



自动驾驶论文讲坛

上采样深度图像及其应用

·本周分享

深度图 (Depth map) 是除点云 (Point Cloud) 以外另一种描述三维场景的数据格式，对它的处理也是自动驾驶领域重要的一环。本次 Journal Club 将会和大家一起学习一种将 Camera 和 Lidar 做数据融合，得到高精度高分辨率深度图像并将其应用于路沿检测 (Curb Detection) 的方法。

参考文献：

[1] J. Dolson, J. Baek, C. Plagemann, and S. Thrun. Upsampling range data in dynamic environments. In CVPR, 2010.

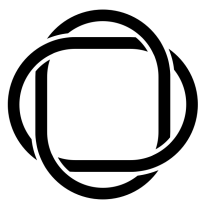
[2] Tan, J.; Li, J.; An, X.; He, H. Robust Curb Detection with Fusion of 3D-Lidar and Camera Data. Sensors 2014, 14, 9046–9073.

·主讲人

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·时间

星期五 03/11/2017
北京时间 12:00 PM
线上会议直播 - Zoom.us



iMorpheus

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The Application of Upsampled Range Data

Xudong Zhang

2017-11-3

[1] J. Dolson, J. Baek, C. Plagemann, and S. Thrun. Upsampling range data in dynamic environments. In CVPR, 2010.

[2] Tan, J.; Li, J.; An, X.; He, H. Robust Curb Detection with Fusion of 3D-Lidar and Camera Data. Sensors 2014, 14, 9046–9073.



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Background

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Discussion



Depth Map

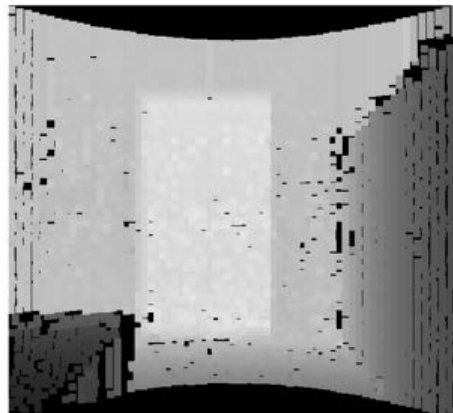
Point Cloud



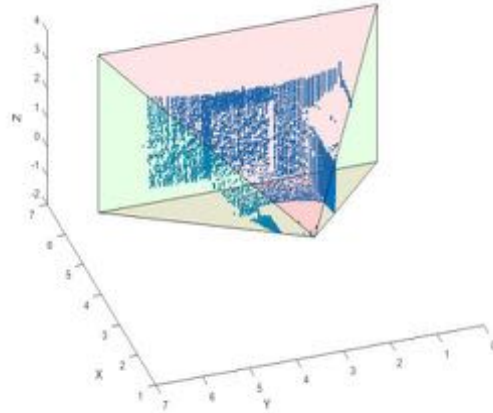
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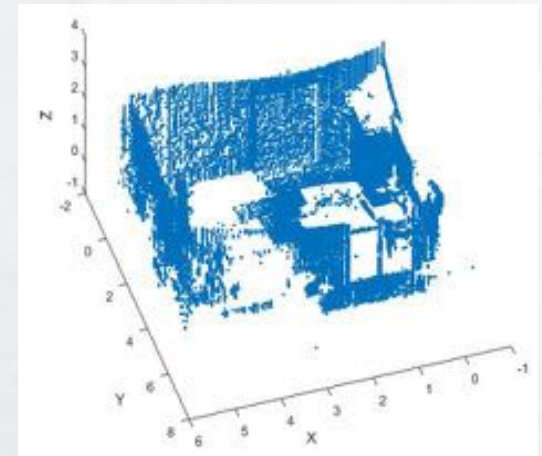
b



e



d



c



Lidar's Point Cloud

1. Accurate & Long range
2. Sparse
3. Expensive
4. Low acquisition rate
5. Available under many situations

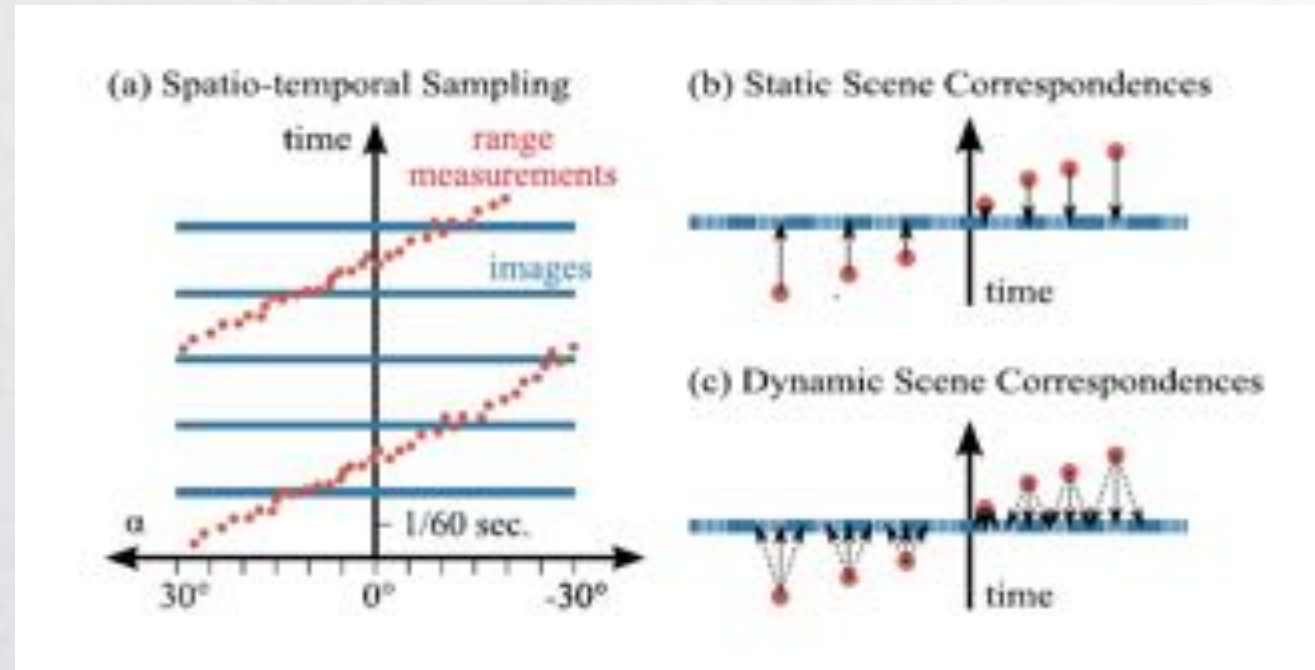


Target: To recover an accurate, dense depth map.

Keyword: Upsampling range data

Method: Corresponding to a single camera frame
or using depth data from neighboring frames

Problem: Different data acquisition rates



Interpolate depth information with a level of accuracy
Assign confidence value
Parallel Framework

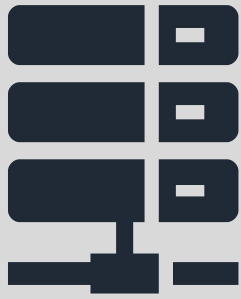


1. Fusion with stereo camera:

Stereo camera systems range error increases quadratically with depth.
→ Accuracy limited ✕

2. Markov Random Fields (MRFs)

Using color information from a camera image
→ Assumption: static within the sweeping time ✕



2

Upsampling range data



d-dimensional filters: (u, v)

