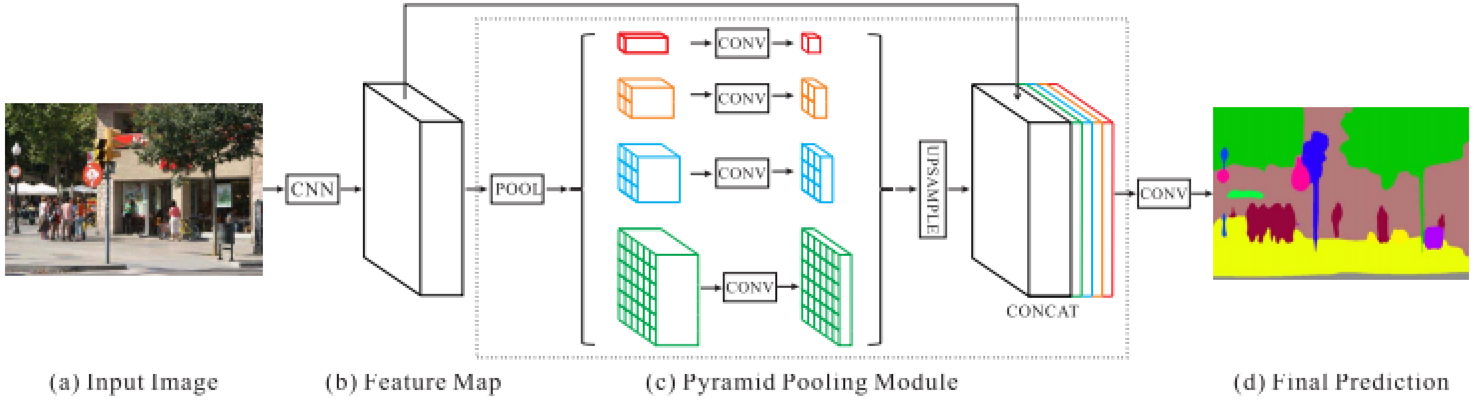
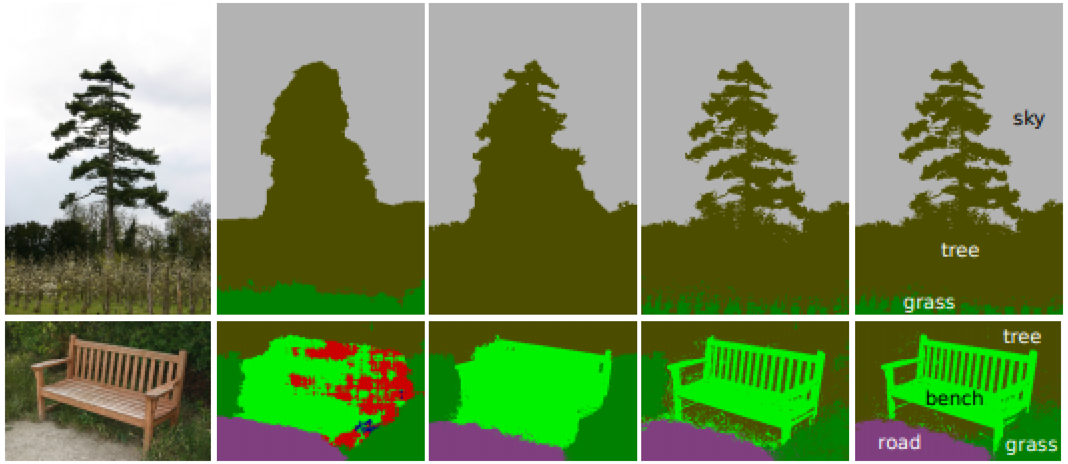


Figure 3. Overview of our proposed PSPNet. Given an input image (a), we first use CNN to get the feature map of the last convolutional layer (b), then a pyramid parsing module is applied to harvest different sub-region representations, followed by upsampling and concatenation layers to form the final feature representation, which carries both local and global context information in (c). Finally, the representation is fed into a convolution layer to get the final per-pixel prediction (d).

