

Stereo — 2D to 3D on an FPGA

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What is Stereo

- Monocular

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- Binocular

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 - 2x HD camera
 - 4 million pixels

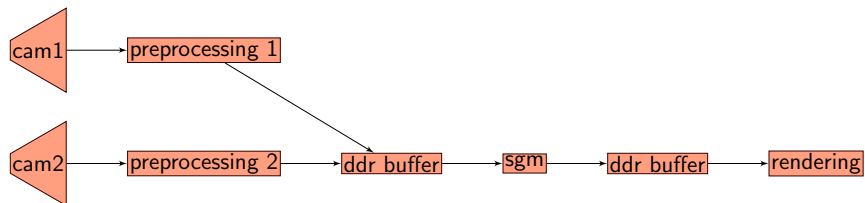
What is Stereo

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 - 2x HD camera
 - 4 million pixels
 - 4.3 Trillion possible correspondences

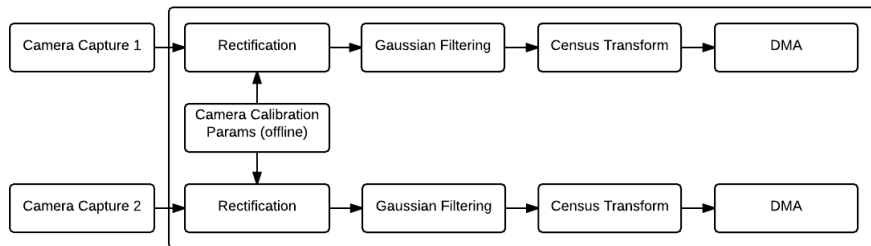
What is Stereo

- Monocular
- Binocular
 - two perspectives
- Algorithmic Idea
- Computationally Difficult
 - 2x HD camera
 - 4 million pixels
 - 4.3 Trillion possible correspondences
 - Even smart algorithms require a lot of power

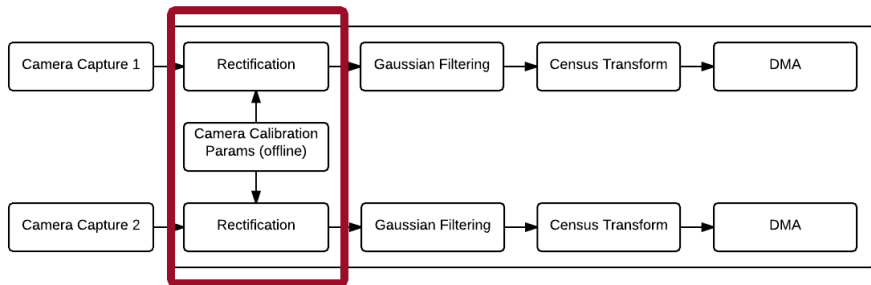
Overall System Layout



Camera Pipeline



Camera Pipeline



Why Rectification?

- Intrinsic optical distortion

Why Rectification?

- Intrinsic optical distortion
- Improper alignment of the cameras (rotation, translation)

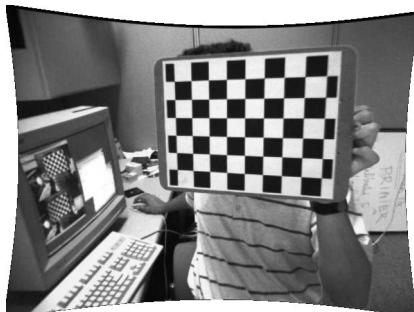
- Calibrate cameras offline (MATLAB)

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- Acquire rotation, translation matrix coefficients

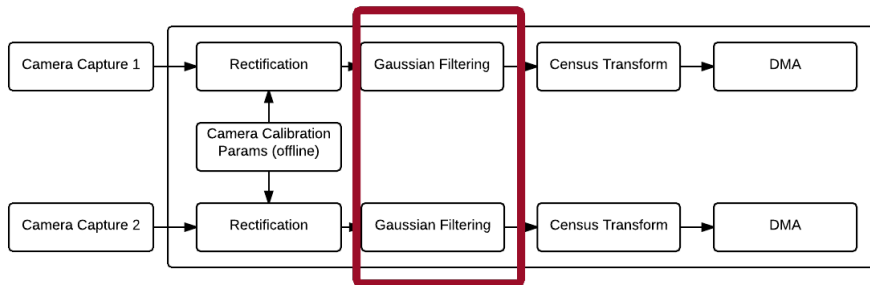
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- Acquire rotation, translation matrix coefficients
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- Apply the matrix transformations to streamed images (real-time)

