



Maiwei AI Lab

Machine Learning, Computer Visio

10张图带你认识图像分割的前世今生

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TERM, TERM POWER



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发展历程

PART ONE

传统分割方法

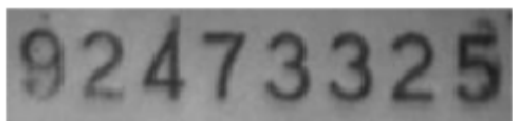


图 4. 原始图像

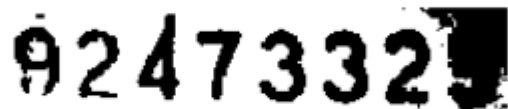


图 5. 阈值低，对亮区效果好，则暗区差

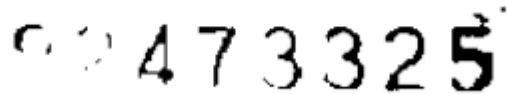
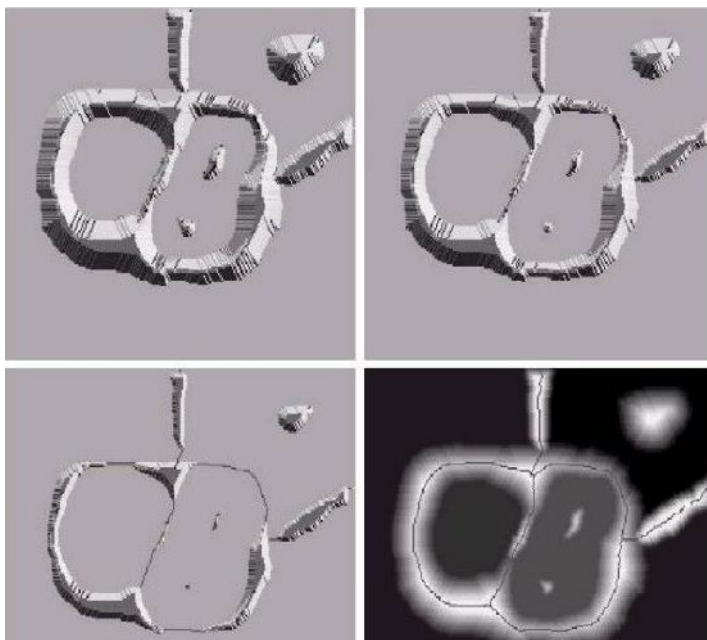


图 6. 阈值高，对暗区效果好，则亮区差



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

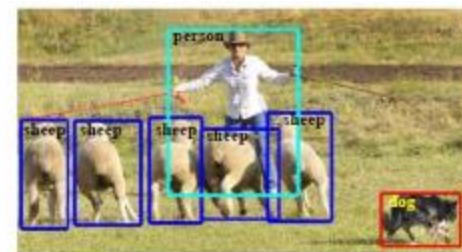


(f) Laplacian 算法





(a) Object Classification




(b) Generic Object Detection
(Bounding Box)



(c) Semantic Segmentation



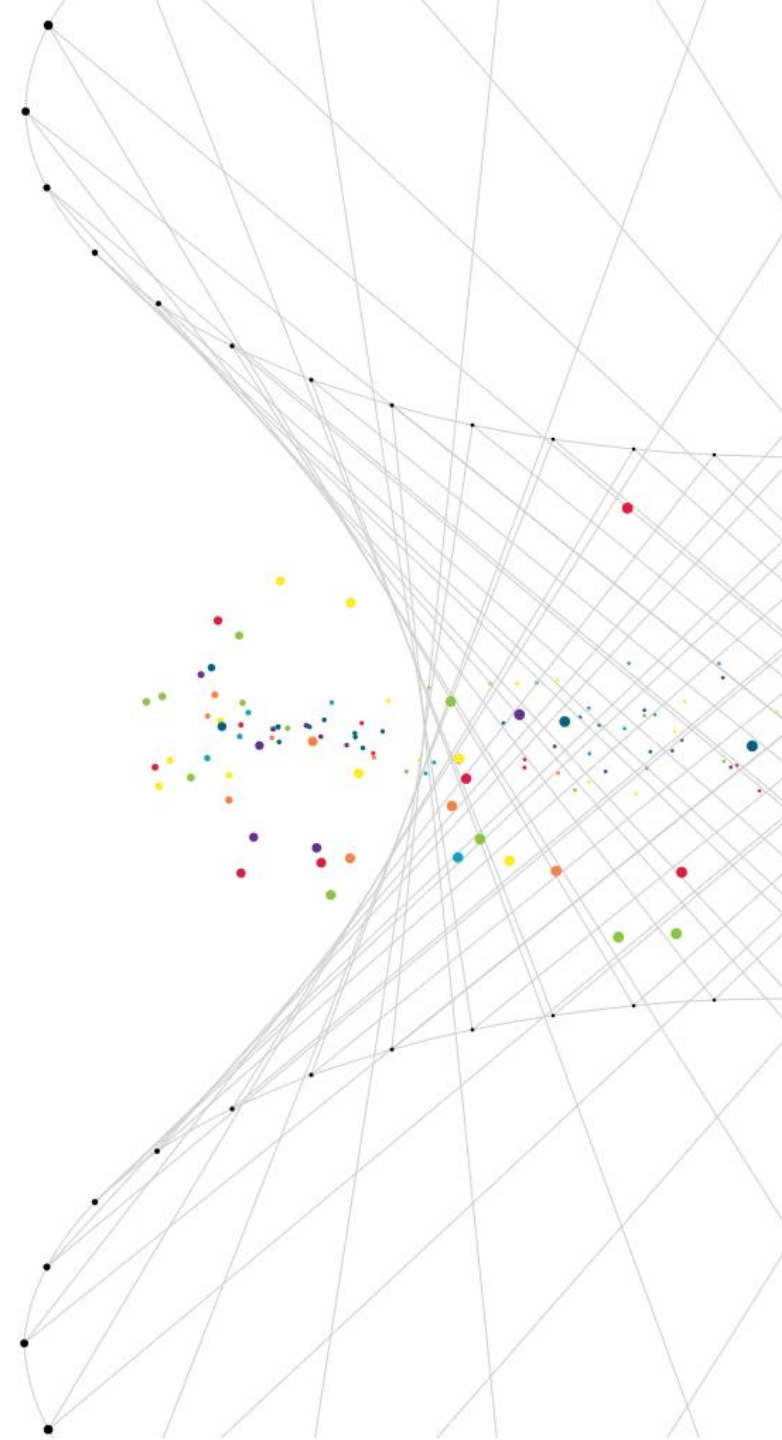
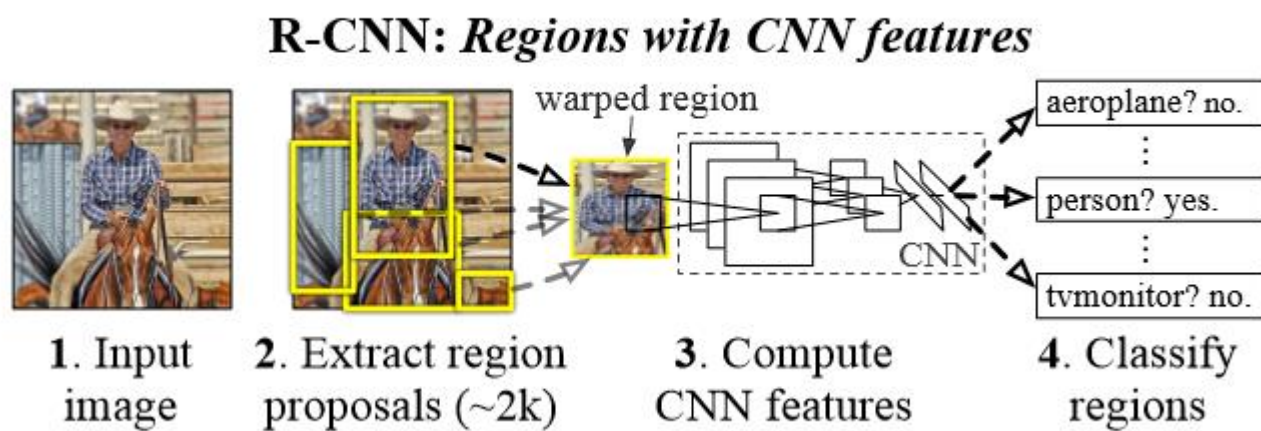
(d) Object Instance Segmentation



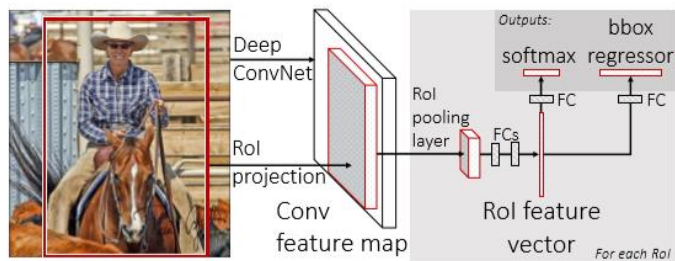
研究现状

PART TWO

传统分割方法

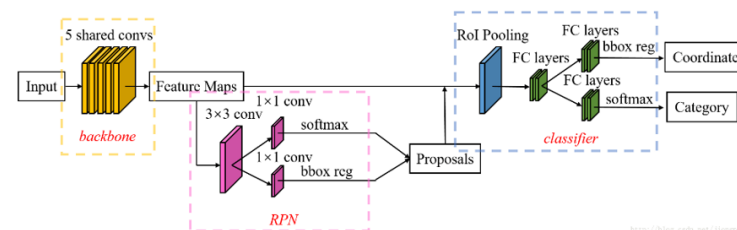
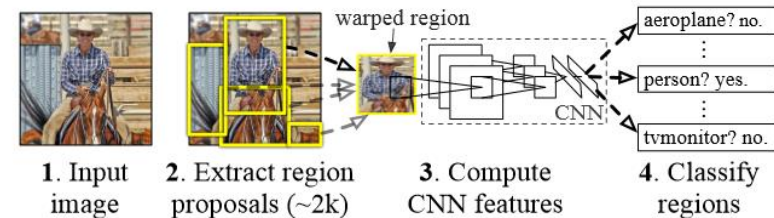