传统分割方法



(a) Image (b) Unary classifiers (c) Robust P^n CRF (d) Fully connected CRF, MCMC inference, 36 hrs (e) Fully connected CRF, our approach, 0.2 seconds

Figure 1: Pixel-level classification with a fully connected CRF. (a) Input image from the MSRC-21 dataset. (b) The response of unary classifiers used by our models. (c) Classification produced by the Robust P^n CRF [9]. (d) Classification produced by MCMC inference [17] in a fully connected pixel-level CRF model; the algorithm was run for 36 hours and only partially converged for the bottom image. (e) Classification produced by our inference algorithm in the fully connected model in 0.2 seconds.

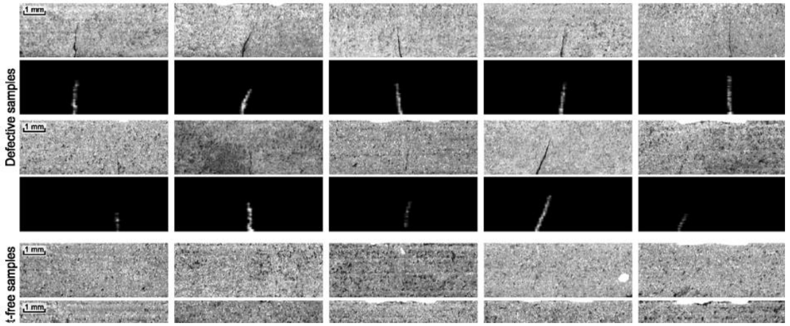
项目推荐

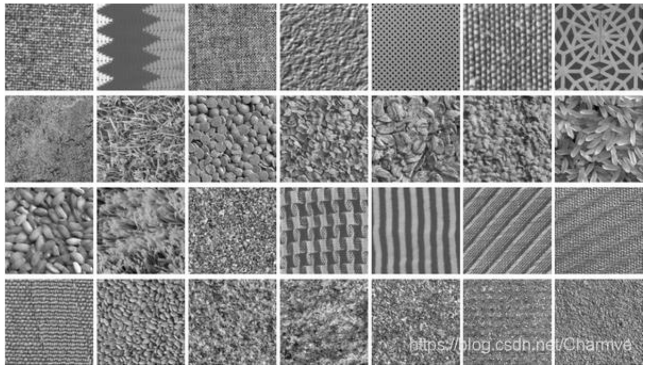
PART THREE

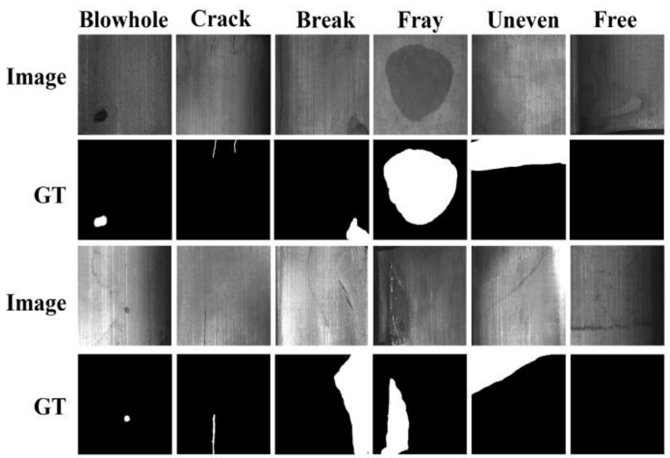
Surface Defect Detection: Dataset & Papers