Rectification: Example



Camera Pipeline



Gaussian Filtering



Original image



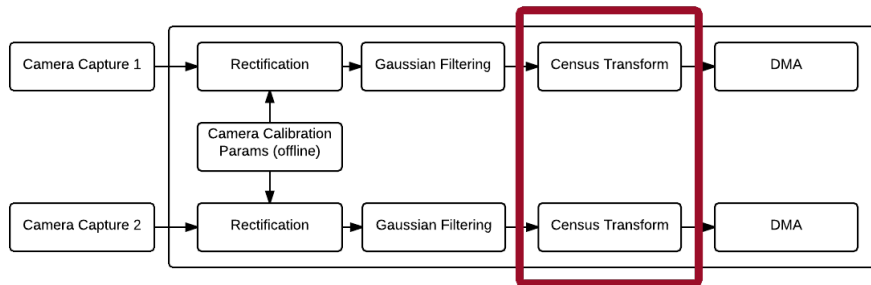
Gaussian Blur applied

Gaussian Filtering

- Reduce noise in the image
- Convolution: weighted sum of surrounding pixels
- Separate horizontal and vertical passes

$$s = \frac{1}{16} \begin{pmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{pmatrix}$$

Camera Pipeline



Disparity

- A shift to the left of an image feature when viewed in the right image
- Disparity cost: associated matching cost between two pixels



- Used to compute disparity matching costs
- 5x5 window for each pixel to represent the information from the surroundings of the pixel
- produces a bit stream



Left Image



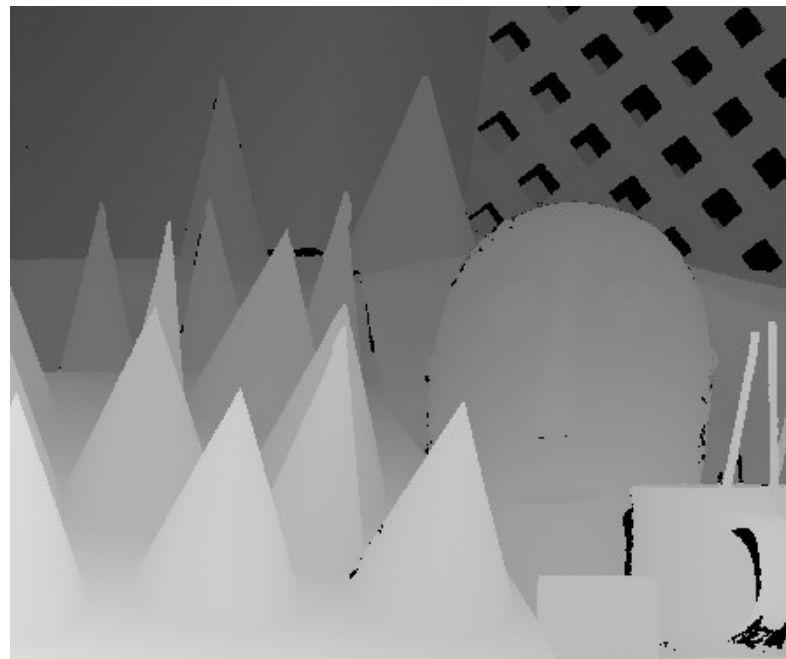
Right Image



Left Image



Right Image



Depth/Disparity Map

Minimize Global Energy

Minimize Global Energy

$$\begin{aligned} E(\mathbf{D}) &= \sum_{\mathbf{p}} C(\mathbf{p}, D_{\mathbf{p}}) \\ &+ \sum_{\mathbf{q} \in N_{\mathbf{p}}} \mathcal{P}_1 \cdot T[|D_{\mathbf{p}} - D_{\mathbf{q}}| = 1] \\ &+ \sum_{\mathbf{q} \in N_{\mathbf{p}}} \mathcal{P}_2 \cdot T[|D_{\mathbf{p}} - D_{\mathbf{q}}| > 1] \end{aligned}$$