PART TWO 研究现状

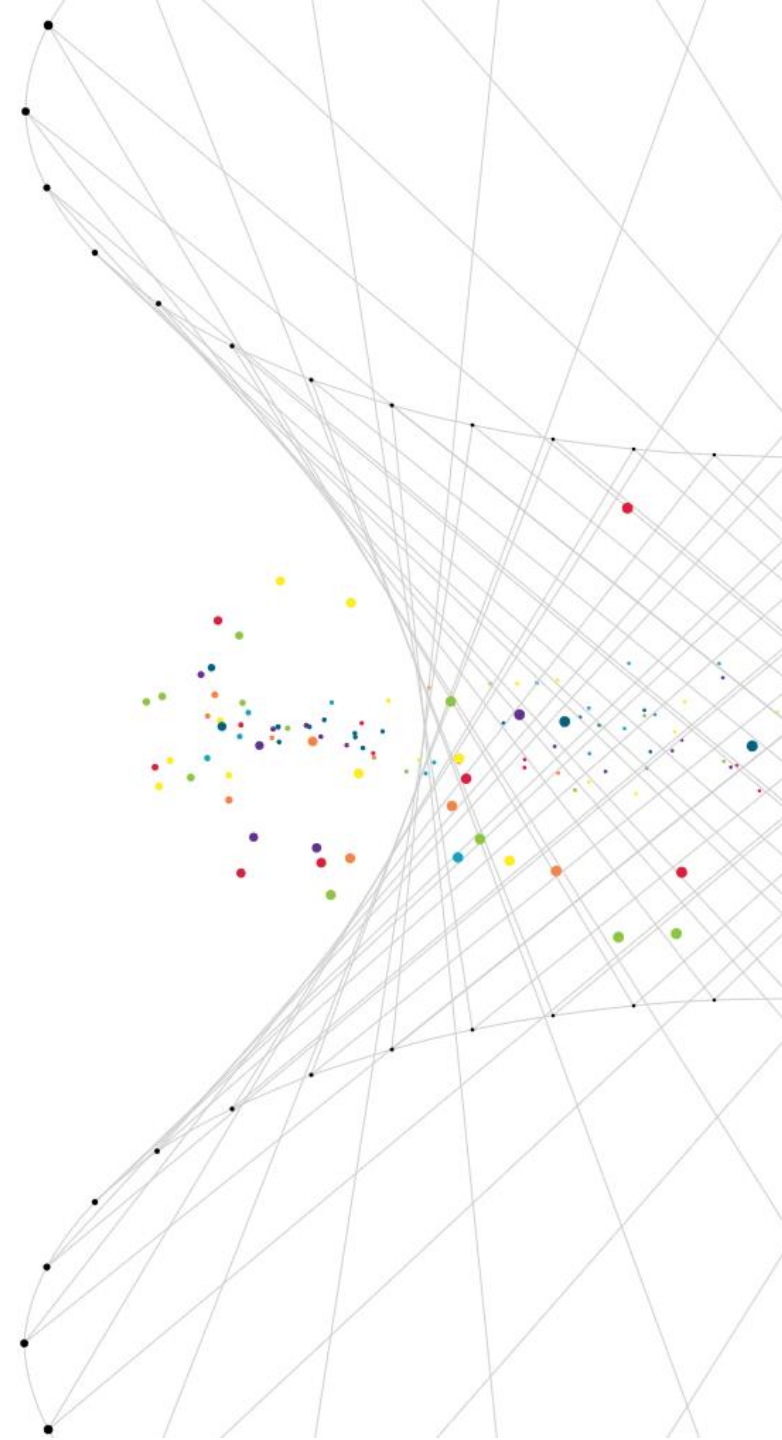
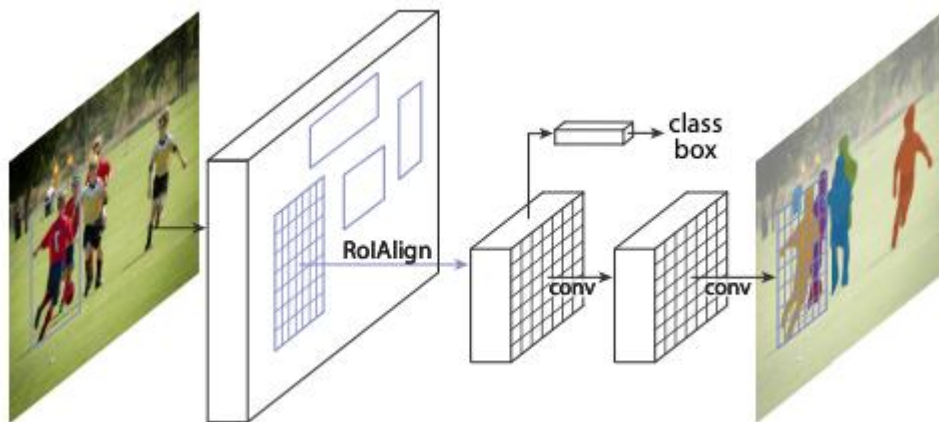


传统分割方法

R-CNN: *Regions with CNN features*

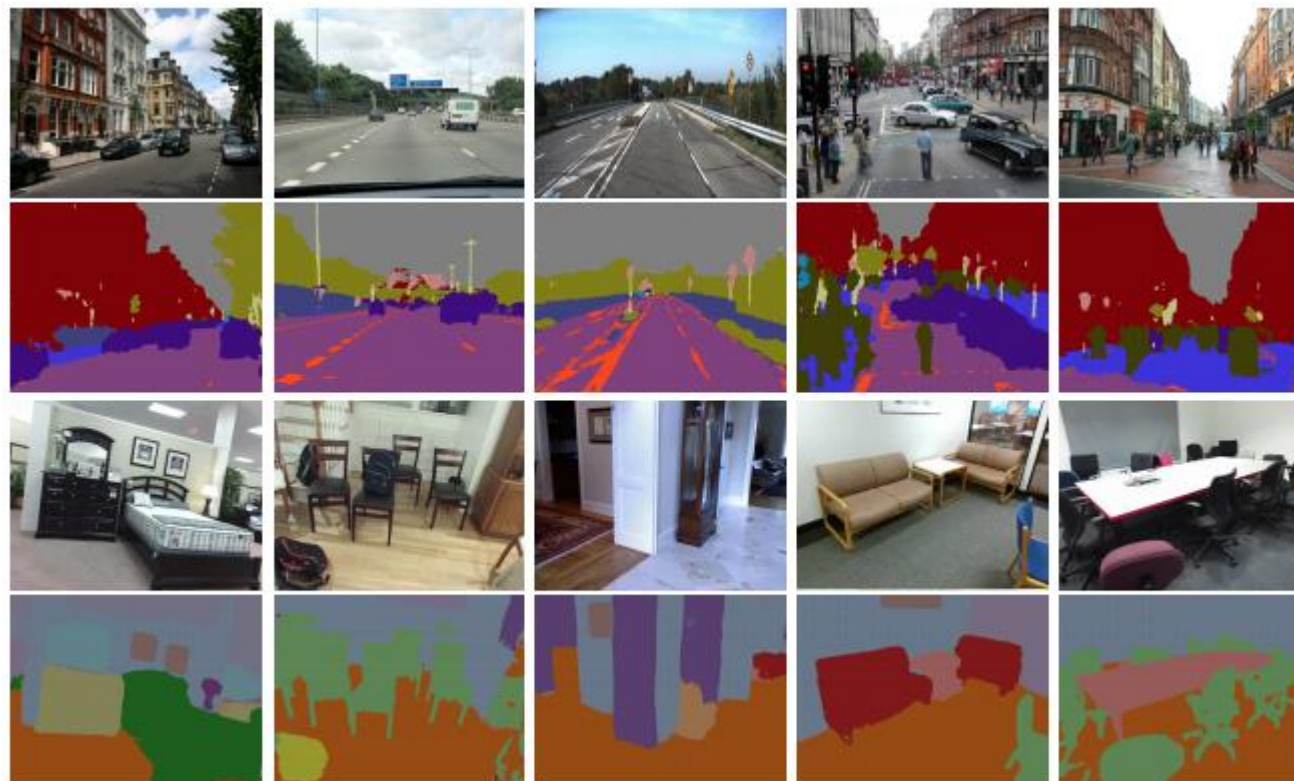
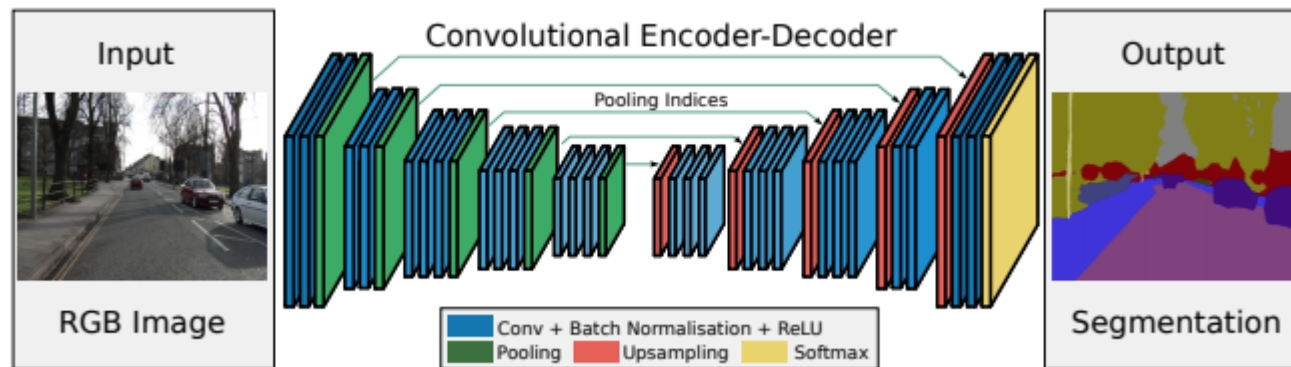