Interpolation: (ρ, u, v, t)
 $(r, g, b, u, v) \rightarrow (\rho, u, v)$

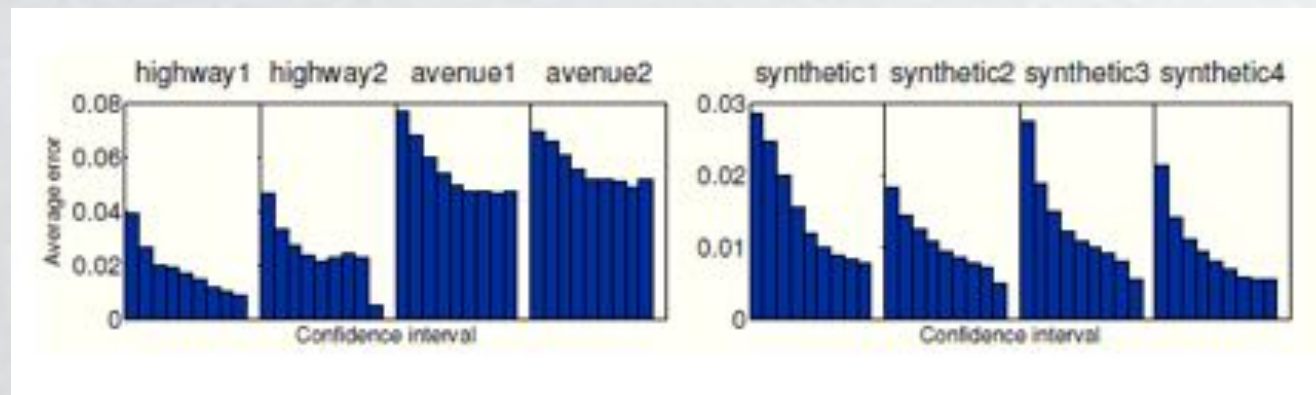
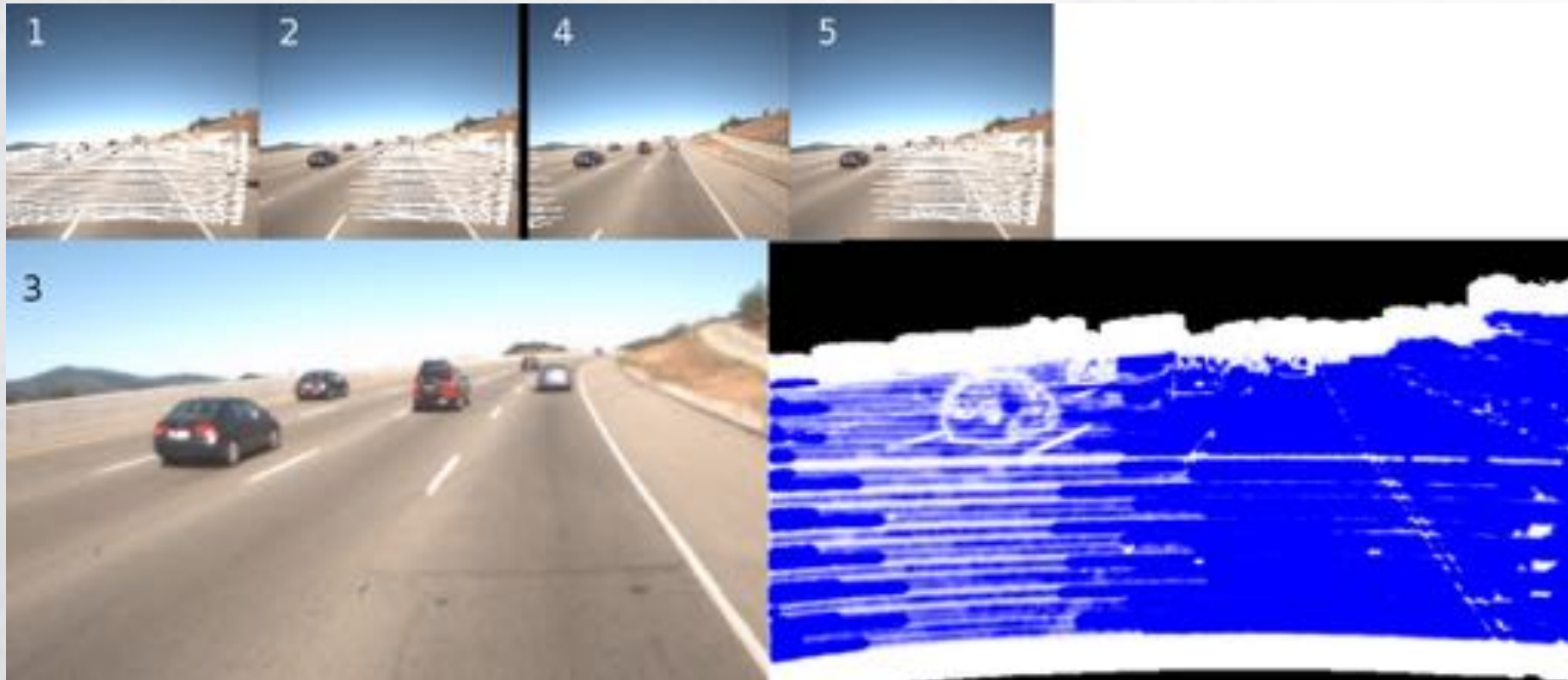
Data Processing & Motion
Priors

Confidence Weighting:
standard deviations

$$\hat{v}_i = \sum_{j=1}^n f(|p_i - p_j|) \cdot v_j \quad (1)$$

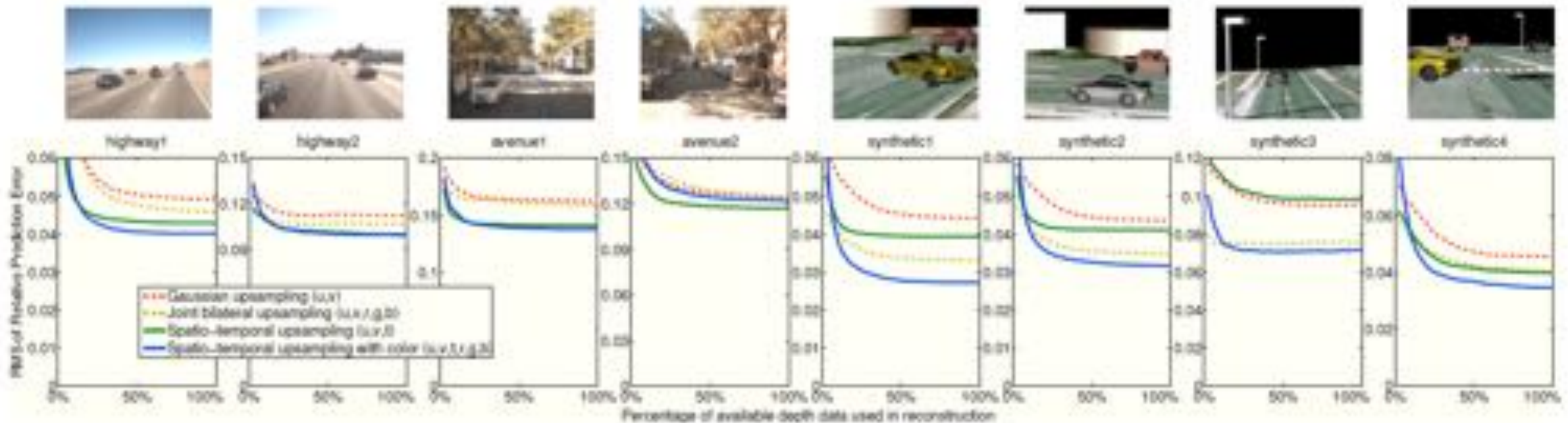
$$f(x) = e^{-|x|^2 / 2\sigma^2} \quad (2)$$

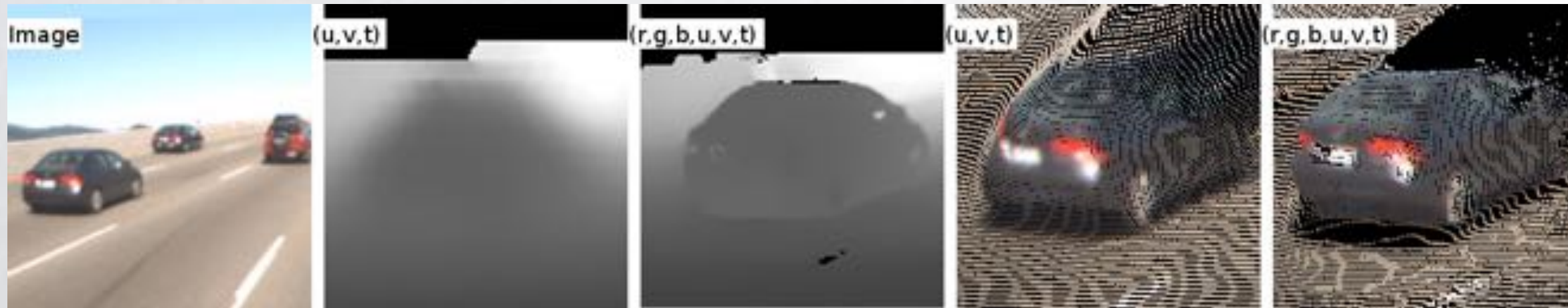
$$p^* = (s_u \cdot \Delta t) \cdot \frac{r_u}{(2d) \operatorname{atan}(\frac{\theta}{2})} \quad (3)$$