Minimize Global Energy

$E(D)$

D is a disparity image

Minimize Global Energy

$$E(D) = \sum_p C(p, D_p)$$

*Similarity Costs for
Each Pixel*

Minimize Global Energy

$$E(\mathbf{D}) = \sum_{\mathbf{p}} C(\mathbf{p}, D_{\mathbf{p}}) + \sum_{\mathbf{q} \in N_{\mathbf{p}}} T [||D_{\mathbf{p}} - D_{\mathbf{q}}| = 1]$$

*Small Disparity Change
(Smoothness)*

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Small Penalty \mathcal{P}_1*

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Object Boundary

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Object Boundary : Large Penalty \mathcal{P}_2

2D Global Minimization

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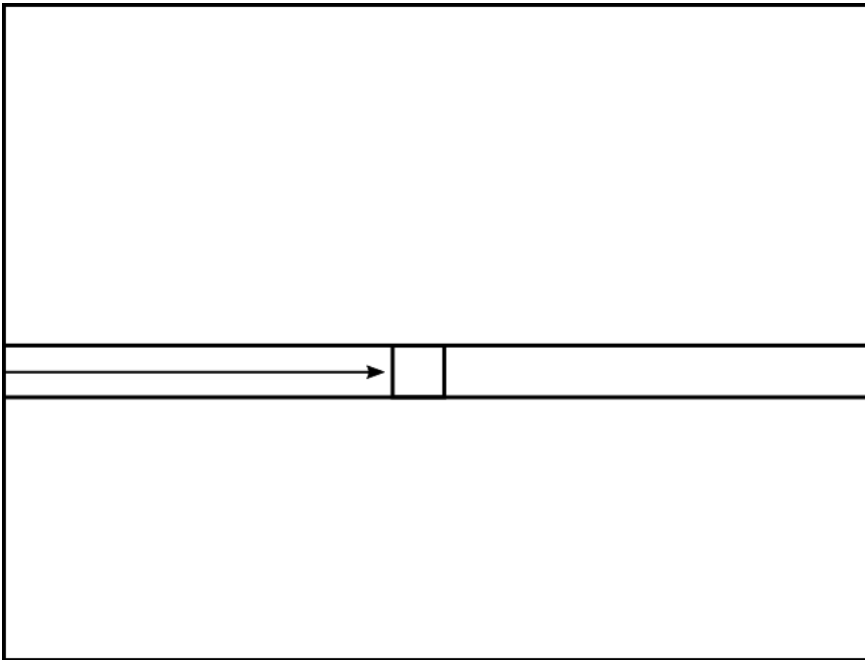
NP - Complete Problem

1D Optimization

- **Dynamic Programming**

1D Optimization

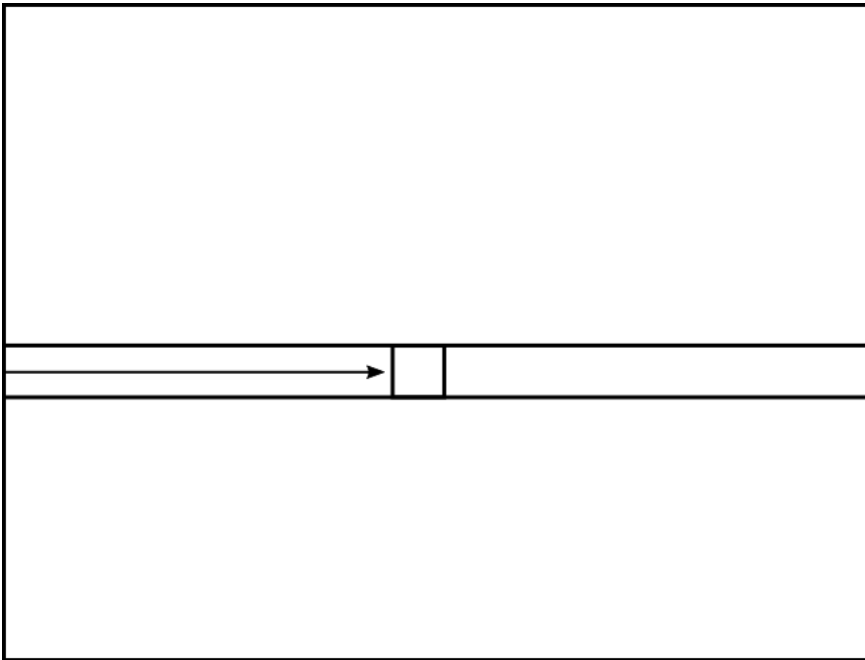
- Dynamic Programming
- Minimize Cost along Horizontal Lines