传统分割方法

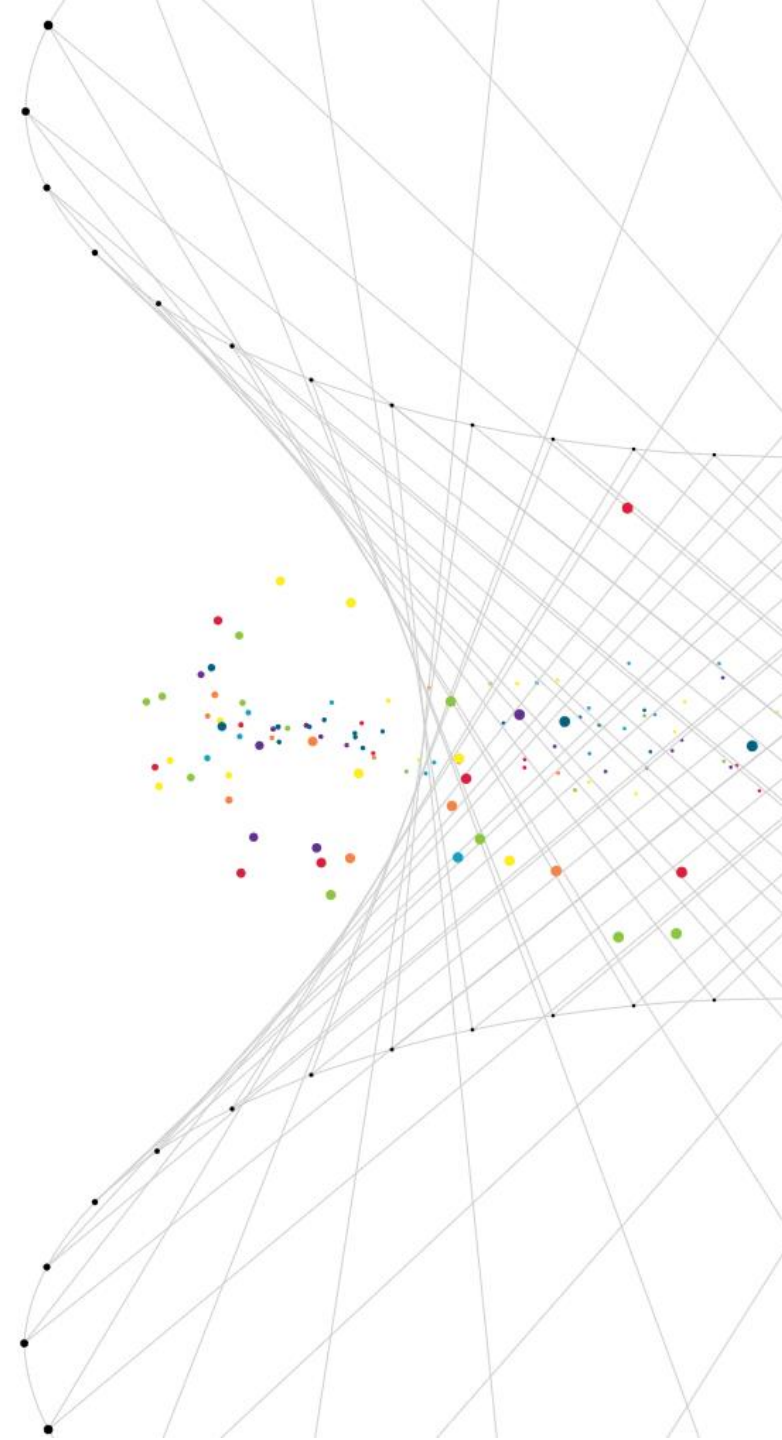
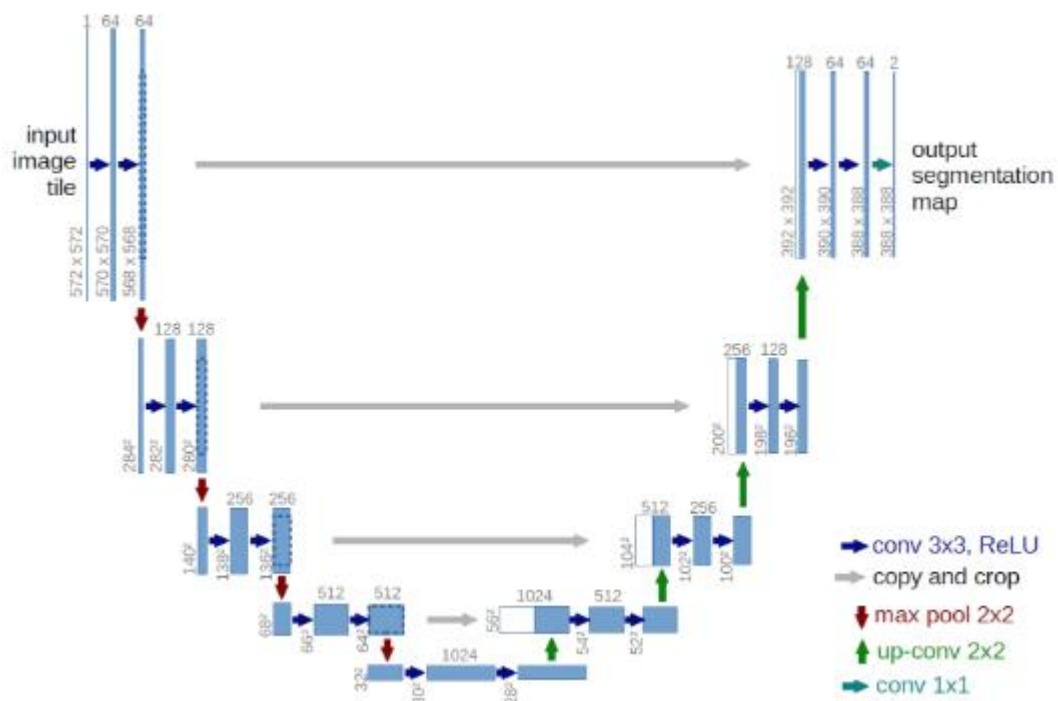


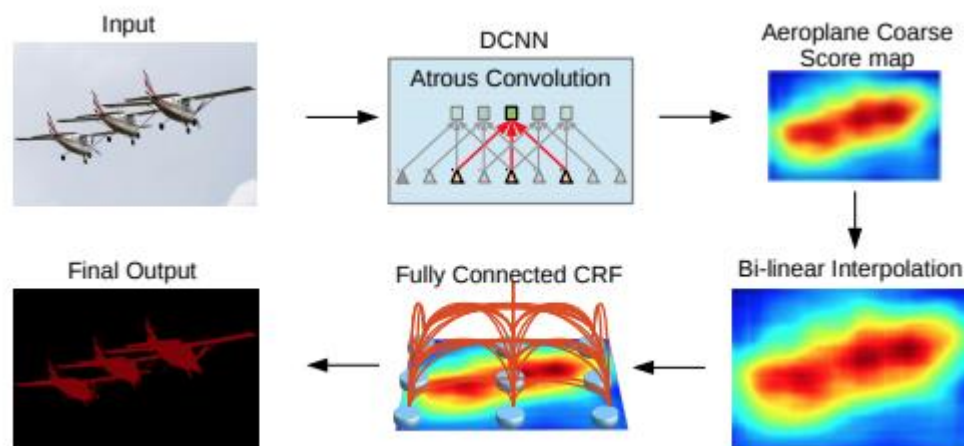
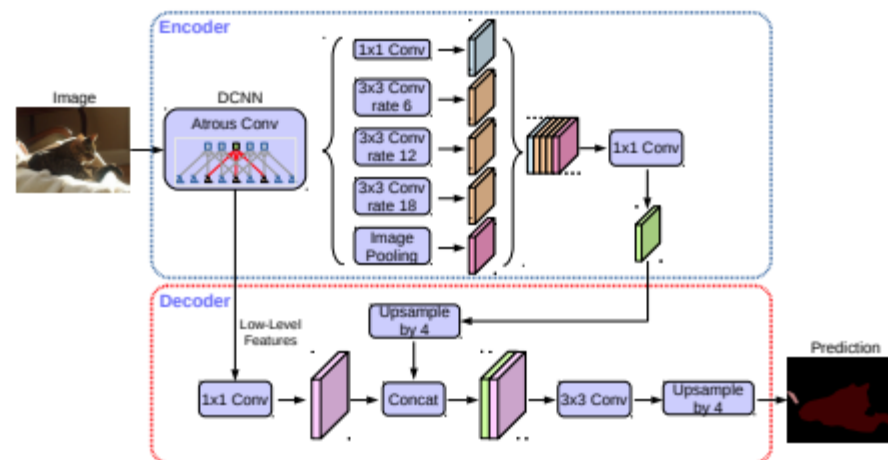
PART TWO 研究现状 ●

