

# Revisiting Dead Leaves Model: Training with Synthetic Data

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# Outline of the Talk

- ① Introduction
  - Challenges
  - Motivation
- ② Proposed Method
- ③ Experiments and Results
- ④ Conclusion and Future Work

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## ① Introduction

- Challenges
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## ② Proposed Method

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# Introduction

- Supervised learning - deep neural networks
  - Excellent performance on many computer vision tasks - image classification, object detection etc.
  - Availability of large datasets - Imagenet, COCO etc.
- Current work - stereo disparity estimation problem
  - The goal is to estimate depth (disparity) using from images captured using two cameras with known distance between them.

# Challenges

- Large scale labeled data - expensive and time consuming
- Stereo data
  - Synchronized capture of images and 3D scene
  - Careful registration of acquired stereo data
- Alternative - synthetic data
  - Inexpensive to generate - ideally infinite data can be generated.
  - Ground truth - easy to obtain
- Synthetic data - shortcomings
  - Lack sufficient realism - domain gap between real and synthetic data
  - Scenes - careful design of background, objects, shapes, color etc.

# Dead Leaves Model - Motivation

- Objective - simplistic generation model with sufficient realism
- Synthetic data - similar statistics as seen in natural images
- Dead leaves model
  - Originally proposed by Matheron <sup>1</sup> to model occlusion of objects
  - Synthetic image - adding independent shapes in layered manner was shown to have similar statistics as natural images<sup>2</sup>
  - Recent work<sup>3</sup> - successfully used generated data to train model for image restoration tasks
- Current work - extend the idea to disparity estimation problem

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<sup>1</sup>G. Matheron, "Mod'ele s'equentiel de partition al'eatoire," Centre de Morphologie Math'ematique, 1968.

<sup>2</sup>A. B. Lee, D. Mumford, and J. Huang, "Occlusion models for natural images: A statistical study of a scale-invariant dead leaves model," International Journal of Computer Vision, vol. 41, no. 1, pp. 35–59, 2001.

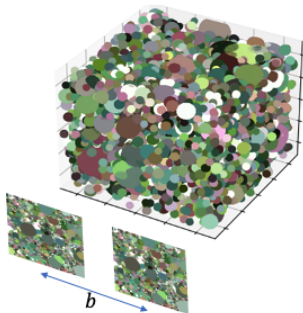
<sup>3</sup>R. Achddou, Y. Gousseau, and S. Ladjal, "Synthetic images as a regularity prior for image restoration neural networks," in Eighth International Conference on Scale Space and Variational Methods in Computer Vision (SSVM), 2021.

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# 3D Dead Leaves Model

- 3D dead leaves space - opaque spheres with random radius
- The radii  $r$  of the spheres - sampled from distribution  $f(r) = Kr^{-3}$
- Stereo images - projected onto parallel camera planes

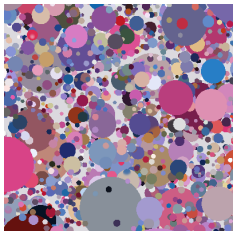


(a) Setup



# 3D Dead Leaves Model

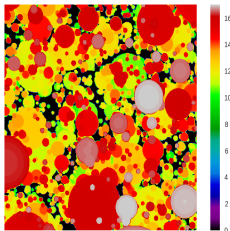
- Ground truth disparity -  $d(x, y) = \frac{fb}{D(x, y)}$ ,  $f$  is camera's focal length,  $b$  is the baseline width between camera centres and  $D(x, y)$  is the depth value at pixel  $(x, y)$



(b) left image



(c) right image

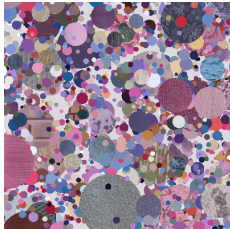


(d) disparity map

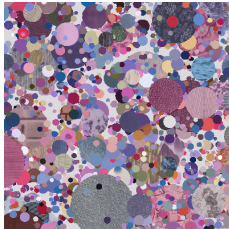
Figure: Sample dead leaves stereo data

# Textured Dead leaves Model

- Adding textures
  - Statistics more closer to natural images
  - More efficient to determine corresponding points in stereo images
  - Improves image gradients in smooth regions
- Texture addition - blending with textures sampled from Brodatz<sup>4</sup> texture database
- Disparity values - not affected by texture addition