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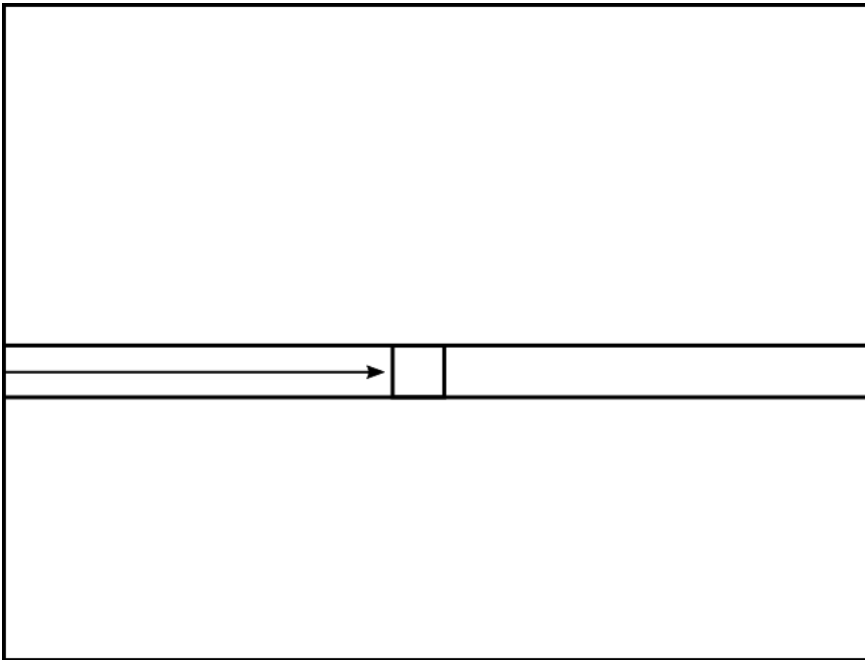
$$S(\mathbf{p}, d) = C(\mathbf{p}, d) + \min \left\{ \begin{array}{l} S(\mathbf{p} - 1, d), \\ S(\mathbf{p} - 1, d - 1) + \mathcal{P}_1, \\ S(\mathbf{p} - 1, d + 1) + \mathcal{P}_1, \\ \min_i S(\mathbf{p} - 1, i) + \mathcal{P}_2 \end{array} \right\}$$



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$$D_{\mathbf{p}} = \operatorname{argmin}_d S(\mathbf{p}, d)$$