传统分割方法

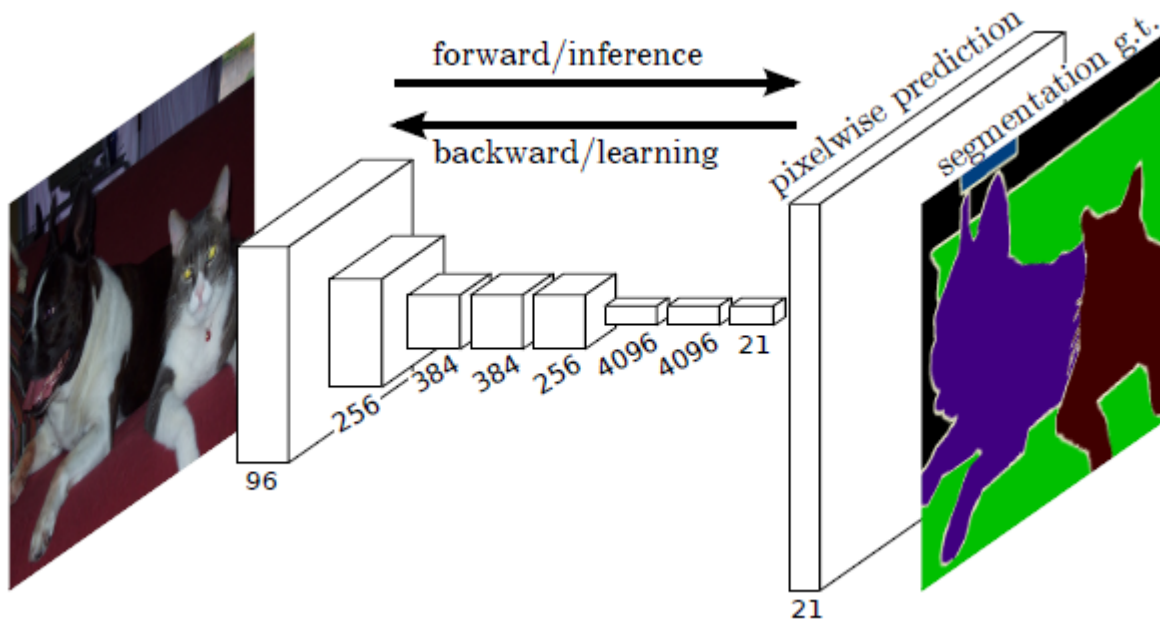


传统分割方法





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

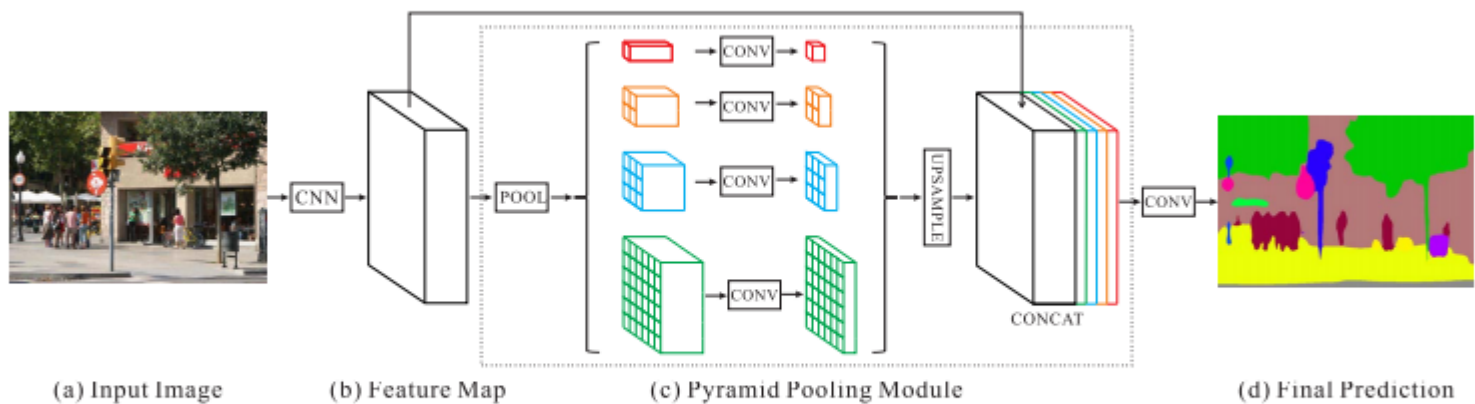


Figure 3. Overview of our proposed PSPNet. Given an input image (a), we first use CNN to get the feature map of the last convolutional layer (b), then a pyramid parsing module is applied to harvest different sub-region representations, followed by upsampling and concatenation layers to form the final 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).

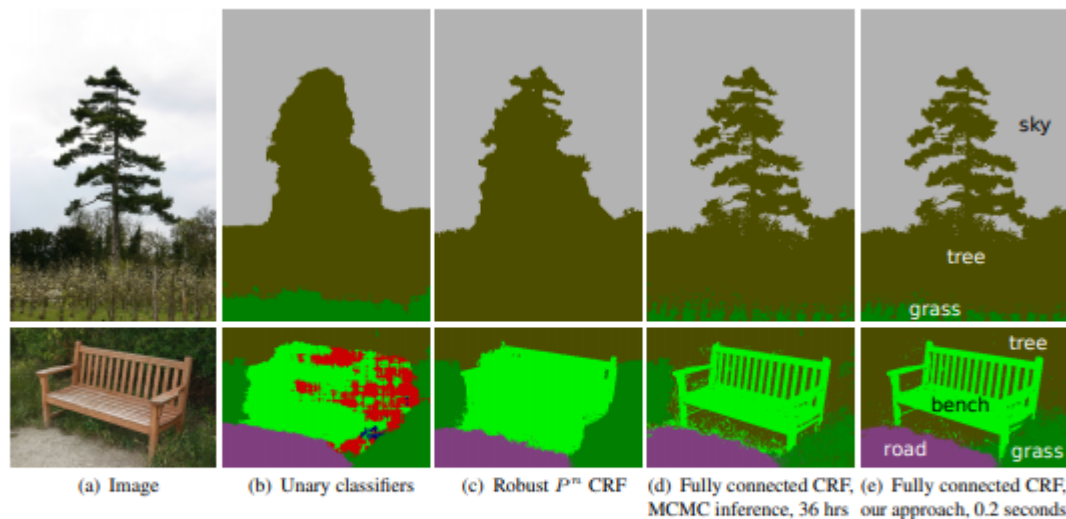


Figure 1: Pixel-level classification with a fully connected CRF. (a) Input image from the MSRC-21 dataset. (b) The response of unary classifiers used by our models. (c) Classification produced by the Robust P^n CRF [9]. (d) Classification produced by MCMC inference [17] in a fully connected pixel-level 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

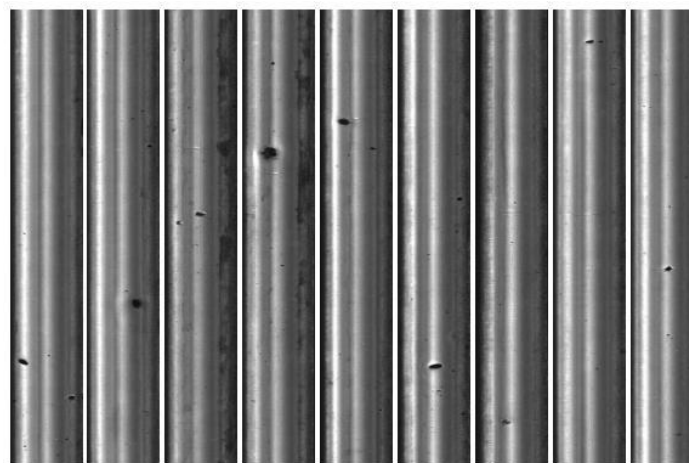
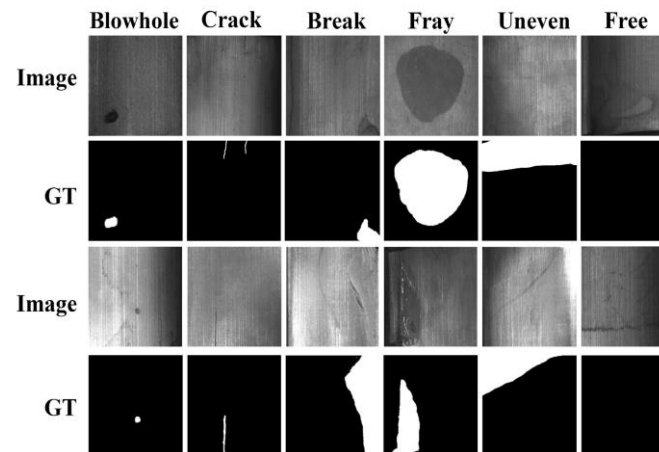
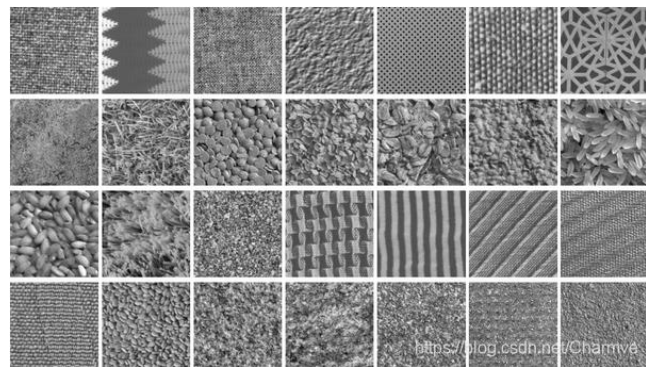
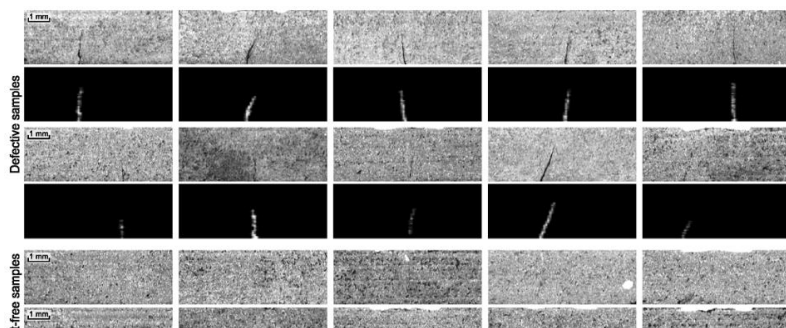
PART THREE

