In Defense of Classical Image Processing: Fast Depth Completion on the CPU

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Presentaition Headlines

- Introduction
- Newer Approaches
- Paper Method
- Results

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INTRODUCTION

What is Depth Completion?



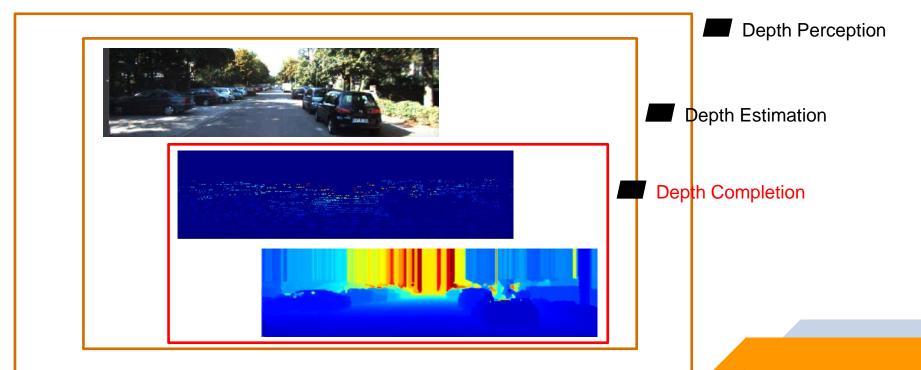
Introduction

- Depth Perception
 - The procedure to Find Depth in 2D
- Depth Estimation
 - Depth Completion
 - Converting Sparse DEPTH Dense map to Depth map





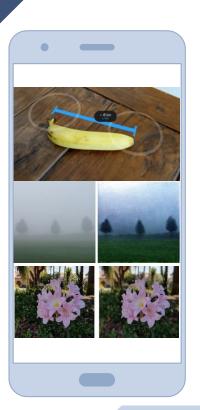
Introduction





Application

- Augmented reality
- Robotics and object trajectory estimation
- Haze and Fog removal
- Portrait mode



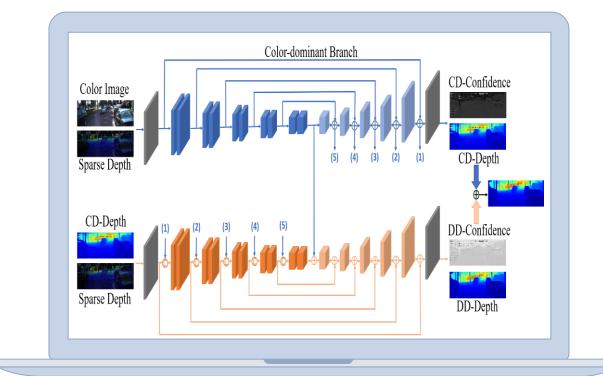
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NEWER APPROACHES

Faster but on GPU

PENet-2020

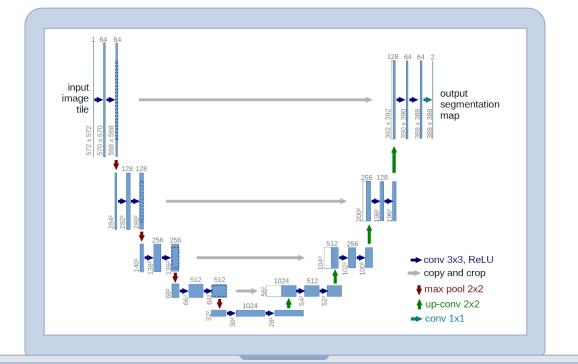
- More Accurate
- Faster (GPU)
- Supervised



	RMSE	MAE	Run Time
PENet[9]	730.08	210	0.04
Classic Method [1]	1288.46	302.6	0.011

Monodepth-2019

- More Accurate
- Faster (GPU)
- Unsupervised
- Multi Loss



3

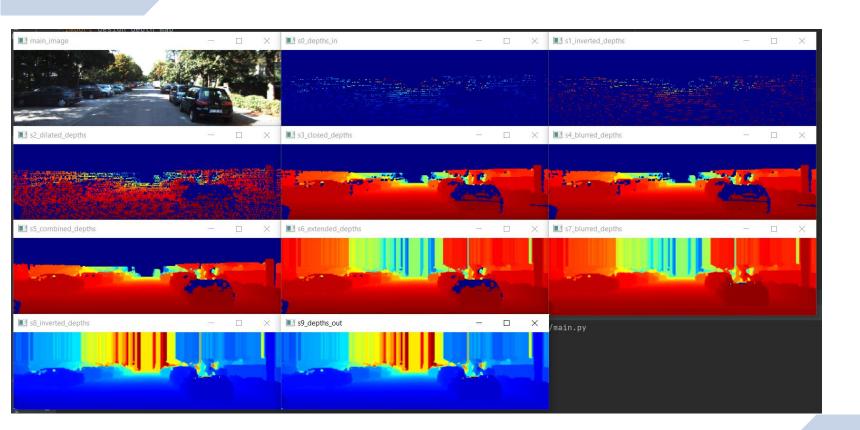
PAPER METHOD

Dive into Classical Image Processing.