Time →

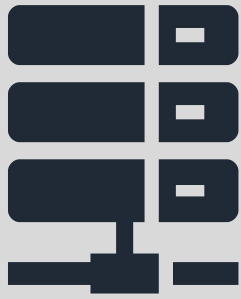




\vee



\times



3

*Application:
Curb Detection*



a



b



c



d



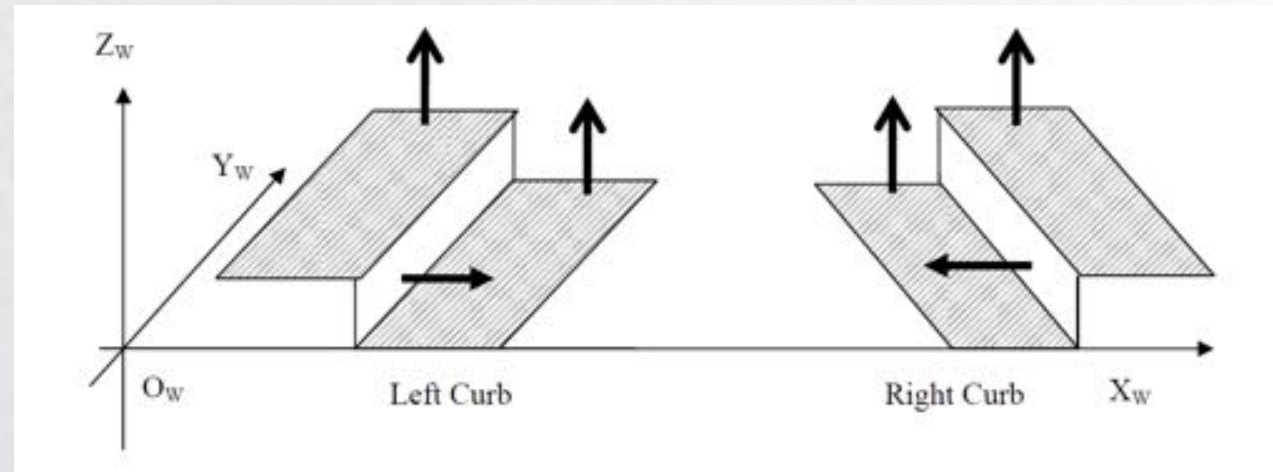
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f

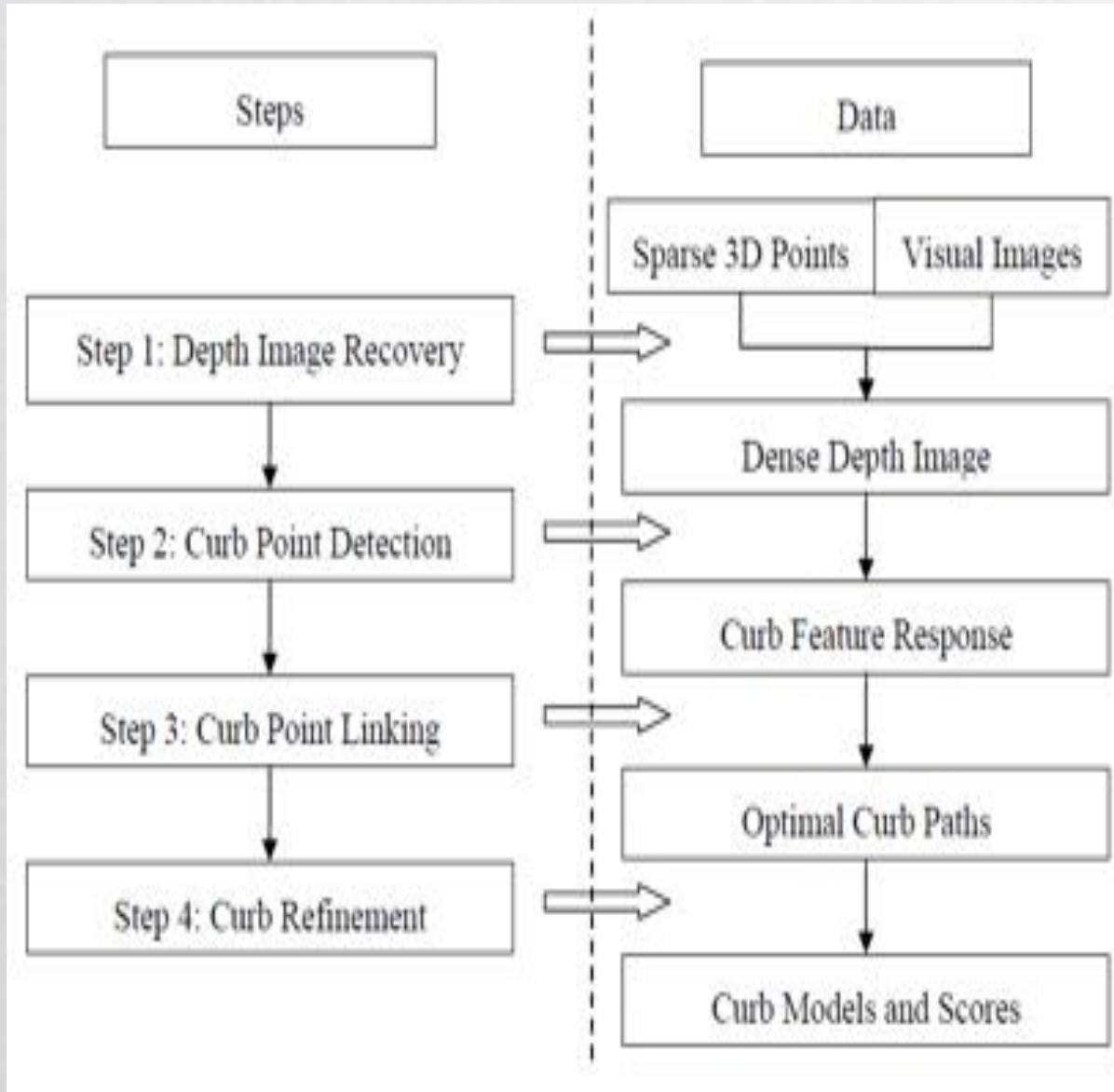


Limit the driving area
Map Building and Vehicle Localization
Curb detection & Lane Line Detection
Lidar? Camera?



Geometric Properties:
Height
Normal
Consistency

Image property:
Edge
Variety

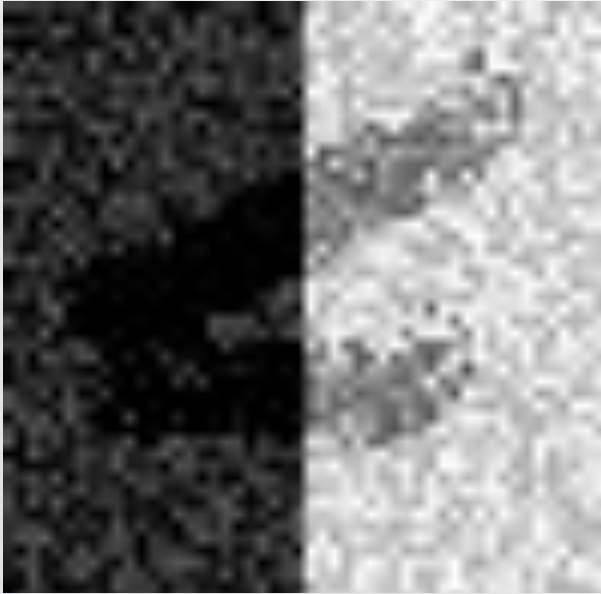


Contributions:

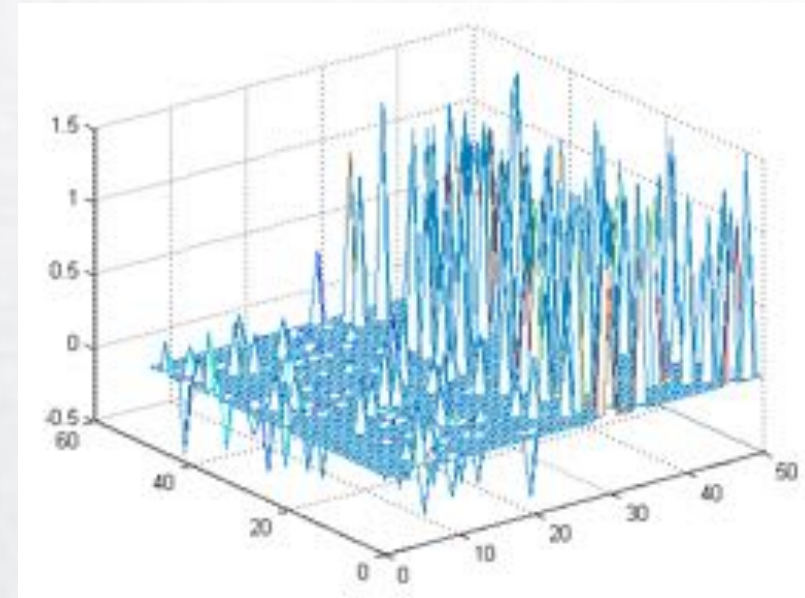
1. The “ first” to use the dense depth map
2. Novel filter-based method
3. Markov Chain model for curb point linking
4. Filtering out the outliers
5. The “ best” result



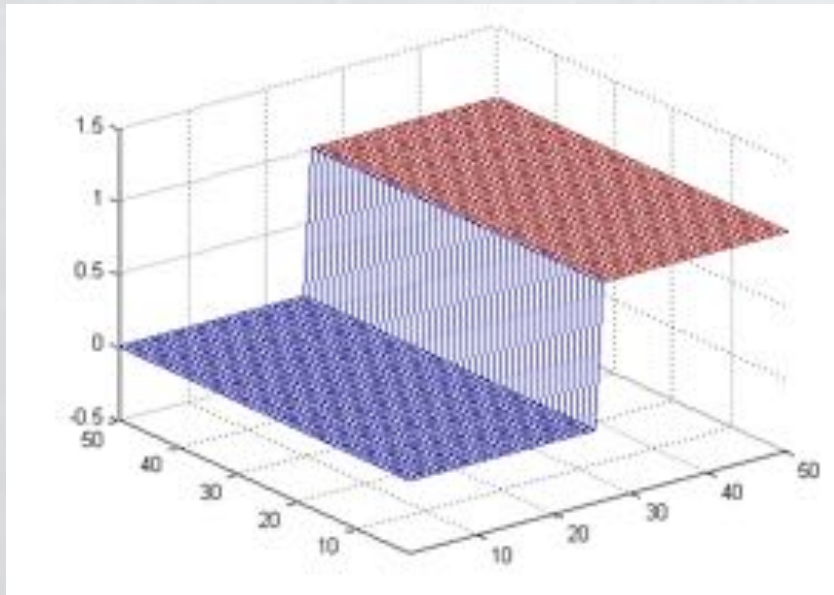
a



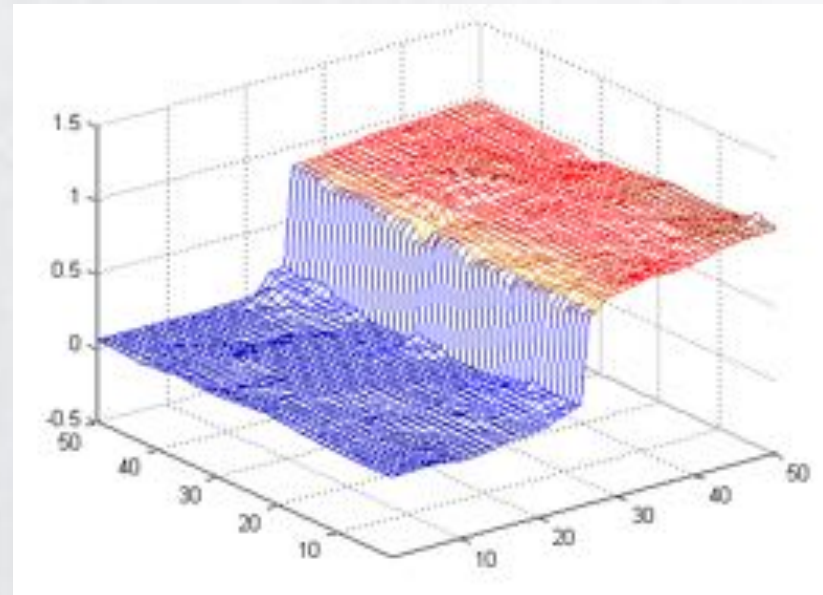
b



c



d





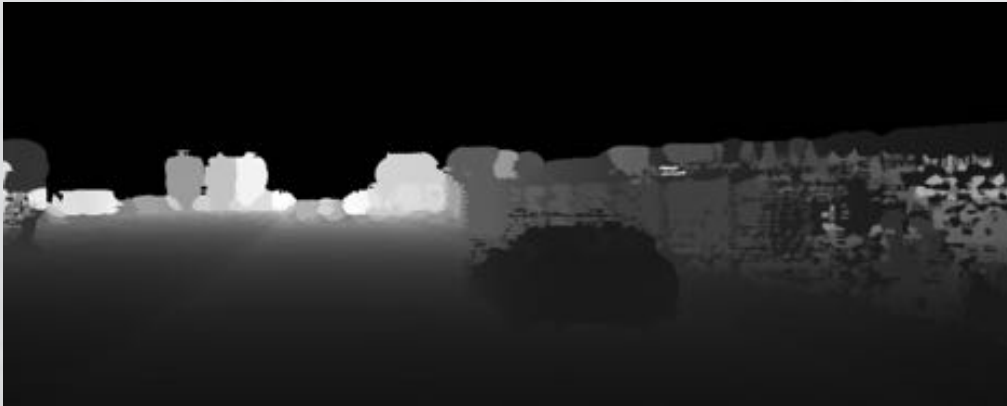
a



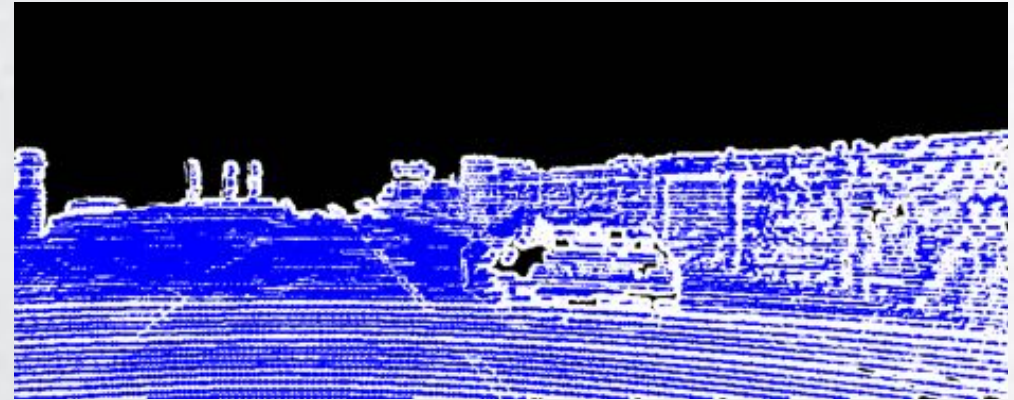
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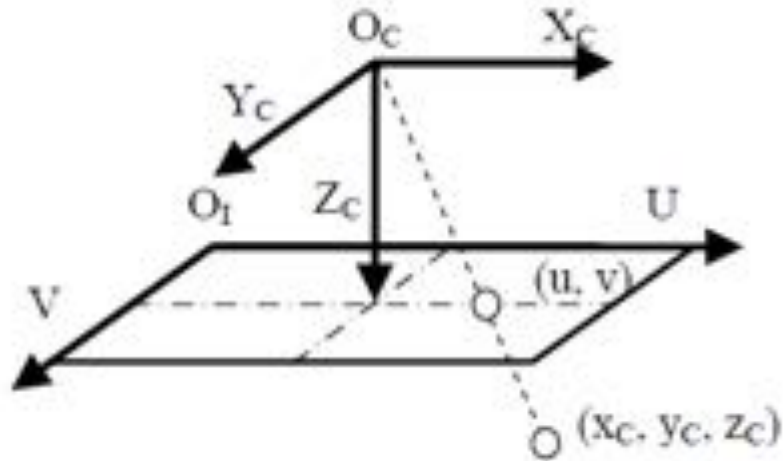