PART THREE 项目推荐

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



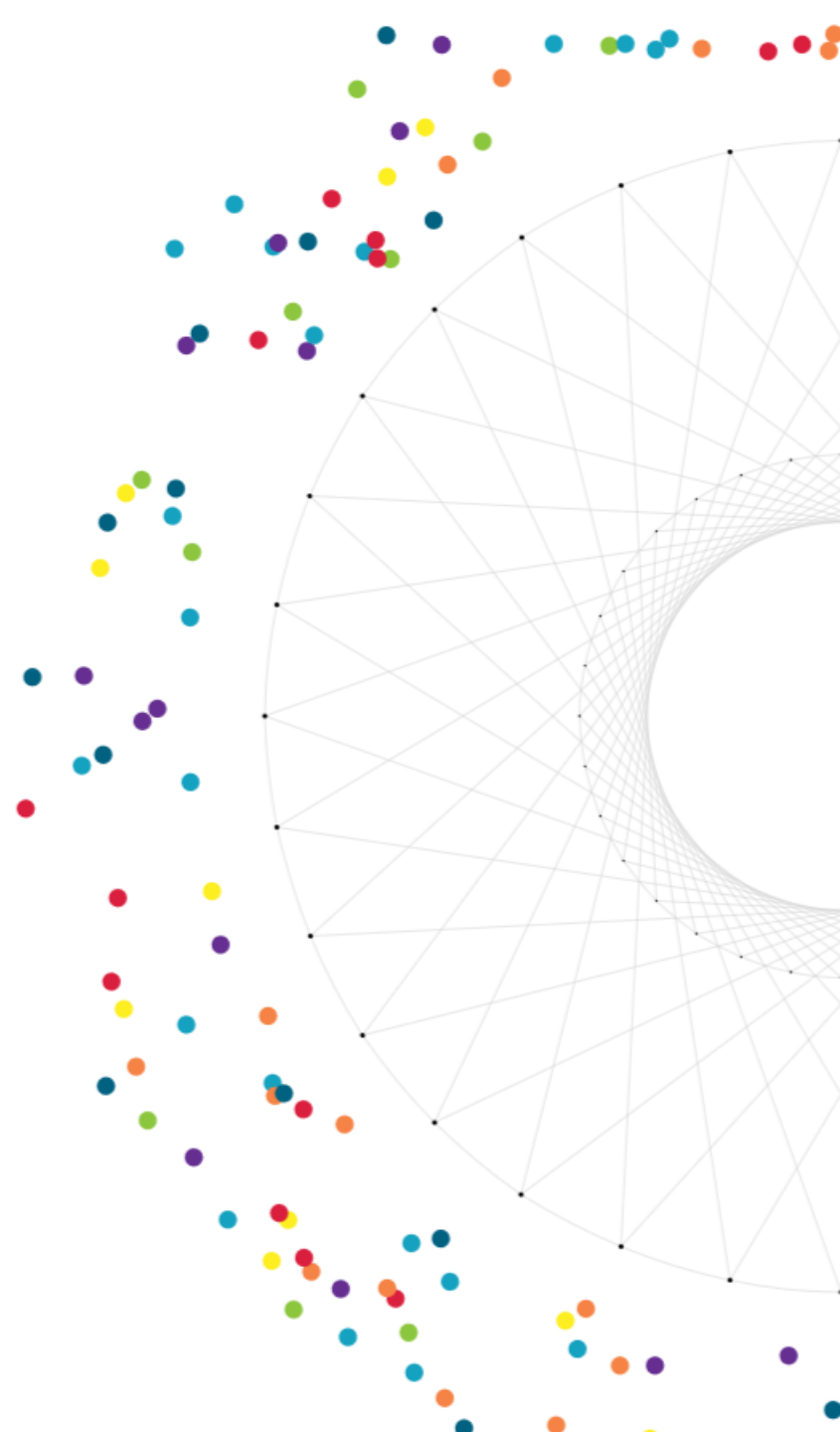
Mirror & Glass Detection in Real-world Scenes

Charmve | English | Chinese



Github Charmve Glass Detect doc Related Work Repo Transparent Object Segmentation

Mirror and Glass Detection/Segmentation

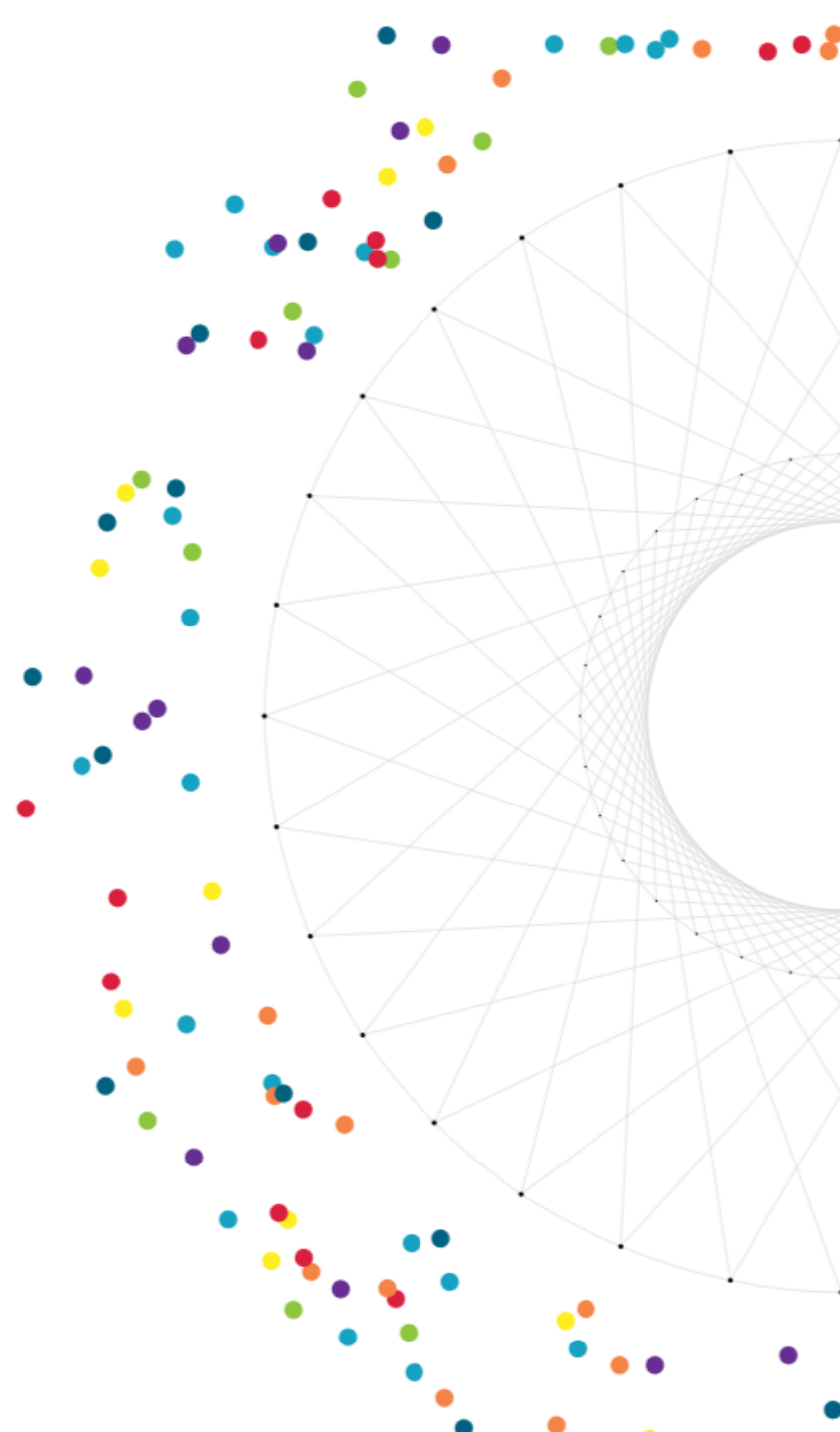


PyTorch for Semantic Segmentation

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](#))



