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# ICG Final Project Demo & Presentation

B04504116 鄭人豪  
B04901069 林志皓

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# Obejective

Reconsstruct 2.5D image from 2 plane image

RGB\*2  $\rightarrow$  RGB-D



Left

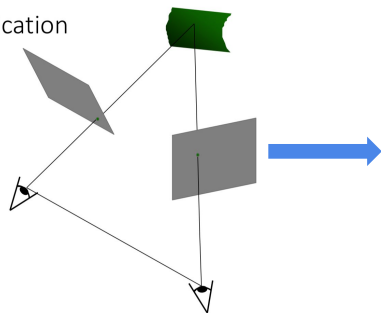


Right



# Pipeline

Image Rectification



RGB images (left & right)

reconstruct



RGB-D image

Stereo Matching

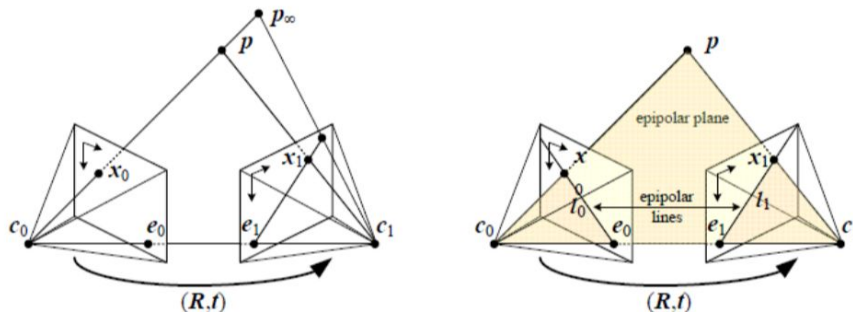


Depth image

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# Introduction - Stereo Matching

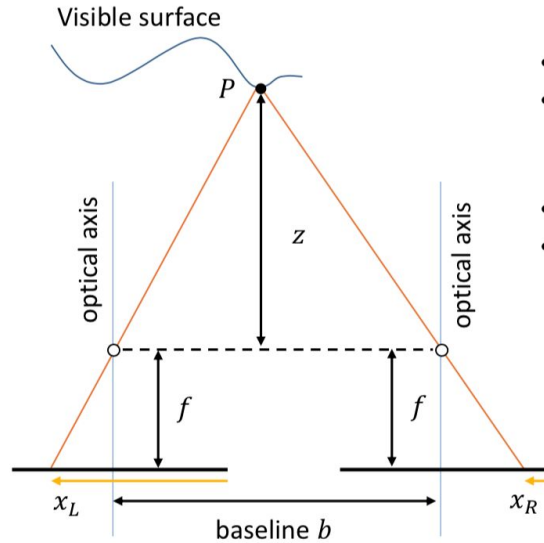
- For pixel  $x_0$  in one image, where is the corresponding point  $x_1$  in another image?
  - **Stereo**: two or more input views
- Based on the epipolar geometry, corresponding points lie on the epipolar lines
  - A **matching** problem



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# Introduction - Stereo Matching

## Depth from Disparity



- Disparity  $d = x_L - x_R$
- It can be derived that
$$d = \frac{f \cdot b}{z}$$
- Disparity = 0 for distant points
- Larger disparity for closer points

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# Pipeline - Stereo Matching

- Cost computation
  - Cost (support) aggregation
  - Disparity optimization
  - Disparity refinement
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# Results



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#### Tsukuba

- \* Elapsed time (cost computation): 2.240678 sec.
- \* Elapsed time (cost aggregation): 381.830109 sec.
- \* Elapsed time (cost computation): 2.282026 sec.
- \* Elapsed time (cost aggregation): 391.524820 sec.
- \* Elapsed time (disparity optimization): 0.015572 sec.
- \* Elapsed time (disparity refinement): 1.173584 sec.

#### Venus

- \* Elapsed time (cost computation): 4.027865 sec.
- \* Elapsed time (cost aggregation): 717.365762 sec.
- \* Elapsed time (cost computation): 3.965656 sec.
- \* Elapsed time (cost aggregation): 734.562450 sec.
- \* Elapsed time (disparity optimization): 0.028704 sec.
- \* Elapsed time (disparity refinement): 1.574592 sec.