8 STEPS TO REDEMPTION



The Authors have used morphology many times





Step 1 – Depth Inverted

Input

How?

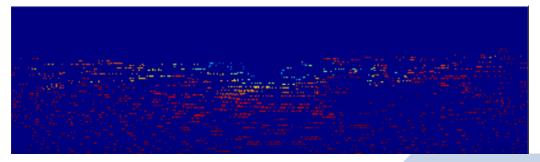
Result = 100 - Input

Why?

Reduce the difference between Valid pixels and Empty pixels to prevent negative impact of dilation on edges.



Result





Step 1 – Depth Inverted

```
s1_inverted_depths = np.copy(depths_in)
valid_pixels = (s1_inverted_depths > 0.1)
s1_inverted_depths[valid_pixels] = \
    max_depth - s1_inverted_depths[valid_pixels]
```



Step 2 – Dilating With Custom Kernel

Input

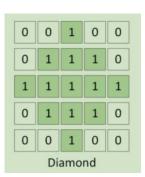
How?

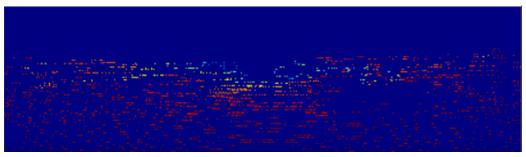
Dilating with 3*3,5*5, 7*7 diamond filter

We can use cross filter here

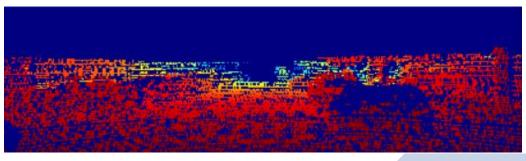
Why?

To Extend Efficient Pixels











Step 2 – Dilating With Custom Kernel

```
dilated far = cv2.dilate(
   dilation kernel far)
dilated med = cv2.dilate(
   np.multiply(s1 inverted depths, valid pixels med),
dilated near = cv2.\overline{dilate}
valid pixels near = (dilated near > 0.1)
valid pixels med = (dilated med > 0.1)
valid pixels far = (dilated far > 0.1)
s2 dilated depths = np.copy(s1 inverted depths)
s2 dilated depths[valid pixels med] = dilated med[valid pixels med]
s2 dilated depths[valid pixels near] = dilated near[valid pixels near]
```



Step 3 – Small Hole Closure

Input

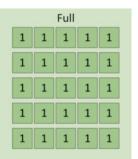
How?

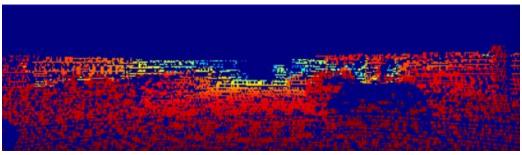
- 1- Closing with 5*5 full filter
- 2- Using Median filter for denoising

7*7 and 3*3 decrease RMSE

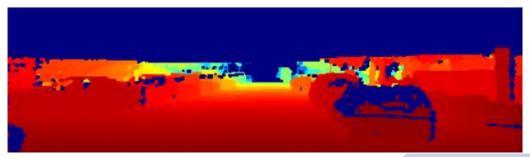
Why?

Fill small holes which is remaining from previous step





Result





Step 3 – Small Hole Closure



Step 4 – Medium Hole Fill

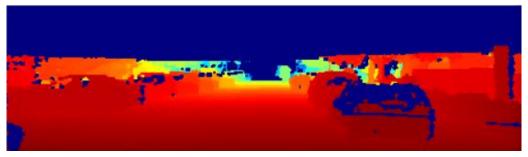
Input

How?

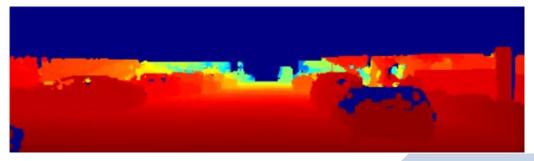
1- Dilating on unchanged pixel with 7*7 Full filter

Why?

Fill Medium Holes



Result





Step 4 - Small Hole Fill

```
top_mask = np.ones(depths_in.shape, dtype=np.bool)
for pixel_col_idx in range(s4_blurred_depths.shape[1]):
    pixel_col = s4_blurred_depths[:, pixel_col_idx]
    top_pixel_row = np.argmax(pixel_col > 0.1)
    top_mask[0:top_pixel_row, pixel_col_idx] = False

valid_pixels = (s4_blurred_depths > 0.1)
empty_pixels = ~valid_pixels & top_mask

dilated = cv2.dilate(s4_blurred_depths, kernels.FULL_KERNEL_7)
s5_dilated_depths = np.copy(s4_blurred_depths)
s5_dilated_depths[empty_pixels] = dilated[empty_pixels]
```



Step 5 – Extension to Top of Frame

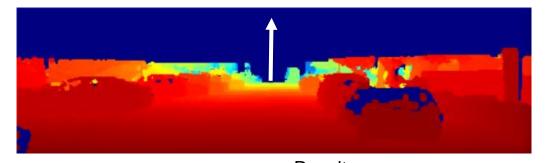
Input

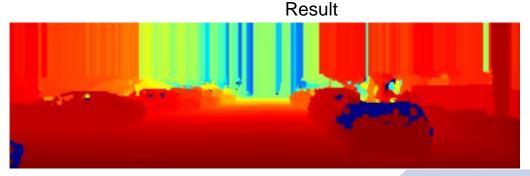
How?

the top value along each column is extrapolated to the top of the image, providing a denser depth map output.