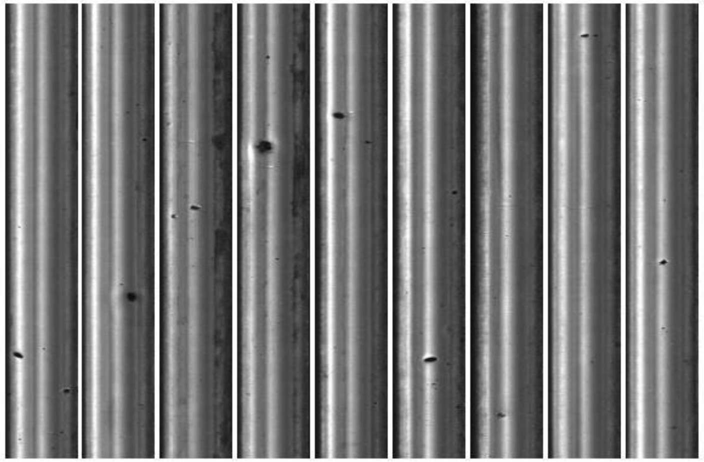
Constantly summarizing open source data sets in the field of surface defect research is very important. Important critical papers from year 2017 have been collected and compiled, which can be viewed in the [*Papers*] folder.

language English language Chinese









GtiHub https://github.com/Charmve/Surface-Defect-Detection

Mirror & Glass Detection in Real-world Scenes

Charmve | English | Chinese

Github Charmve | Glass Detect | doc Related Work | Repo Transparent Object Segmentation

Mirror and Glass Detection/Segmentation

GtiHub https://github.com/Charmve/Semantic-Segmentation-PyTorch

PyTorch for Semantic Segmentation

This repository contains some models for semantic segmentation and the pipeline of training and testing models, implemented in PyTorch

Models

1. Vanilla FCN: FCN32, FCN16, FCN8, in the versions of VGG, ResNet and DenseNet respectively (Fully convolutional networks for semantic segmentation)
2. U-Net (U-net: Convolutional networks for biomedical image segmentation)
3. SegNet (Segnet: A deep convolutional encoder-decoder architecture for image segmentation)
4. PSPNet (Pyramid scene parsing network)
5. GCN (Large Kernel Matters)
6. DUC, HDC (understanding convolution for semantic segmentation)
7. Mask-RCNN (paper, code from FAIR, **code PyTorch**)

GtiHub https://github.com/Charmve/Semantic-Segmentation-PyTorch

传统分割方法

Scene-Text-Detection

Tracking the latest progress in Scene Text Detection and Recognition: Must-read papers well organized with code and dataset.