#### Teddy

- \* Elapsed time (cost computation): 9.067297 sec.
- \* Elapsed time (cost aggregation): 1488.150797 sec.
- \* Elapsed time (cost computation): 8.334749 sec.
- \* Elapsed time (cost aggregation): 1452.823378 sec.
- \* Elapsed time (disparity optimization): 0.121340 sec.
- \* Elapsed time (disparity refinement): 2.727065 sec.

#### Cones

- \* Elapsed time (cost computation): 8.328705 sec.
- \* Elapsed time (cost aggregation): 1016.414072 sec.
- \* Elapsed time (cost computation): 8.331107 sec.
- \* Elapsed time (cost aggregation): 1004.053331 sec.
- \* Elapsed time (disparity optimization): 0.109782 sec.
- \* Elapsed time (disparity refinement): 2.274131 sec.

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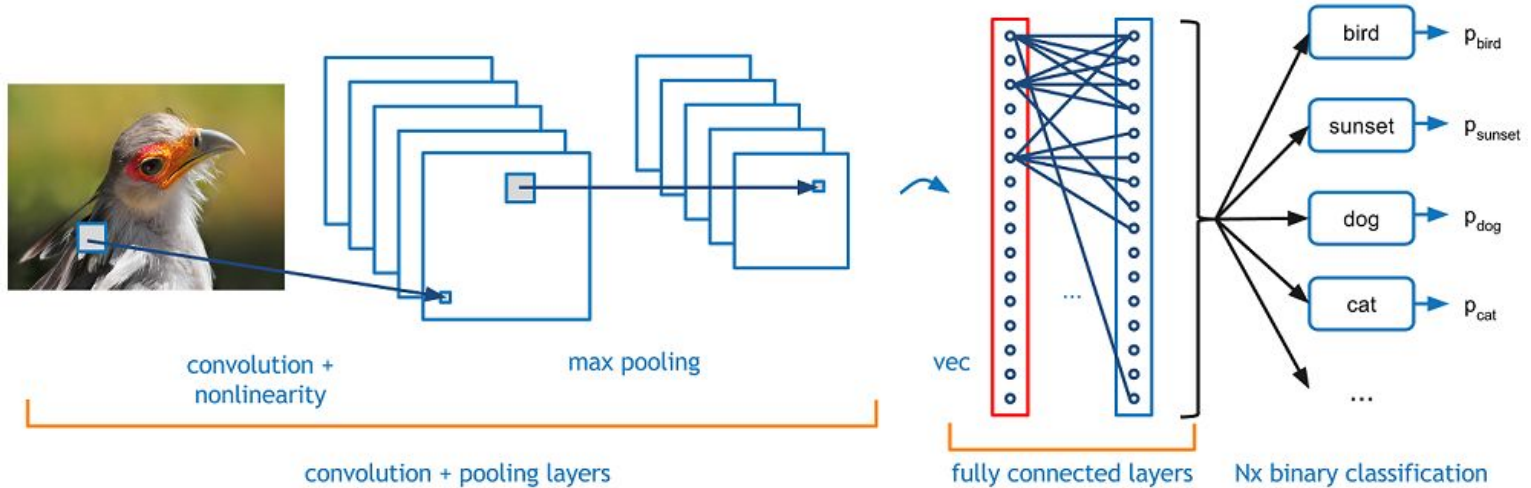
## **Drawbacks** of traditional method