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

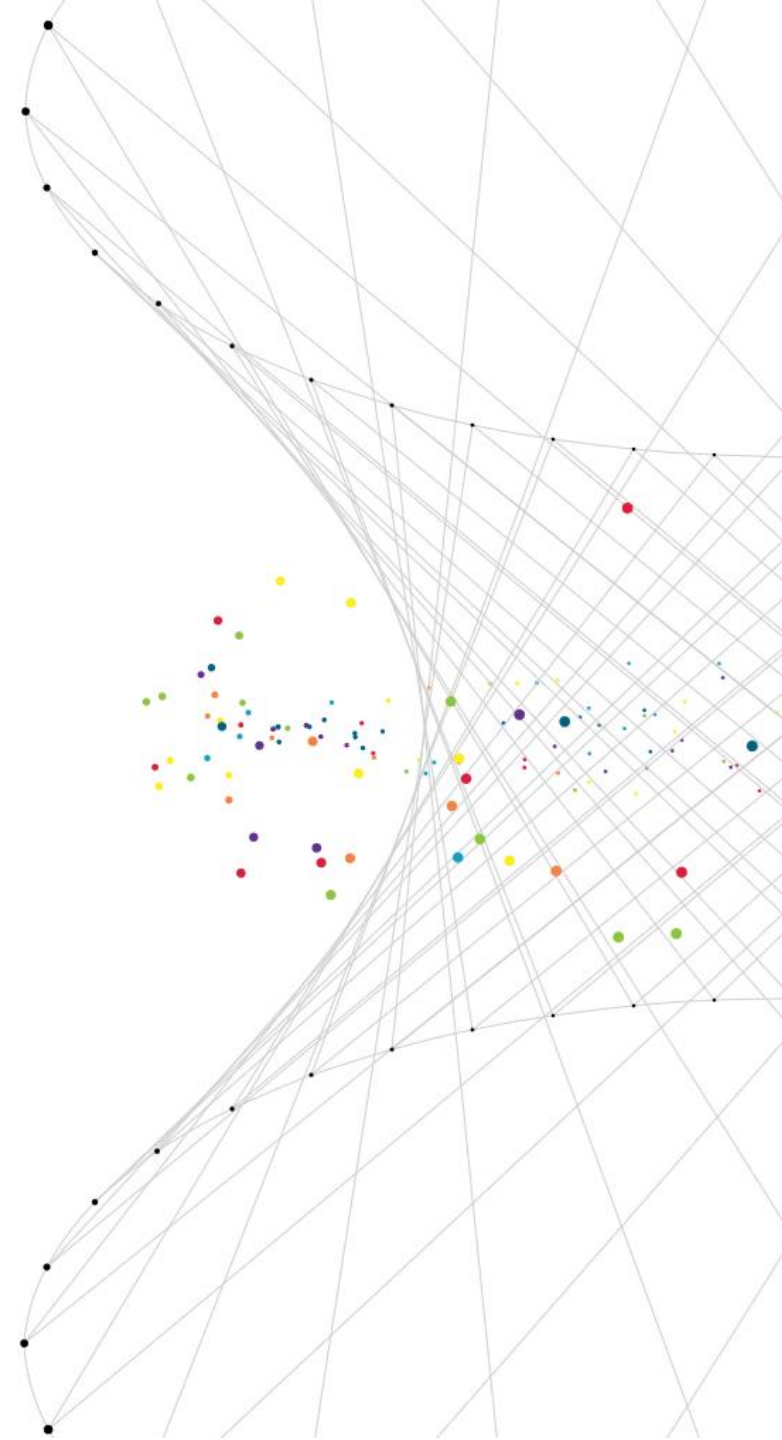
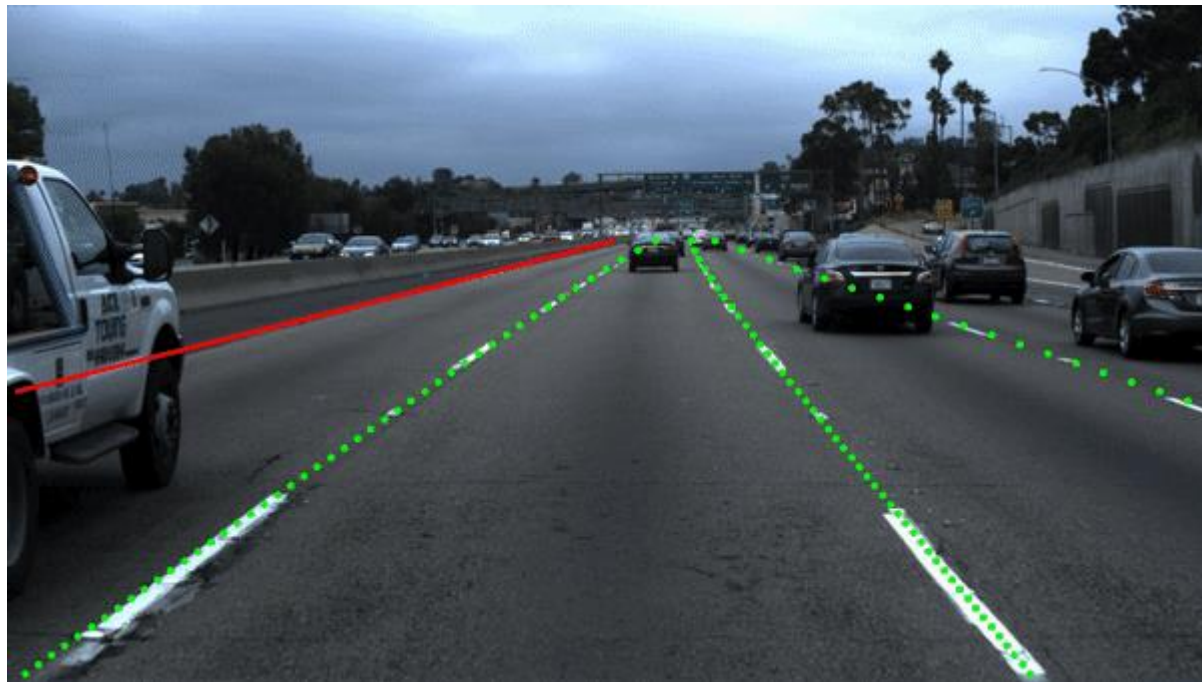


GitHub <https://github.com/Charmve/Scene-Text-Detection>


PART THREE 项目推荐 ●



Awesome-Lane-Detection

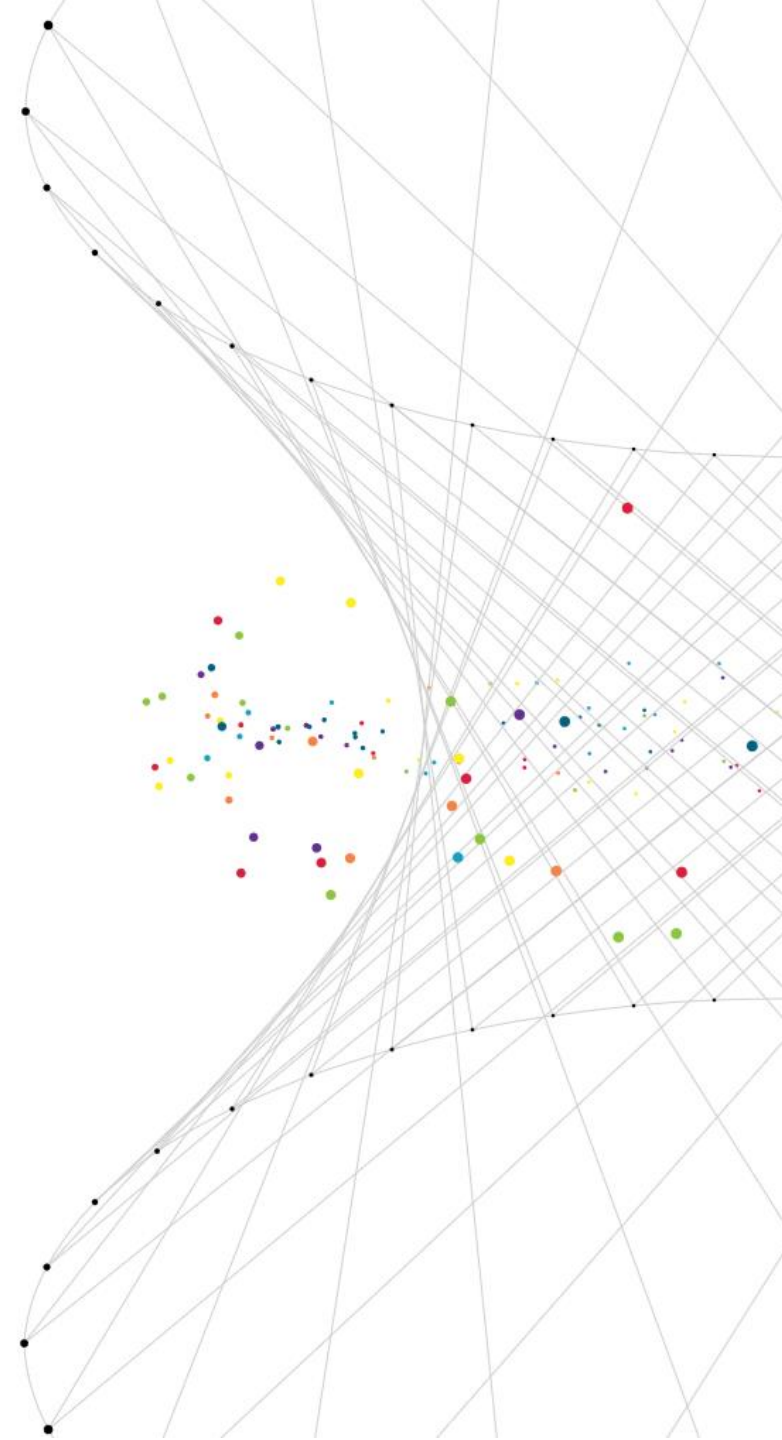
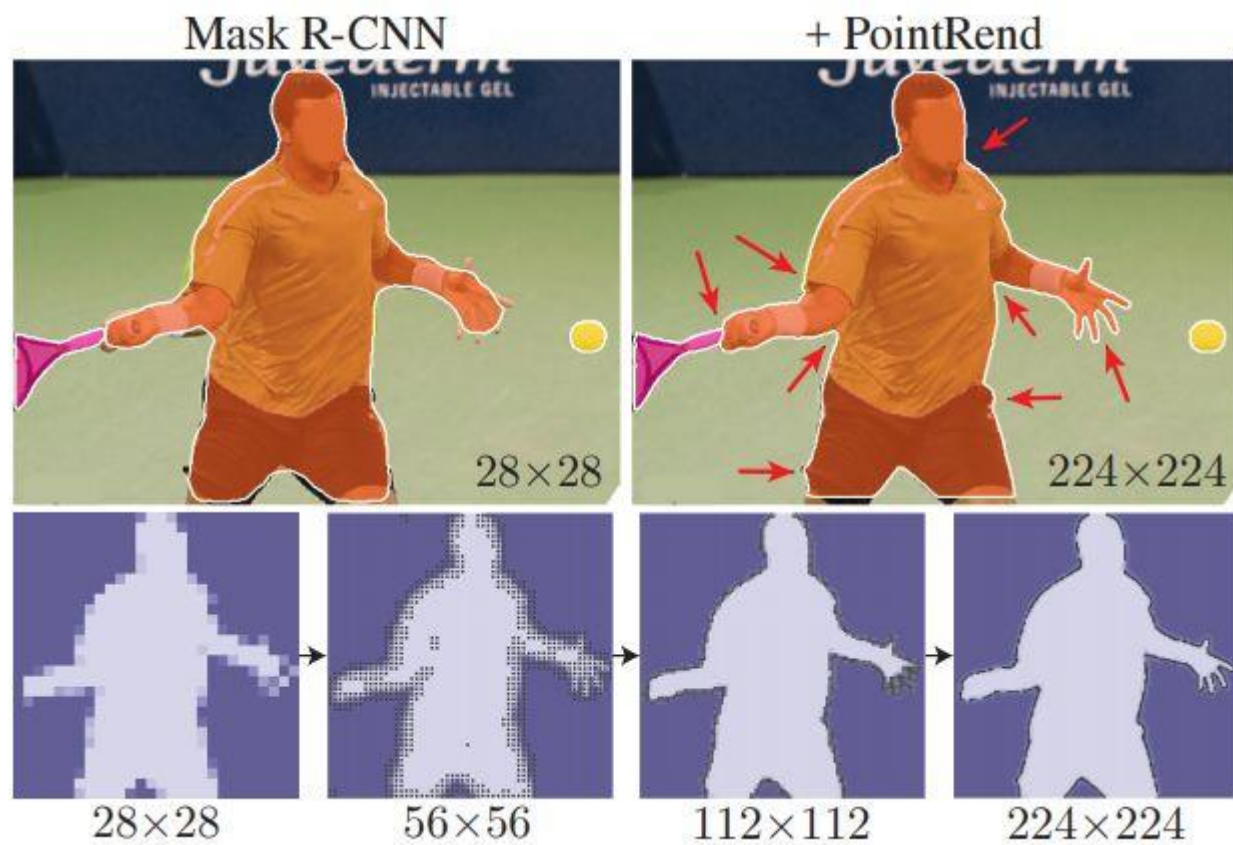