c



d





$$u = f_x \times \frac{x_c}{z_c} + c_x$$

$$v = f_y \times \frac{y_c}{z_c} + c_y$$

$$x_c(u, v) = \frac{u - c_x}{f_x} \times d(u, v)$$

$$y_c(u, v) = \frac{v - c_y}{f_y} \times d(u, v)$$

$$z_c(u, v) = d(u, v)$$

$$\begin{bmatrix} x_w \\ y_w \\ z_w \end{bmatrix} = R^{-1} \bullet \left(\begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} - T \right)$$

road region: $z_w < T_z$



$$u = \frac{x}{z} \times f_x + c_x$$

$$v = \frac{y}{z} \times f_y + c_y$$

$$d(u, v) = z$$

$$\nabla \equiv \hat{x} \frac{\partial}{\partial x} + \hat{y} \frac{\partial}{\partial y} + \hat{z} \frac{\partial}{\partial z}$$

$$\frac{\partial}{\partial x} = \frac{\partial}{\partial u} \frac{\partial u}{\partial x} + \frac{\partial}{\partial v} \frac{\partial v}{\partial x} + \frac{\partial}{\partial d} \frac{\partial d}{\partial x}$$

$$\frac{\partial}{\partial y} = \frac{\partial}{\partial u} \frac{\partial u}{\partial y} + \frac{\partial}{\partial v} \frac{\partial v}{\partial y} + \frac{\partial}{\partial d} \frac{\partial d}{\partial y}$$

$$\frac{\partial}{\partial z} = \frac{\partial}{\partial u} \frac{\partial u}{\partial z} + \frac{\partial}{\partial v} \frac{\partial v}{\partial z} + \frac{\partial}{\partial d} \frac{\partial d}{\partial z}$$

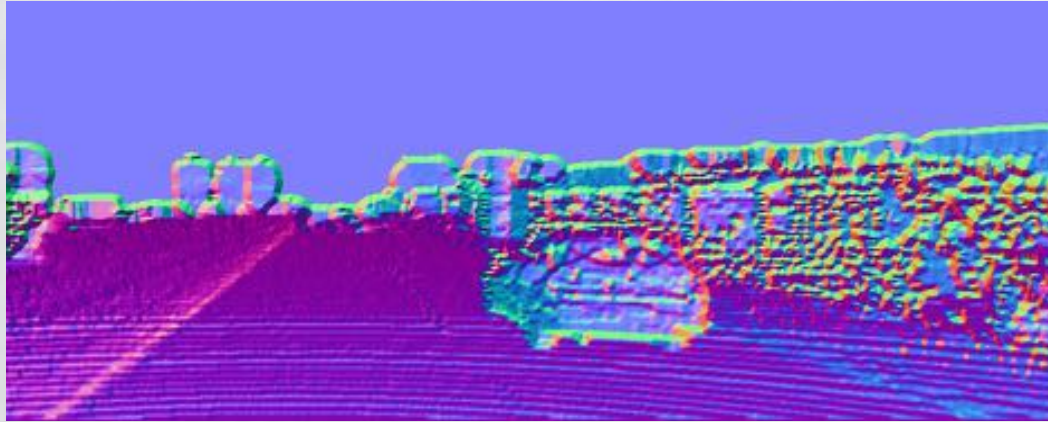
$$\nabla \equiv [\hat{x} \quad \hat{y} \quad \hat{z}] \bullet \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -\frac{x}{z} & -\frac{y}{z} & 1 \end{bmatrix} \bullet \begin{bmatrix} \frac{\partial}{\partial u} \times \frac{f_x}{z} \\ \frac{\partial}{\partial v} \times \frac{f_y}{z} \\ \frac{\partial}{\partial d} \end{bmatrix}$$

$$Sobel_u = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} / 8$$

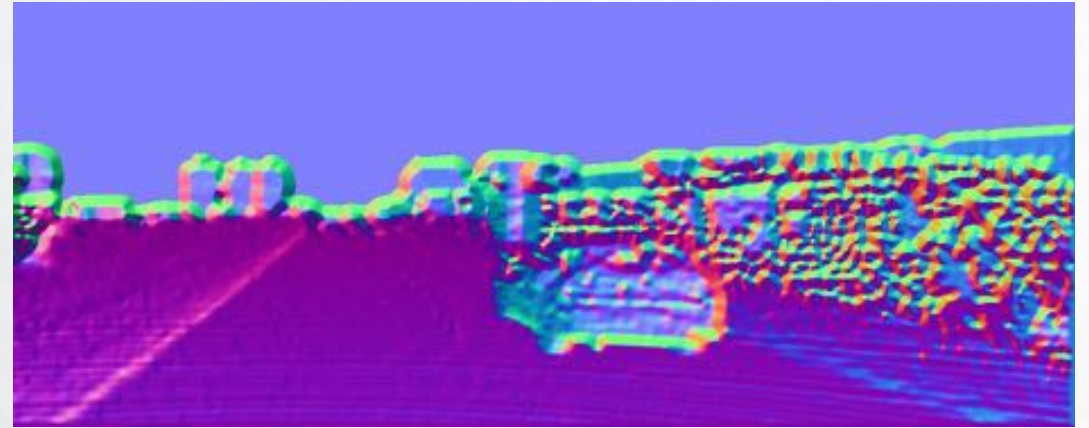
$$Sobel_v = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} / 8$$



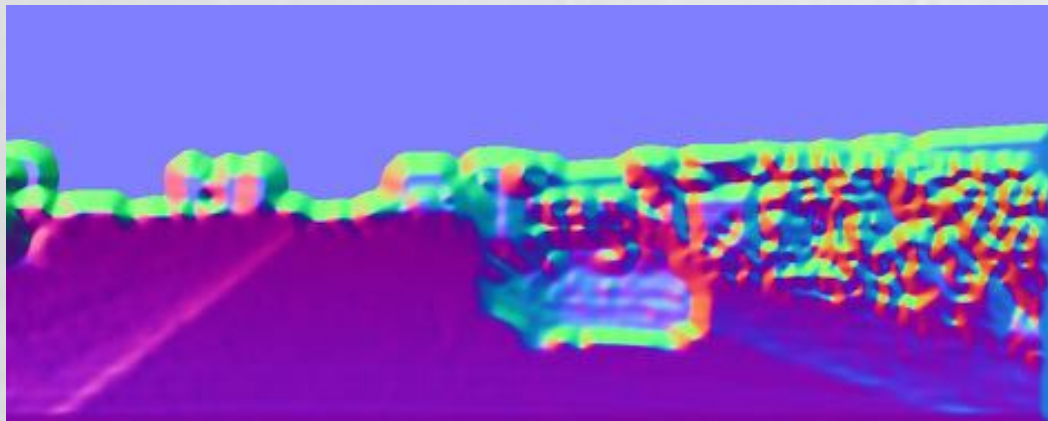
X_w right side Y_w point ahead Z_w upside
 (N_x, N_y, N_z) : $r=(N_x + 1)/2$, $g=(N_y + 1)/2$, $b=(N_z + 1)/2$