Author: Wei ZHANG

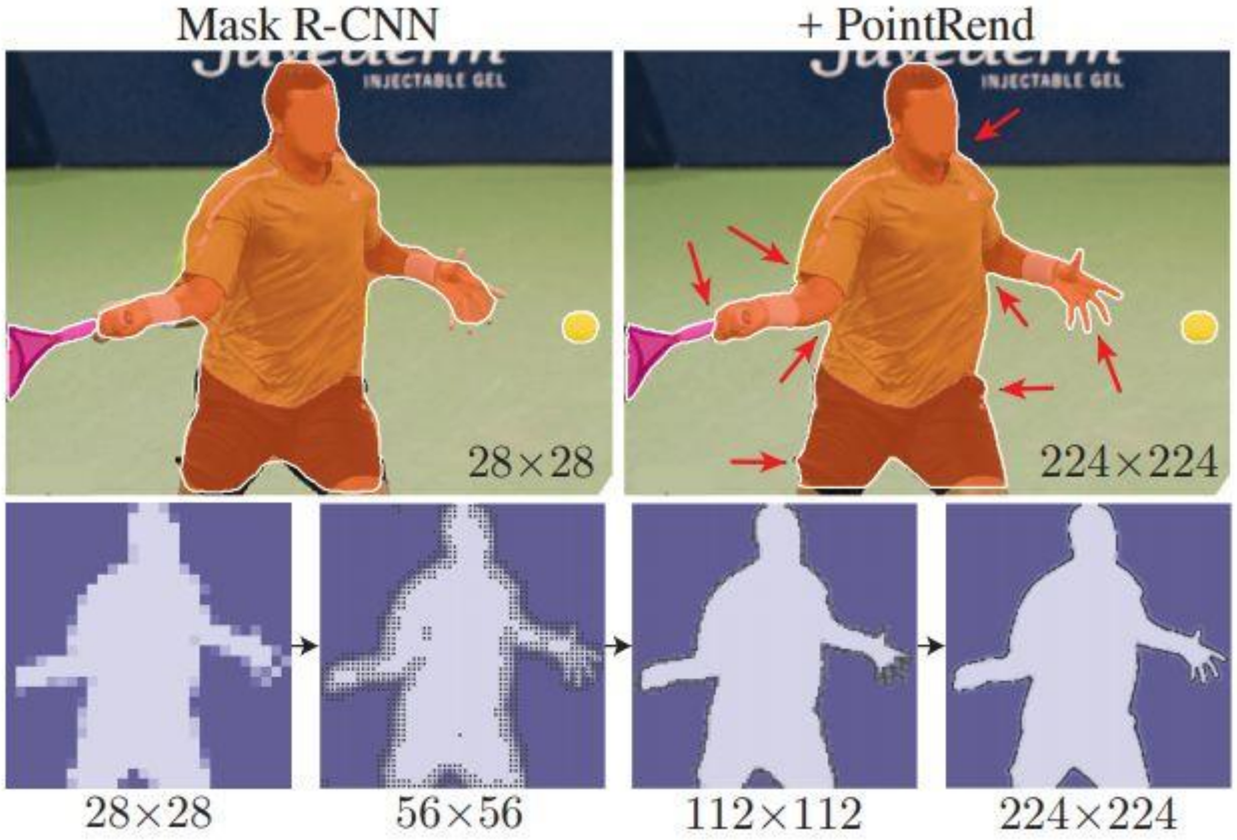
- 1.Datasets
  - 1.1 Horizontal-Text Datasets
  - 1.2 Arbitrary-Quadrilateral-Text Datasets
  - 1.3 Irregular-Text Datasets
  - 1.4 Synthetic Datasets
  - 1.5 Comparison of Datasets
- 2. Survey
- 3. Evaluation
- 4. OCR Service
- 5. References and Code

GtiHub https://github.com/Charmve/Scene-Text-Detection

🏆 Awesome-Lane-Detection

GtiHub https://github.com/Charmve/Awesome-Lane-Detection

创新应用
PART FOUR


Mask R-CNN
+ PointRend
28×28
224×224
28×28
56×56
112×112
224×224

End-to-end Animal Image Matting

CVPR 2020

[arXiv | Project Page | Video | Code | Related Work]

GtiHub https://github.com/JizhiziLi/animal-matting

PART FOUR 创新应用

参考文献

PART FIVE

PART FIVE 参考文献

[1] Wu H, Wiesner-Hanks T, Stewart E L, et al. Autonomous End-to-end Detection of Northern Leaf Blight directly from Aerial Imagery[J].

[2] Doudkin A A, Inyutin A V, Petrovsky A I, et al. Three-level neural network for data clusterization on images of infected crop field[J]. Journal of Research and Applications in Agricultural Engineering, 2007, 52(1): 5-7.

[3]净浩泽，图像分割综述. 2019.07. https://blog.csdn.net/electech6/article/details/95242875

[4]张伟，江户川柯壮．从R-CNN到YOLO，2020 图像目标检测算法综述. 2020.10. https://blog.csdn.net/Charmve/article/details/109252834

农业机械学

基于全卷积网络的林业航拍图

刘文定[1,2] 田洪宝[1,2] 谢将

Identification Methods for

Based on

LIU Wending[1,2] TIAN Hongb

PLOS | ONE

RESEARCH ARTICLE

Detection of Laurel Wilt Disease in Avocado Using Low Altitude Aerial Imaging

Ana I. de Castro, Reza Ehsani, Randy C. Ploetz, Jonathan H. Crane, Sherrie Buchanon

Abstract

OPEN ACCESS

PLOS ONE | DOI:10.1371/journal.pone.0124642 April 30, 2015

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