Streaking Issues



Left Image

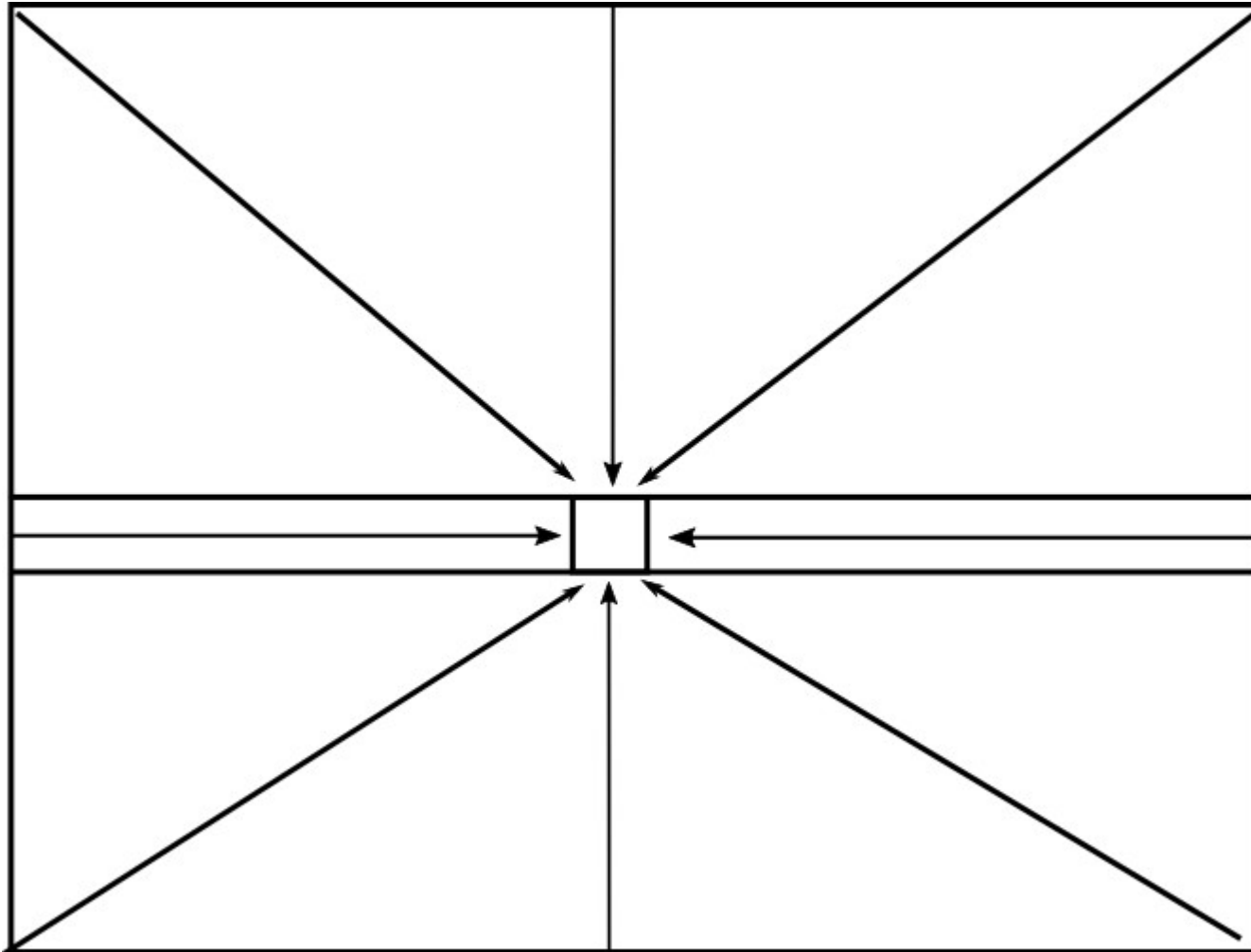


Right Image

Streaking Issues



Use Multiple Directions



Use Multiple Directions

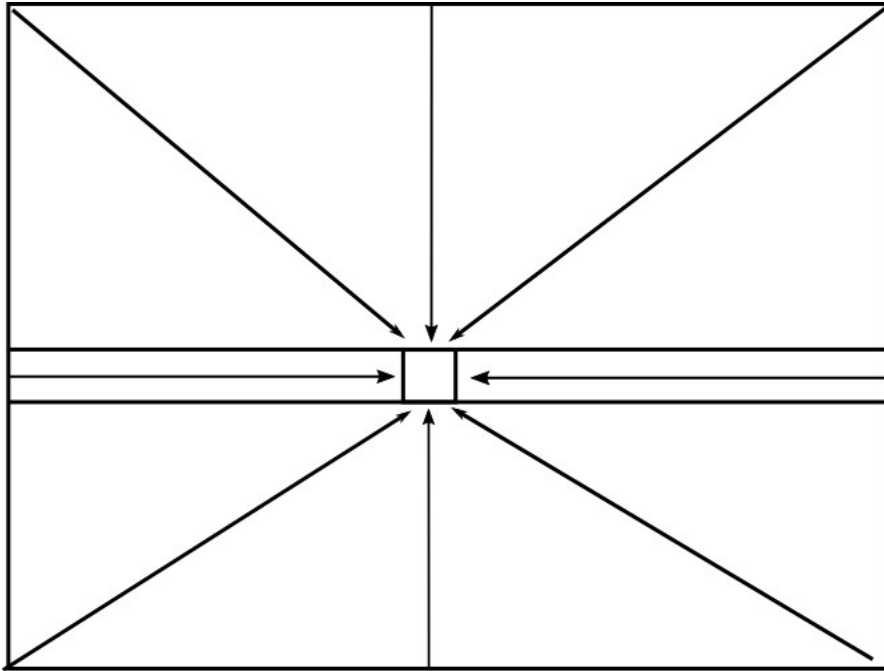
$$L_r(\mathbf{p}, d) = C(\mathbf{p}, d)$$