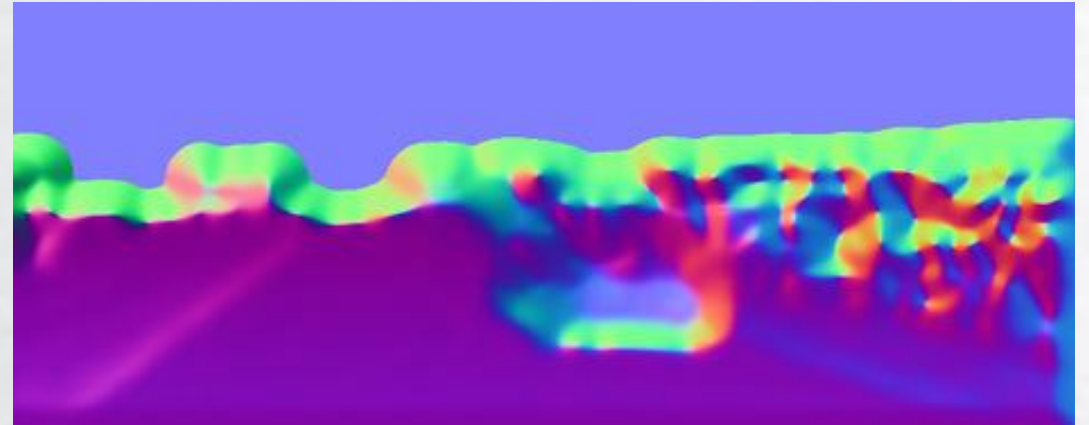
$\sigma_s = 1$



$\sigma_s = 2$



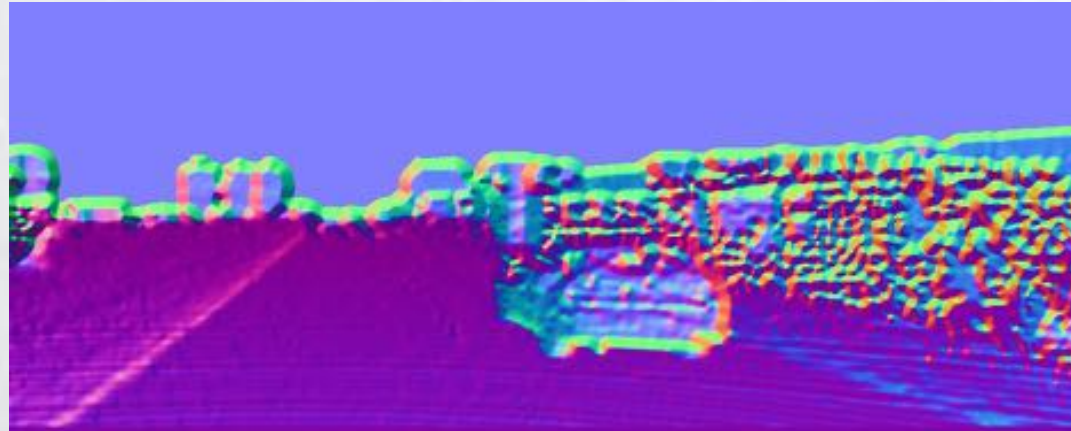
$\sigma_s = 4$



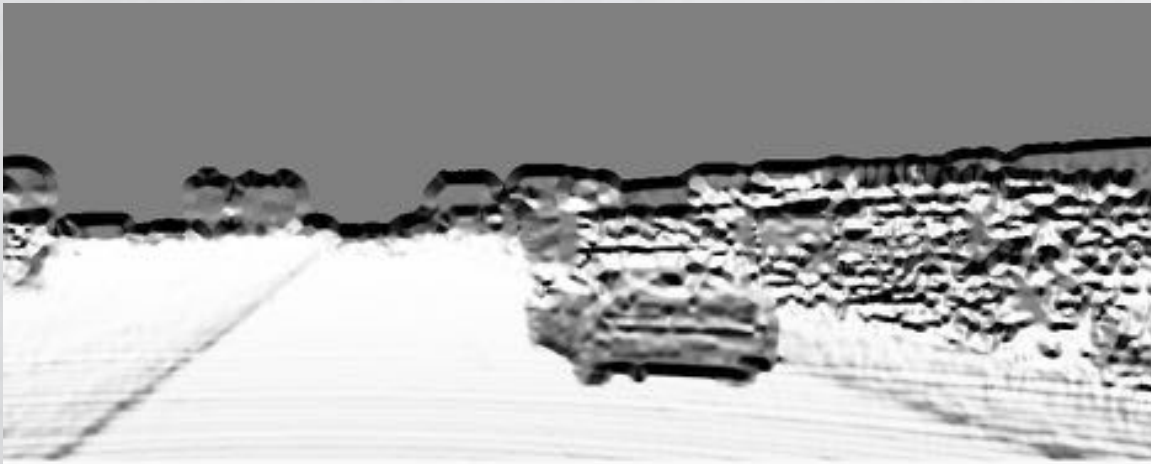
$\sigma_s = 8$



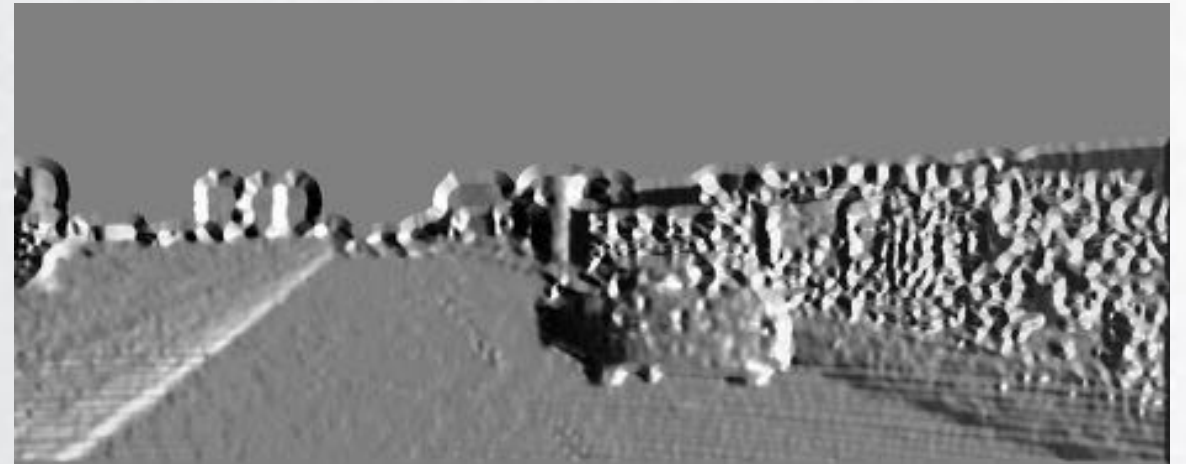
X_w right side
 Y_w point ahead
 Z_w upside