(a) left image

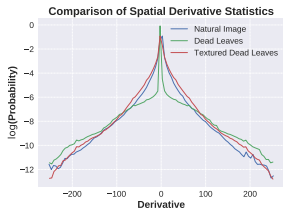


(b) right image

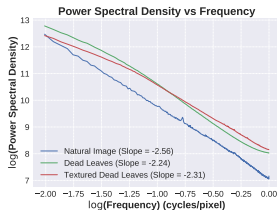
Figure: Sample textured dead leaves data

# Significance of Dead Leaves Model

- Marginal and joint distributions of spatial derivatives - similar to natural images
- Power spectrum - exhibit  $\frac{1}{f^2}$  observed in natural images



(a) Marginal Distribution



(b) Power Spectrum

Figure: Comparison of statistics of dead leaves with natural images

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# Experiment Details

- Dataset generation
  - Each scene - 20,000 spheres projected on  $1024 \times 1024$  resolution camera planes
  - Every scene - 3 focal length values and 9 baseline widths, total of 27 stereo pairs
  - 480 scenes -  $27 \times 480 = 12,960$  size of generated dataset
- Model training
  - Architecture - Pyramid Stereo Matching network (PSMNet)<sup>5</sup>
  - 3250 iterations with batch size of 12
  - Training images - random crops of size  $256 \times 512$
- Evaluation datasets - KITTI 2012, KITTI 2015 and Scene Flow.

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<sup>5</sup>J.-R. Chang and Y.-S. Chen, "Pyramid stereo matching network," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 5410–5418.

# Performance Comparison

- Evaluation metric - End Point Error

$$EPE = \frac{1}{M} \sum_{i=1}^M |disp_{pred}^i - disp_{GT}^i|$$

- Model trained only on synthetic data - no additional fine-tuning on evaluation datasets
- Dead leaves trained models - comparable performance

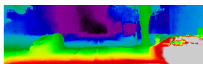
Training Dataset	KITTI 2012	KITTI 2015	Scene Flow	
			Train	Test
Scene Flow	1.35	1.83	-	1.09
Dead Leaves	3.01	3.14	13.26	11.52
Textured Dead Leaves	3.38	2.29	9.97	8.3

# Visual Comparison

RGB Image

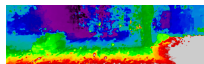


Scene Flow



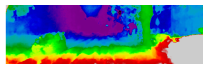
EPE = 1.623

Dead Leaves

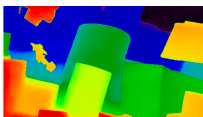
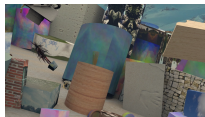


EPE = 2.452

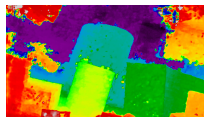
Textured  
Dead Leaves



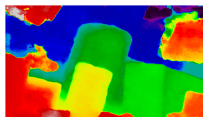
EPE = 1.955



EPE = 0.760



EPE = 4.681



EPE = 3.512

- Texture addition - smoother and noise-free estimates

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# Conclusion and Future Work

- Dead leaves - simplistic and computationally inexpensive model, easy to generate large scale data
- Trained model - good generalizability on synthetic and real world data with no additional fine-tuning
- Future work
  - Synthetic images - pin-hole camera assumption
  - Inclusion real world effects - lens blur, shot noise etc. lead to statistics closer to natural images

# References

- [1] P. C. Madhusudana, Seok-Jun Lee and Hamid R. Sheikh, "Revisiting Dead Leaves Model: Training with Synthetic Data", in IEEE Signal Processing Letters, vol. 29, pp. 209-213, 2022.
- [2] J.-R. Chang and Y.-S. Chen, "Pyramid stereo matching network," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 5410–5418.
- [3] A. B. Lee, D. Mumford, and J. Huang, "Occlusion models for natural images: A statistical study of a scale-invariant dead leaves model," International Journal of Computer Vision, vol. 41, no. 1, pp. 35–59, 2001.

Thank You!