Why?

To account for tall objects such as trees, poles, and buildings To account for tall objects such as trees, poles, and buildings that extend above the top of LIDAR points







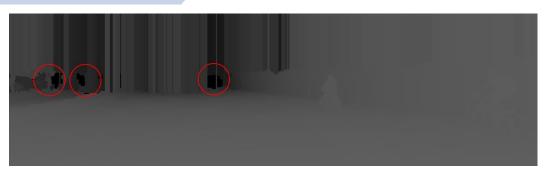
Step 5 – Extension to Top of Frame



Step 6 - Large Hole Fill

How?

Why?







Step 6 - Large Hole Fill

```
s7_blurred_depths = np.copy(s6_extended_depths)
for i in range(6):
    empty_pixels = (s7_blurred_depths < 0.1) & top_mask
    dilated = cv2.dilate(s7_blurred_depths, kernels.FULL_KERNEL_31)
    s7_blurred_depths[empty_pixels] = dilated[empty_pixels]</pre>
```



Step 7 - Median and Gaussian Blur

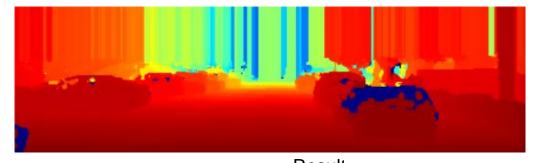
Input

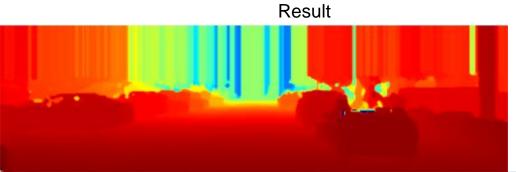
How?

- $1-5 \times 5$ kernel median blur
- 2-5 x 5 kernel Gaussian blur

Why?

To remove these outliers







Step 7 - Median and Gaussian Blur

```
s7_blurred_depths = np.copy(s6_extended_depths)
for i in range(6):
    empty_pixels = (s7_blurred_depths < 0.1) & top_mask
    dilated = cv2.dilate(s7_blurred_depths, kernels.FULL_KERNEL_31)
    s7_blurred_depths[empty_pixels] = dilated[empty_pixels]

blurred = cv2.medianBlur(s7_blurred_depths, 5)
valid_pixels = (s7_blurred_depths > 0.1) & top_mask
s7_blurred_depths[valid_pixels] = blurred[valid_pixels]
blurred = cv2.GaussianBlur(s7_blurred_depths, (5, 5), 0)
valid_pixels = (s7_blurred_depths > 0.1) & top_mask
s7_blurred_depths[valid_pixels] = blurred[valid_pixels]
```



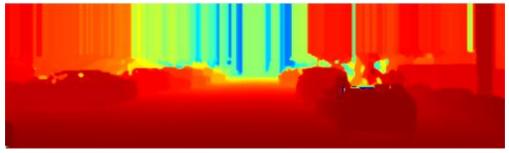
Step 8 – Depth Inversion

Input

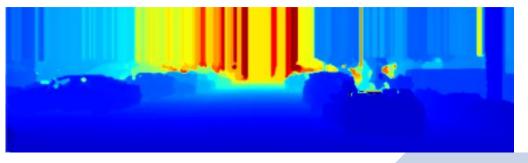
How?

Result = 100 - Input

Why?



Result





Step 8 – Depth Inversion

```
s8_inverted_depths = np.copy(s7_blurred_depths)
valid_pixels = np.where(s8_inverted_depths > 0.1)
s8_inverted_depths[valid_pixels] = \
    max_depth - s8_inverted_depths[valid_pixels]
depths_out = s8_inverted_depths
```

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RESULT



Method	iRMSE (1/km)	iMAE (1/km)	RMSE (mm)	MAE (mm)	Runtime (s)
NadarayaW	6.34	1.84	1852.60	416.77	0.05
SparseConvs	4.94	1.78	1601.33	481.27	0.01
NN+CNN	3.25	1.29	1419.75	416.14	0.02
Ours (IP-Basic)	3.78	1.29	1288.46	302.60	0.011

	Dataset	RMSE	MAE
Paper Implementation	KITTI Test Set	1288.46	302.6
My Implementation	KITTI Validation Cropped	1651.34	696.7



An Issue