$$+ \min \{ L_r(\mathbf{p} - r, d),$$

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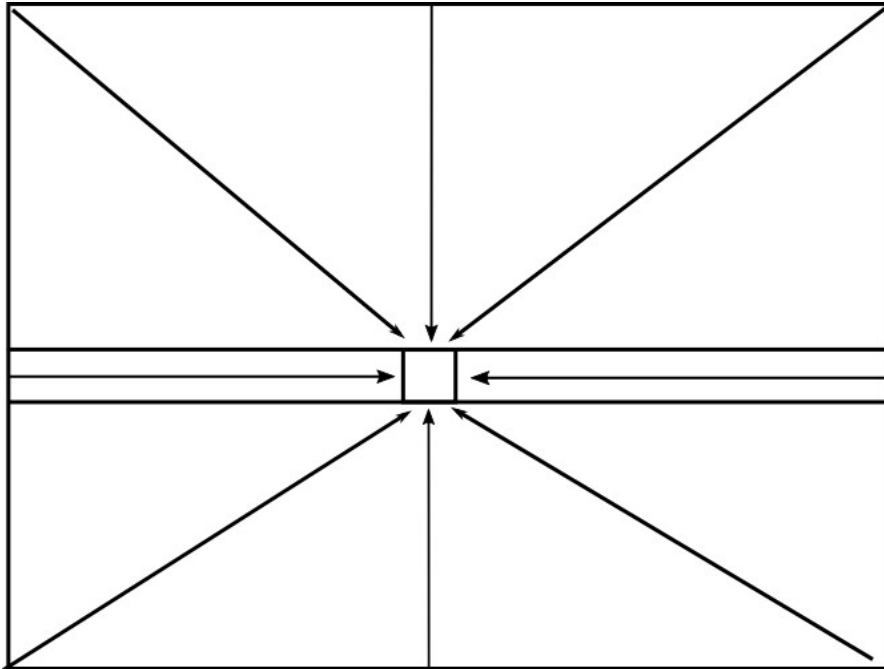
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Use Multiple Directions

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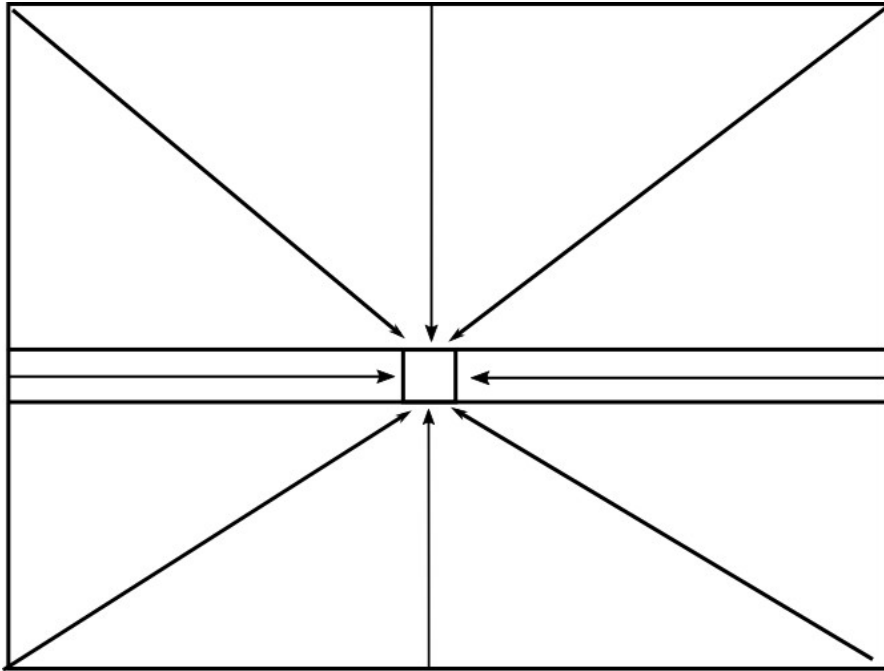


***r** varies over 8 directions*

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Total Cost : $S(p, d) = \sum_r L_r(\mathbf{p}, d)$