GitHub <https://github.com/Charmve/Awesome-Lane-Detection>

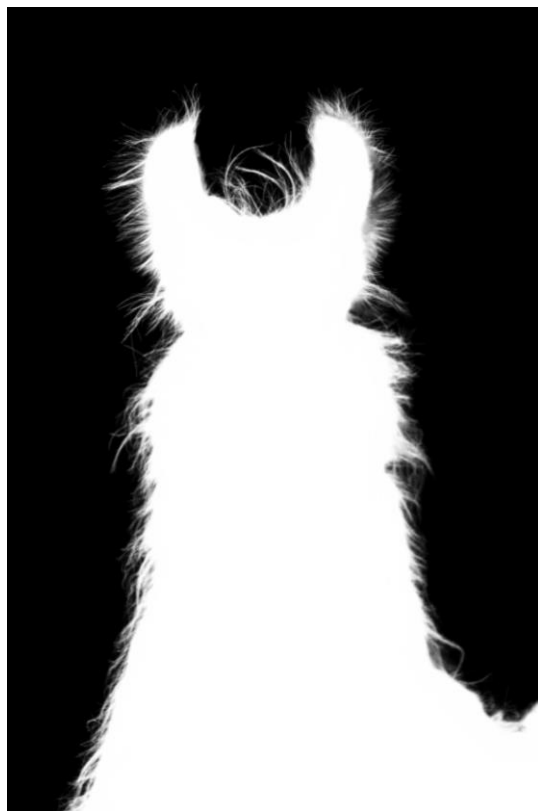


创新应用

PART FOUR



End-to-end Animal Image Matting

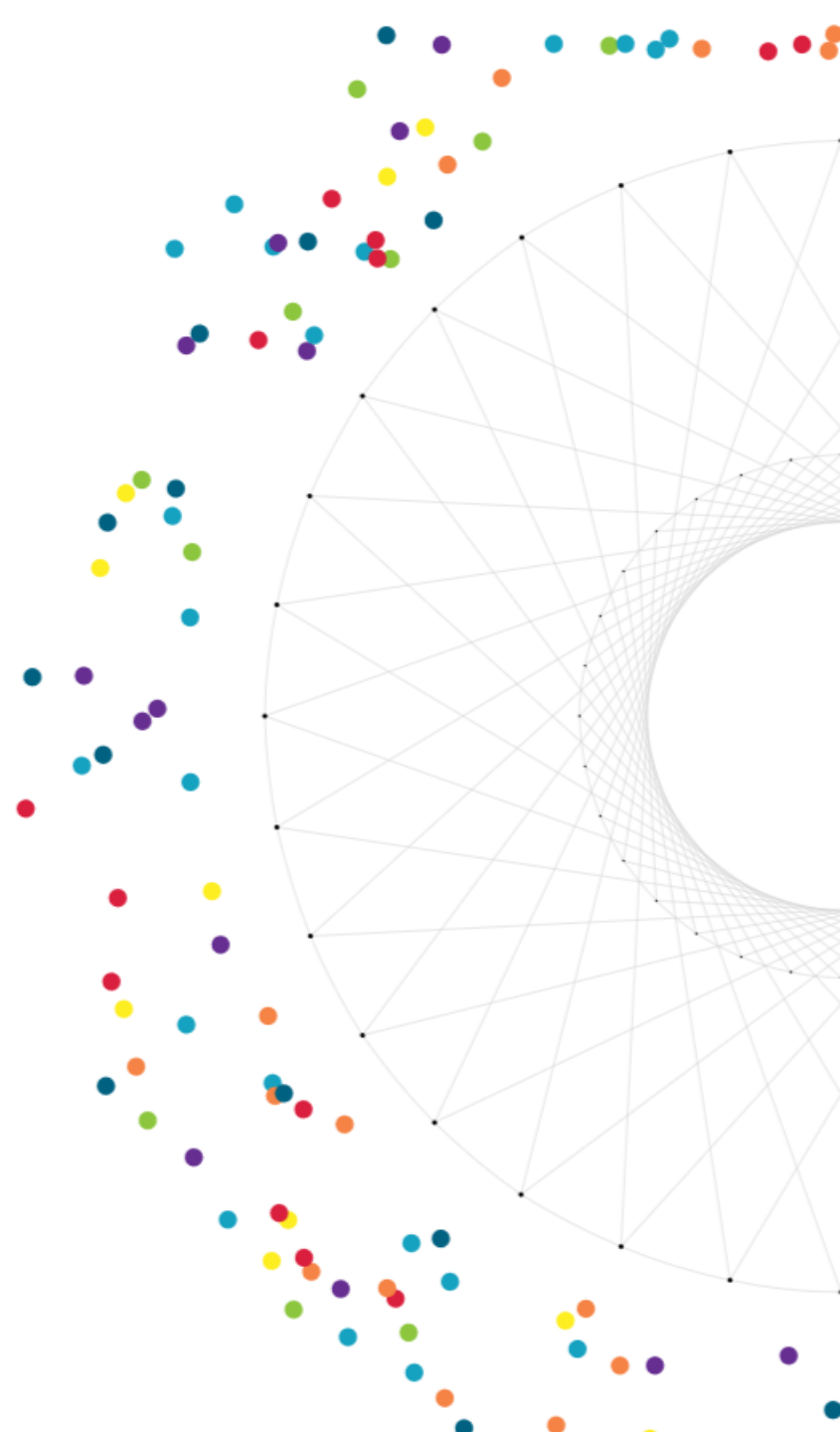


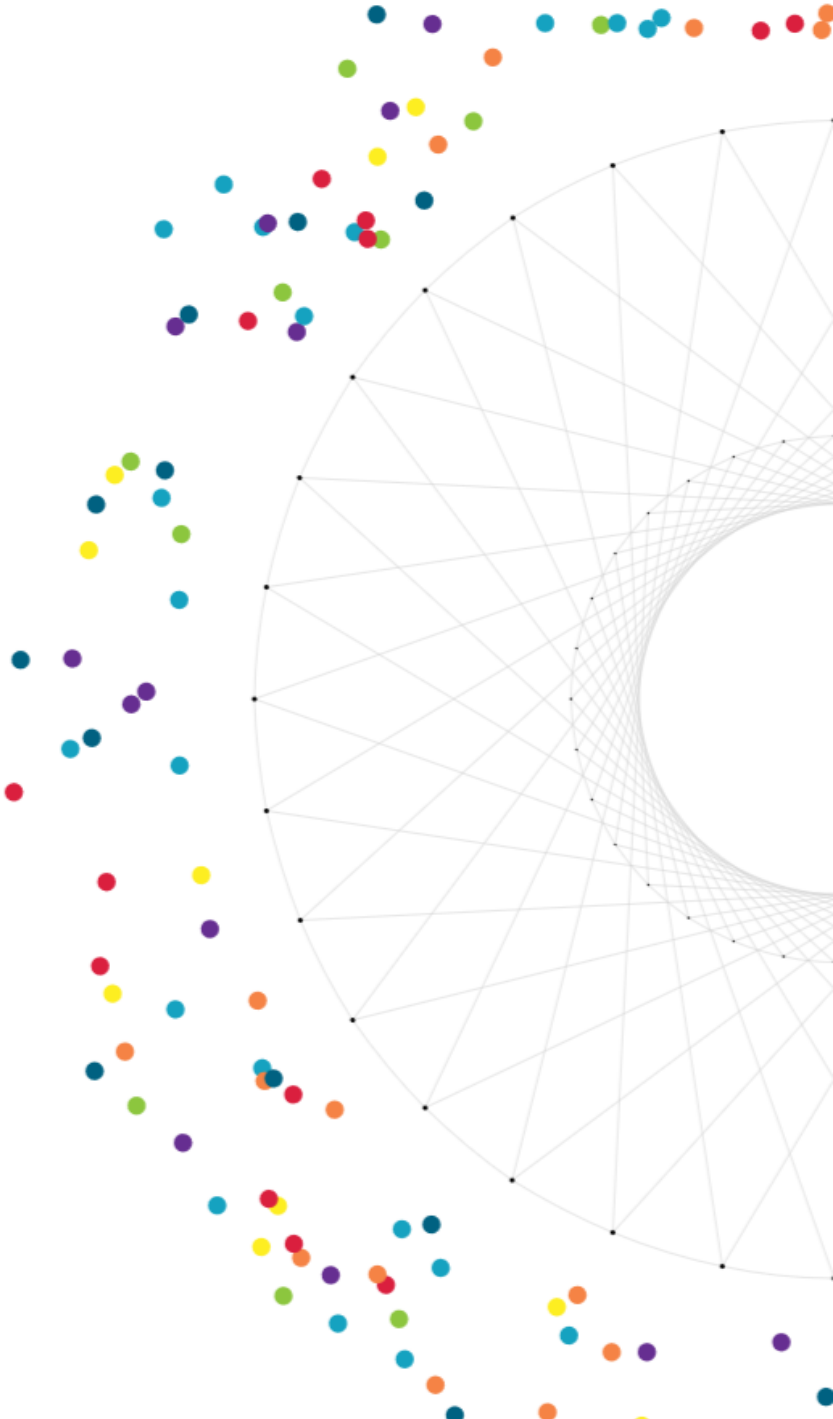
CVPR 2020


[[arXiv](#) | [Project Page](#) | [Video](#) | [Code](#) | [Related Work](#)]



GitHub <https://github.com/JizhiziLi/animal-matting>







参考文献

PART FIVE

[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

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¹

(1. 北京林业大学工学院, 北京 100083; 2. 林业装备与

摘要: 针对航拍林虫害图像的虫害区域不规则和传统识别方法 networks, FCN) 的虫害区域识别方法。采用八旋翼无人机航拍虫 型训练: 将VGG16模型的全连接层替换为卷积层并通过上采样/ 采用跳跃结构融合多种特征信息, 有效提升识别精度, 并通 在5种全卷积神经网络中区域识别精度最高, 其识别结果的像素/ 与K-means、脉冲耦合神经网络、复合梯度分水岭算法相比 出50.19%、35.67%和18.86个百分点, 单幅分割时间分别降 准确识别, 为林区虫害监测和防治提供基础。

关键词: 林业虫害监测; 航拍; 图像识别; 全卷积F

中图分类号: TP79; S763.3 (遥感技术的应用; 虫

Identification Methods for Based on

LIU Wending^{1,2} TIAN Hongbao^{1,2}

(1. School of Te

2. Key Laboratory of State Forestry and G

Abstract: Aiming at the problem of ir forestry pest images in the following pest image segmentation based on f of pest area. First of all, the insect photograph technique over the pr we replaced the full connection) implementing upsampling; ther speed of the model; finally, v recognition accuracy, and finv had the highest recognition accuracy of the segmentation single image is 4.31s. C algorithm, its pixel accu above 50.19%, 35.67% respectively. This met basis for pest detectio...

收稿日期: 2018-09-14 修回日期: 2018-11-12
基金项目: 中央高校基本科研业务费专项资金项目(2016023000)
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通信作者: 田洪宝(1978—), 男, 教授, 博士生导师, 主要从事图像处理与人工智能研究, E-mail: 11tianhongbao@bjfu.edu.cn

PLOS ONE

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

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* rehsani@ufl.edu

Abstract