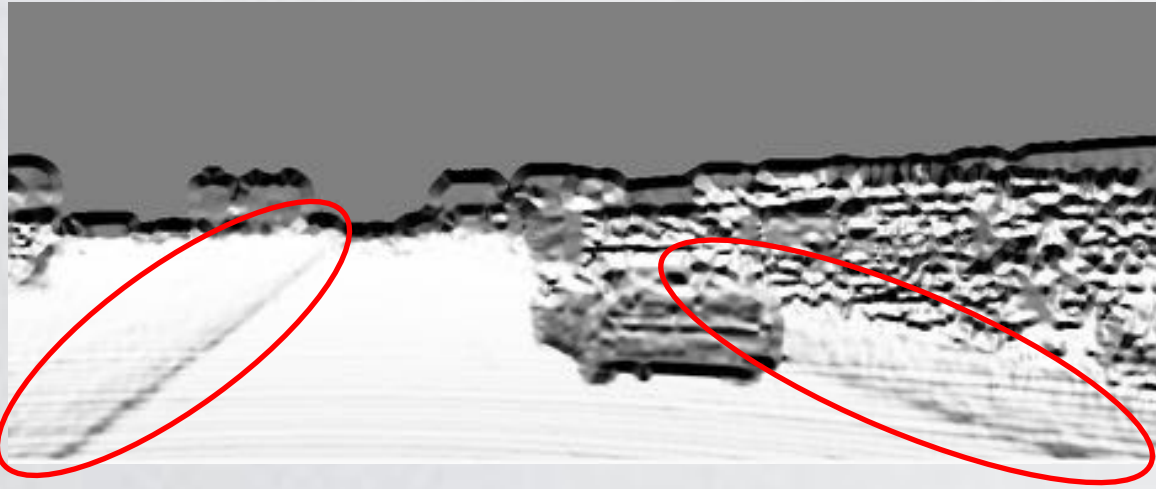
Normal image



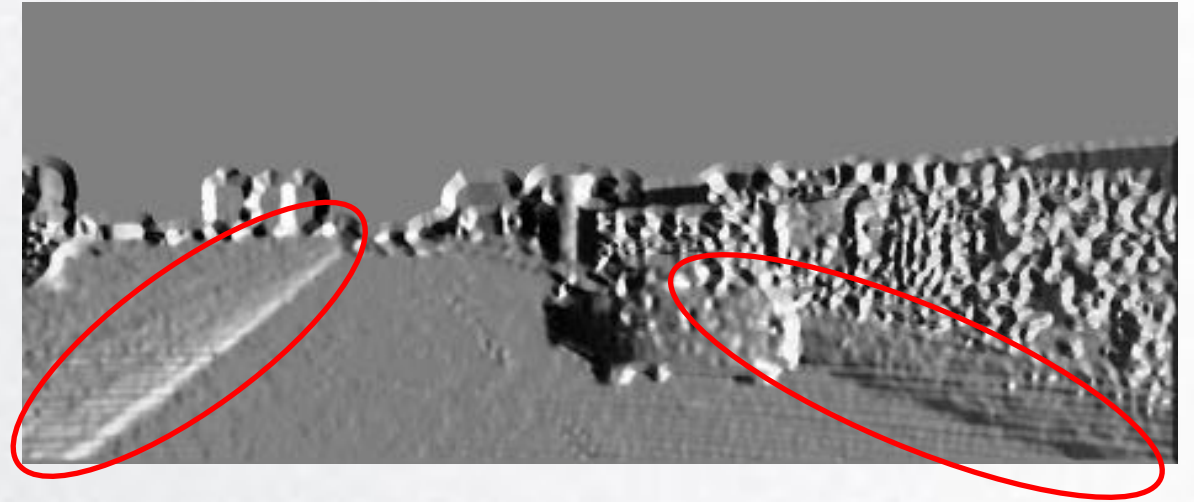
Normal projection in Z_w



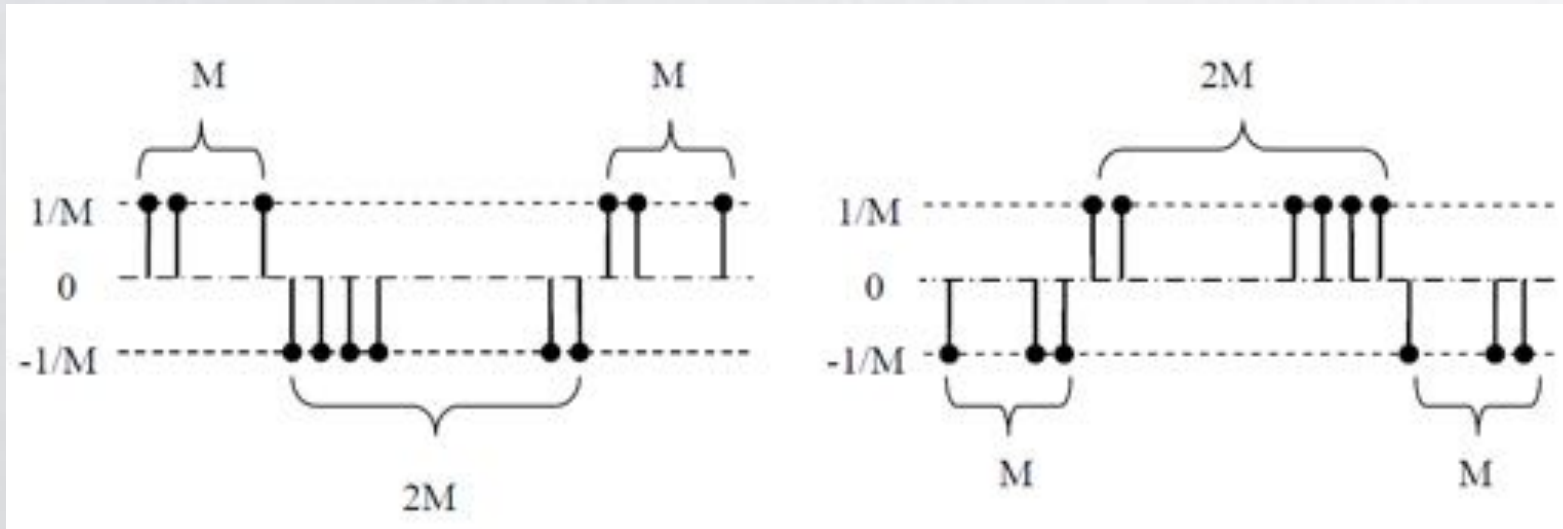
Normal projection in X_w



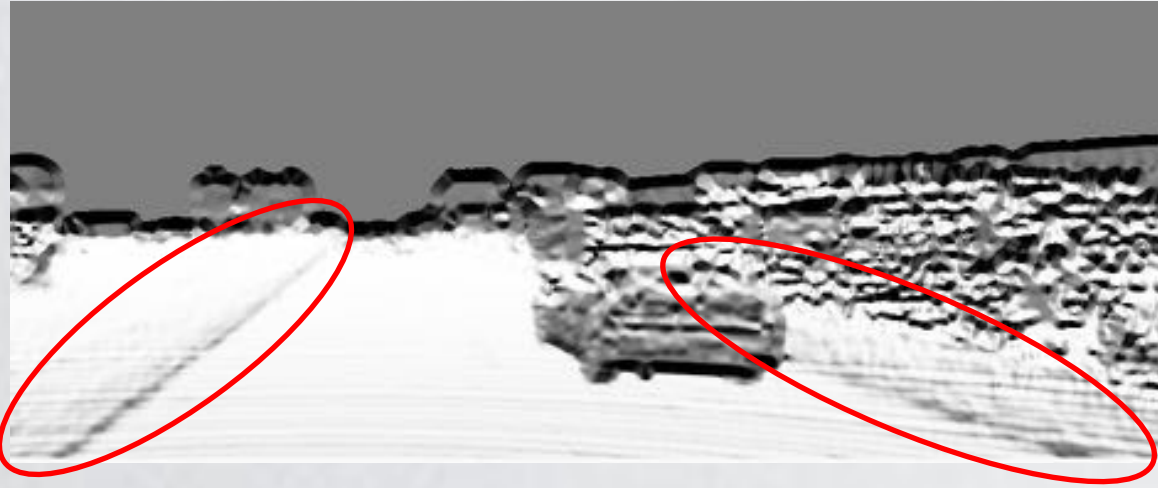
Normal projection in Z_w



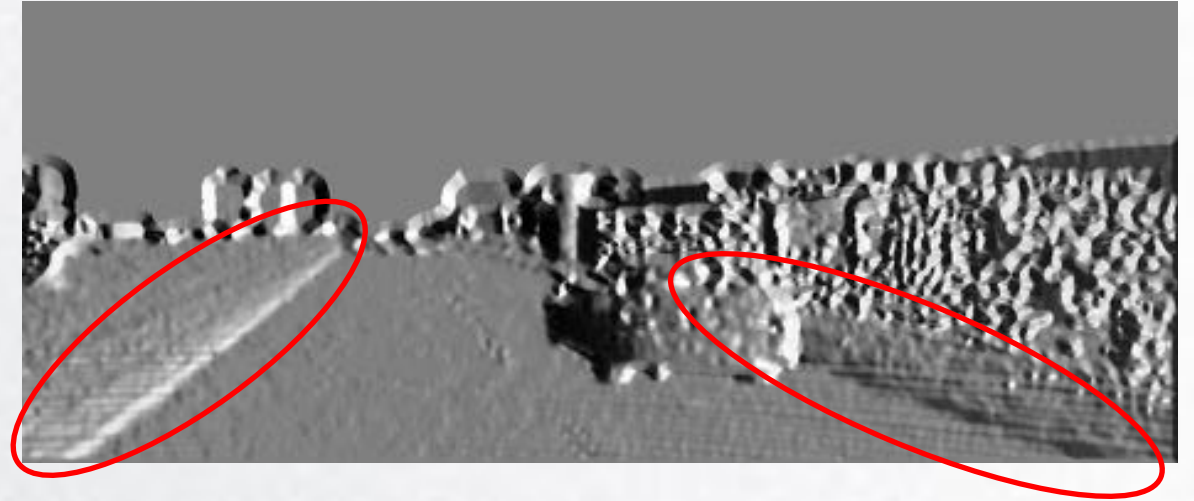
Normal projection in X_w



“bright-dark-bright” pattern & “dark-bright-dark” pattern



Normal projection in Z_w



Normal projection in X_w



Left side curb feature



Right side curb feature



Markov Chain

Economic Predicting, Management decision, Weather forecasting

$$P\{X_{n+1} = j | X_0 = i_0, \dots, X_{n-1} = i_{n-1}, X_n = i_n\} = P\{X_{n+1} = j | X_n = i\}$$