Semi Global Matching

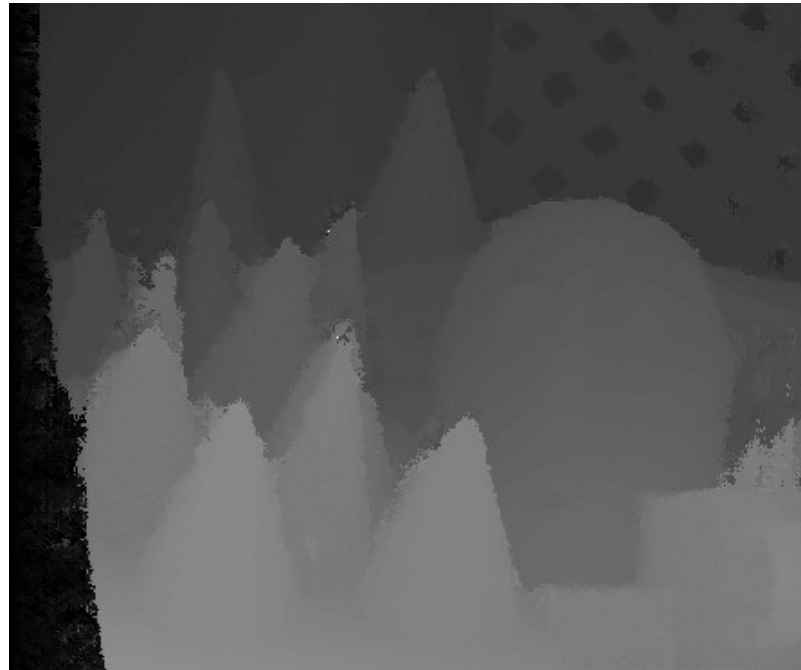


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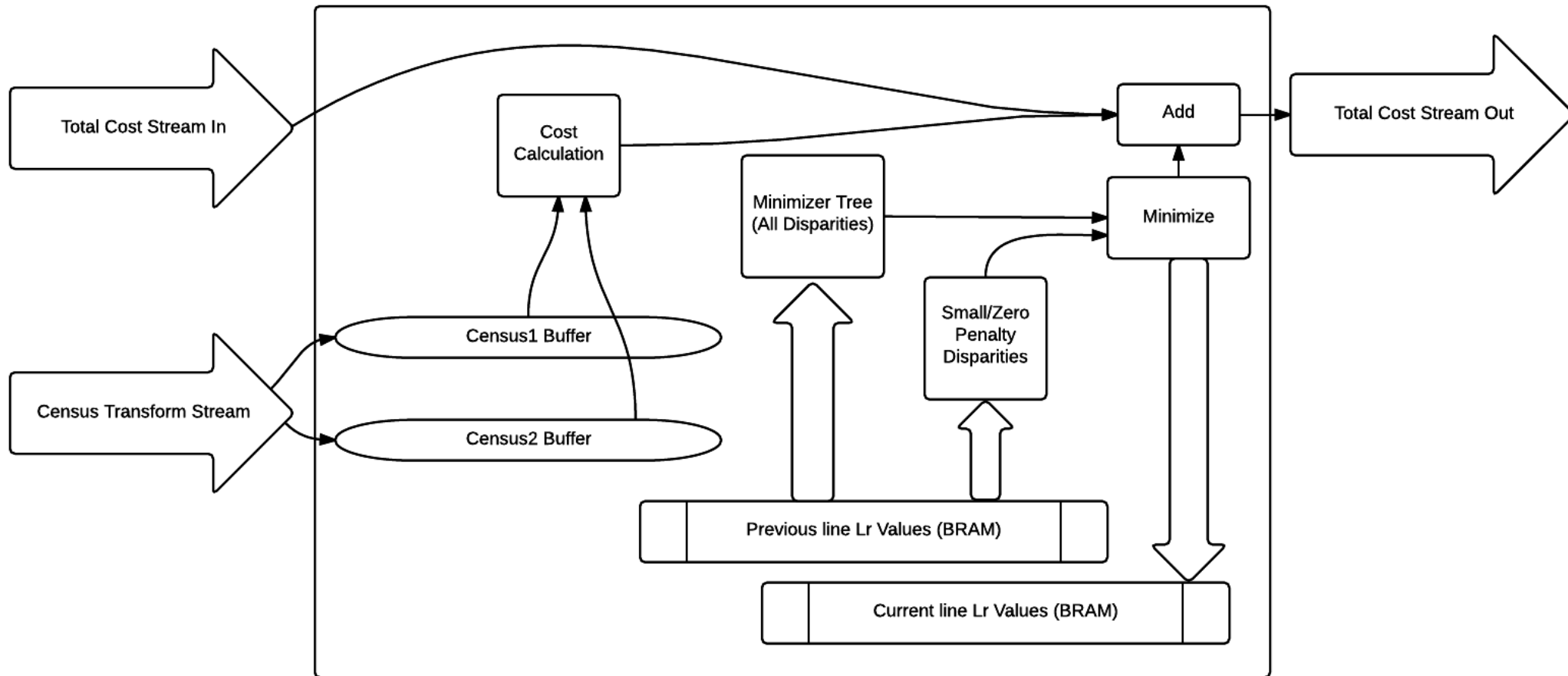