Laurel wilt is a lethal disease of plants in the Lauraceae plant family, including avocado (*Persea americana*). This devastating disease has spread rapidly along the southeastern seaboard of the United States and has begun to affect commercial avocado production in Florida. The main objective of this study was to evaluate the potential to discriminate laurel wilt-affected avocado trees using aerial images taken with a modified camera during helicopter surveys at low-altitude in the commercial avocado production area. The ability to distinguish laurel wilt-affected trees from other factors that produce similar external symptoms was also studied. *RecoGB* digital values of healthy trees and laurel wilt-affected trees, as well as fruit stress and vines covering trees were used to calculate several vegetation indices (VIs), band ratios, and VI combinations. These indices were subjected to analysis of variance (ANOVA) and an M-statistic was performed in order to quantify the separability of those classes. Significant differences in spectral values among laurel wilt affected and healthy trees were observed in all vegetation indices calculated, although the best results were achieved with Excess Red (ExR), (Red-Green) and Combination 1 (COMB1) in all locations. *BIG* showed a very good potential for separate the other factors with symptoms similar to laurel wilt-affected trees. These consistent results prove the usefulness of using a modified camera (*RecoGB*) to discriminate laurel wilt-affected avocado trees from healthy trees, as well as from other factors that cause the same symptoms and suggest performing the classification in further research. According to our results, ExR and BIG should be utilized to develop an algorithm or decision rules to classify aerial images, since they showed the highest capacity to discriminate laurel wilt-affected trees. This methodology may allow the rapid detection of laurel wilt-affected trees using low altitude aerial images and be a valuable tool in mitigating this important threat to Florida avocado production.

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



Charmve

Maiwei AI Lab



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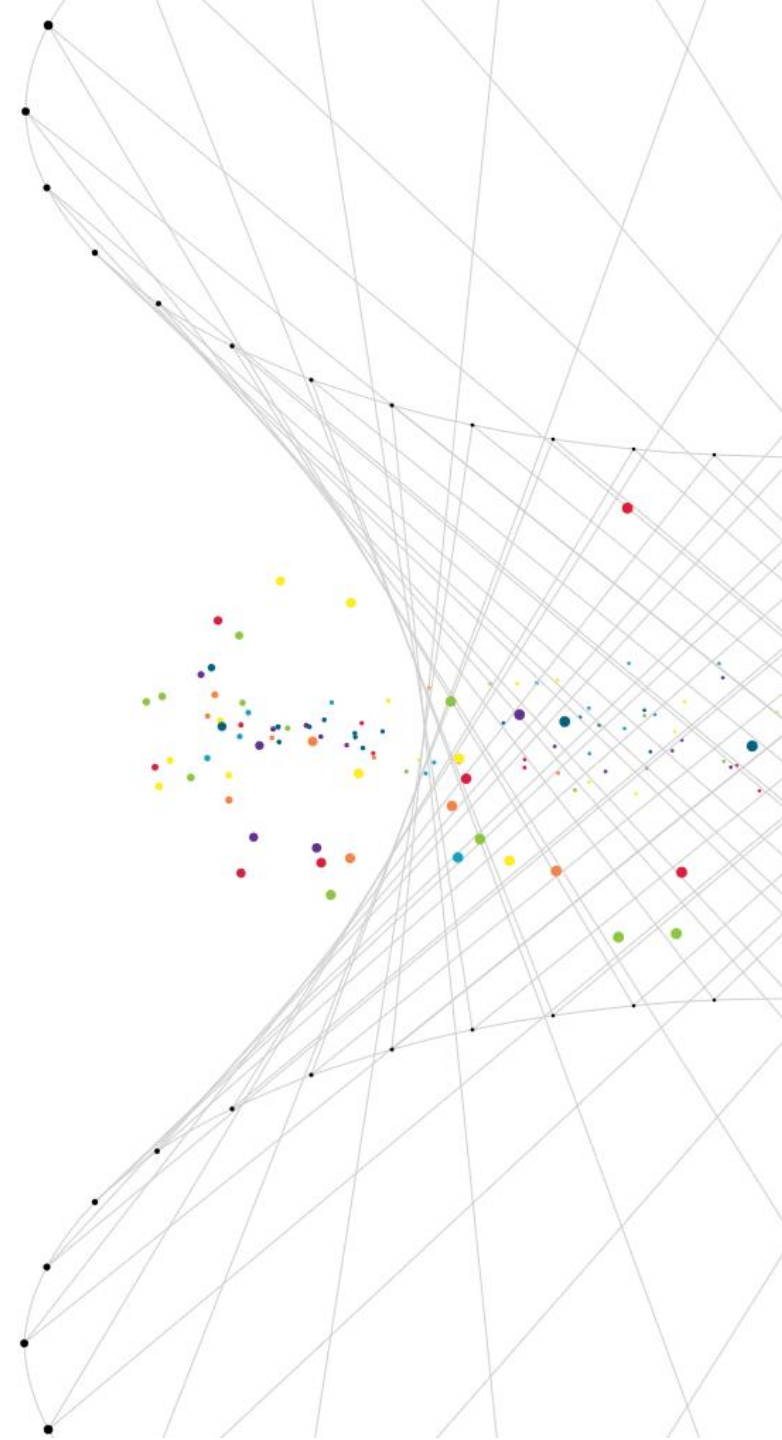
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MaiweiAI-com | WeChat ID:Yida_Zhang2

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