1. Extremely slow
  2. Accuracy with limitation
  3. Sensitive to light, color consistency
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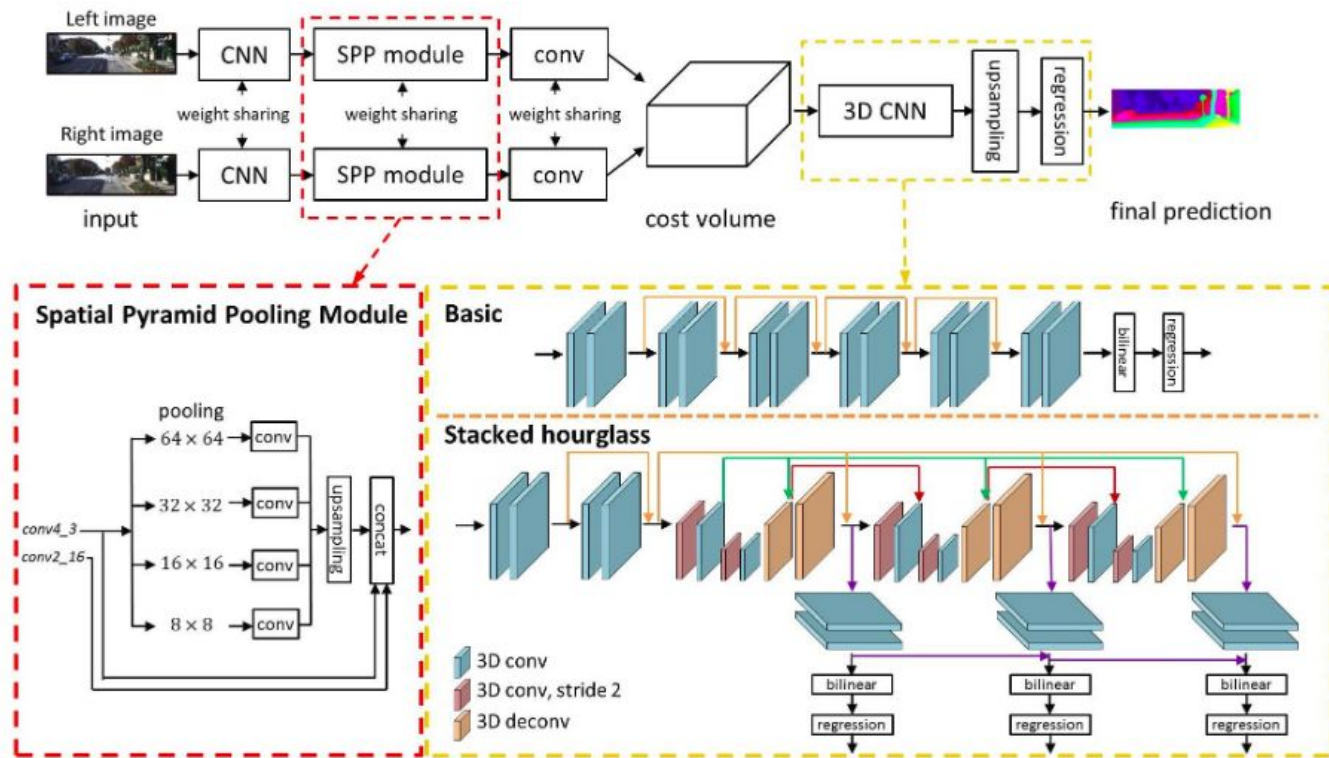
# Deep learning

Advantage: fast, can handle harsh case

based on Convolutional Neural Network



# PSMNet 2018 state-of-the-art



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# KITTI Dataset



left image



right image

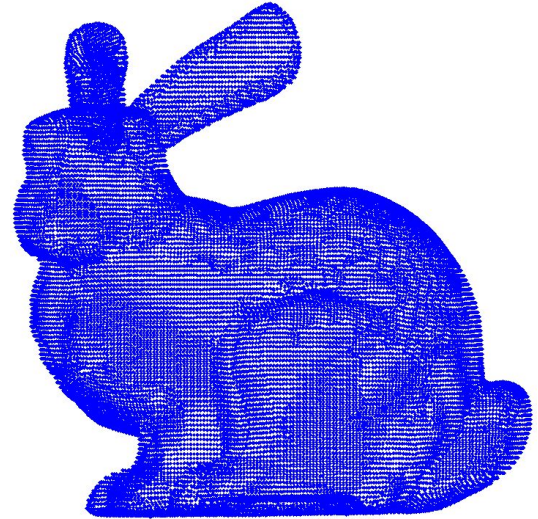
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# 3D Reconstruction

match RGB and depth information for each pixel

and generate **point clouds** data



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# Implementation

using python to process RGB & depth information

generate **vertex coordinations** and **colors**

render with **python / WebGL**

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# Demo Time !

```
def normalize_vertices(vertices, width, height):
    vertices = np.array(vertices).reshape(-1, 3)

    depth = vertices[:, 2]
    scale = 5
    vertices[:, 0] = (vertices[:, 0] - width//2) * scale / width
    vertices[:, 1] = (vertices[:, 1] - height//2) * scale / height
    vertices[:, 2] = (depth - depth.mean()) * scale / (depth.max() - depth.min())
    vertices = vertices.reshape(-1, )
    return list(vertices)

def normalize_colors(colors):
    colors = np.array(colors)
    colors = (colors / 400).round(5)
    return list(colors)

def create():
    rgb_img = cv.imread(args.rgb)
    height, width, _ = rgb_img.shape
    if args.depth.endswith('pfm'):
        depth = readPFM(args.depth)
    elif args.depth.endswith('npy'):
        depth = np.load(args.depth)
```

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