Right Image

No Streaking!!!



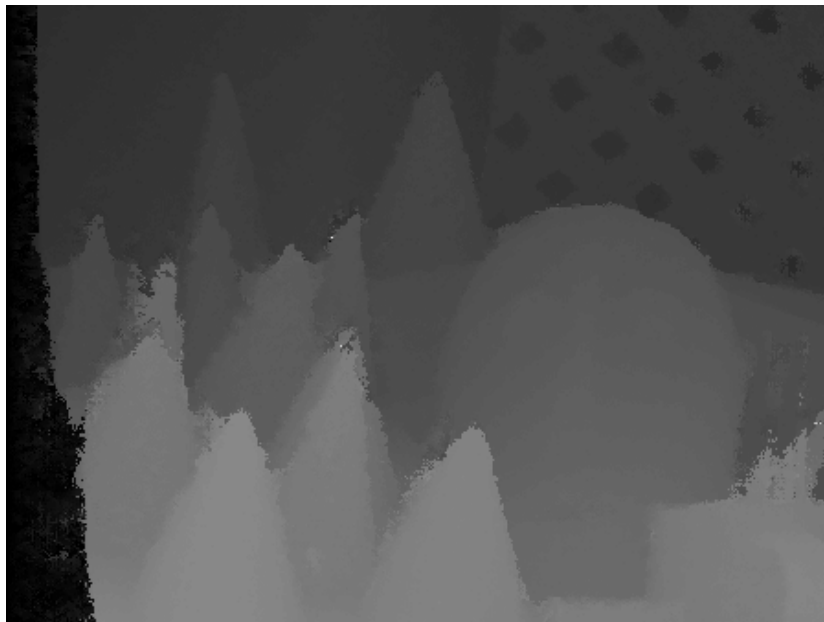
Streaming Design



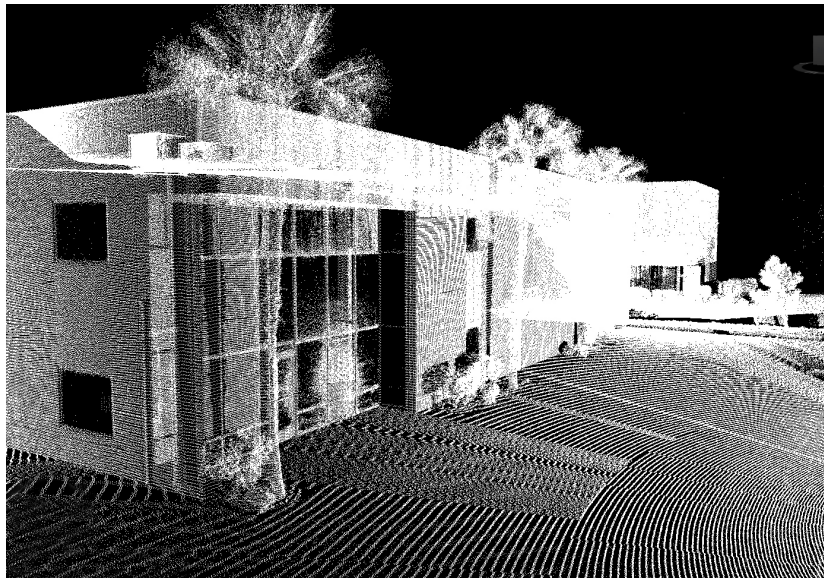
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Depth Map Rendering



Point Cloud Rendering



Timeline