Linking & isolating noises

$$nodePot(X_i^k) = \frac{1}{Z_i} \times (1 - \exp(-(\frac{f_{(i,k)}}{\sigma_n})^2))$$

$$Z_i = \sum_k (1 - \exp(-(\frac{f_{(i,k)}}{\sigma_n})^2))$$

Left



Right





$$edgePot(X_{i+1}^j, X_i^k) = e_x(X_{i+1}^j, X_i^k) \times e_f(X_{i+1}^j, X_i^k)$$

$$e_x(X_{i+1}^j, X_i^k) = \exp\left(-\frac{(j-k)^2}{\sigma_x^2}\right)$$

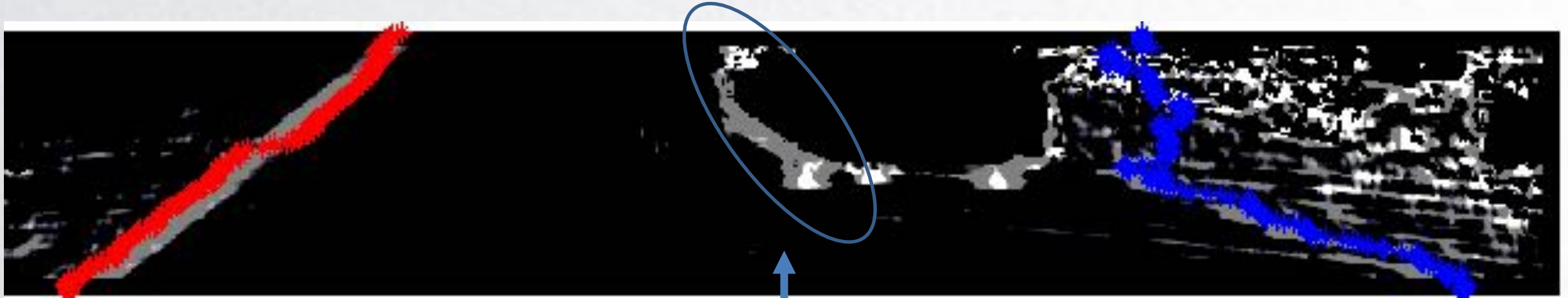
$$e_f(X_{i+1}^j, X_i^k) = \exp\left(-\frac{(f_{(i+1,j)} - f_{(i,k)})^2}{\sigma_f^2}\right)$$

Position and Feature

$$p(X_{i+1}^j) = nodePot(X_{i+1}^j) \times \max_{k \in N(j)} (p(X_i^k) \times edgePot(X_i^k, X_{i+1}^j))$$

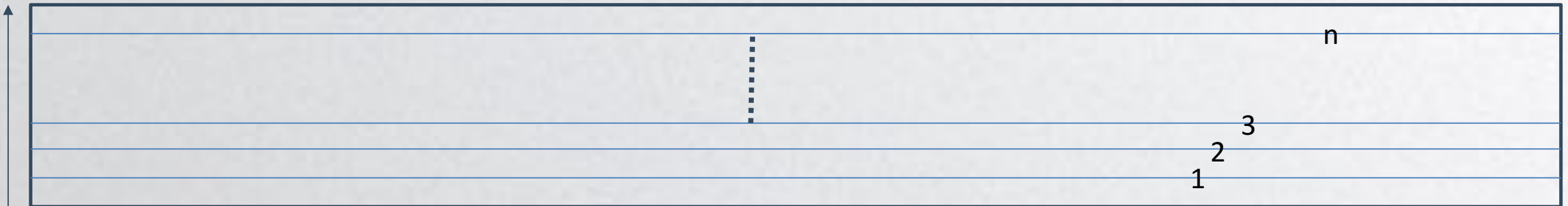
$$link(X_{i+1}^j) = \arg \max_k \max_{k \in N(j)} (p(X_i^k) \times edgePot(X_i^k, X_{i+1}^j))$$

Linking



Why not?

Because the program functions row by row.





Curve-fitting

$$u = a \times v^2 + b \times v + c$$

Weighted Curve-fitting

$$\min_{a,b,c} \sum_i w_i \times (u_i - a \times v_i^2 - b \times v_i - c)^2$$

Weighted Least Square Method

$$\begin{bmatrix} \sum_i w_i \times u_i \times v_i^2 \\ \sum_i w_i \times u_i \times v_i^1 \\ \sum_i w_i \times u_i \times 1 \end{bmatrix} = \begin{bmatrix} \sum_i w_i \times v_i^4 & \sum_i w_i \times v_i^3 & \sum_i w_i \times v_i^2 \\ \sum_i w_i \times v_i^3 & \sum_i w_i \times v_i^2 & \sum_i w_i \times v_i^1 \\ \sum_i w_i \times v_i^2 & \sum_i w_i \times v_i^1 & \sum_i w_i \times 1 \end{bmatrix} \cdot \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

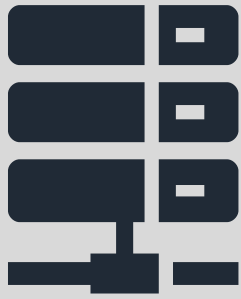


$$score = \sum_i w_i \times \exp\left(-\frac{(u_i - a \times v_i^2 - b \times v_i - c)^2}{\sigma_{sc}^2}\right)$$



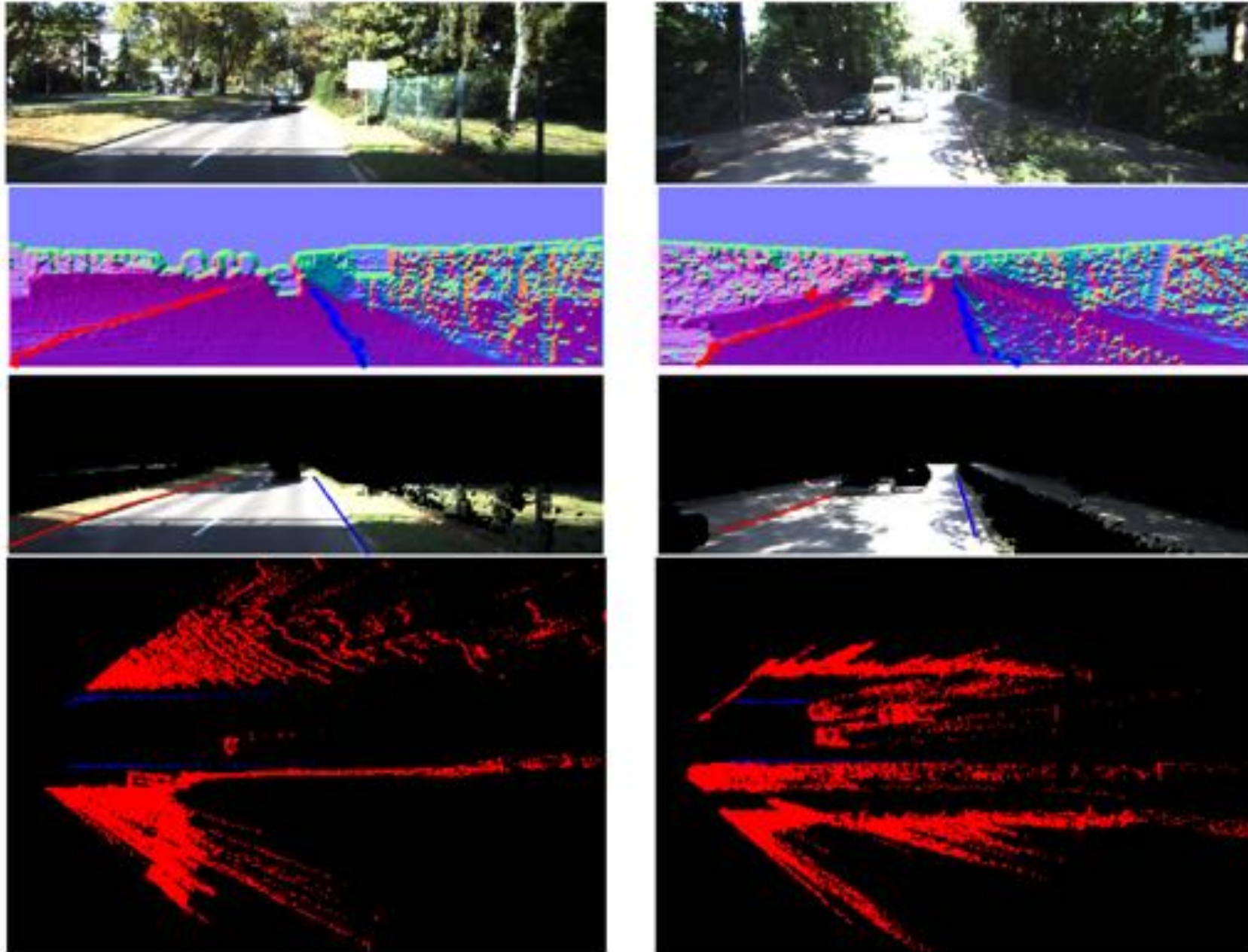
Left score = 36.6604

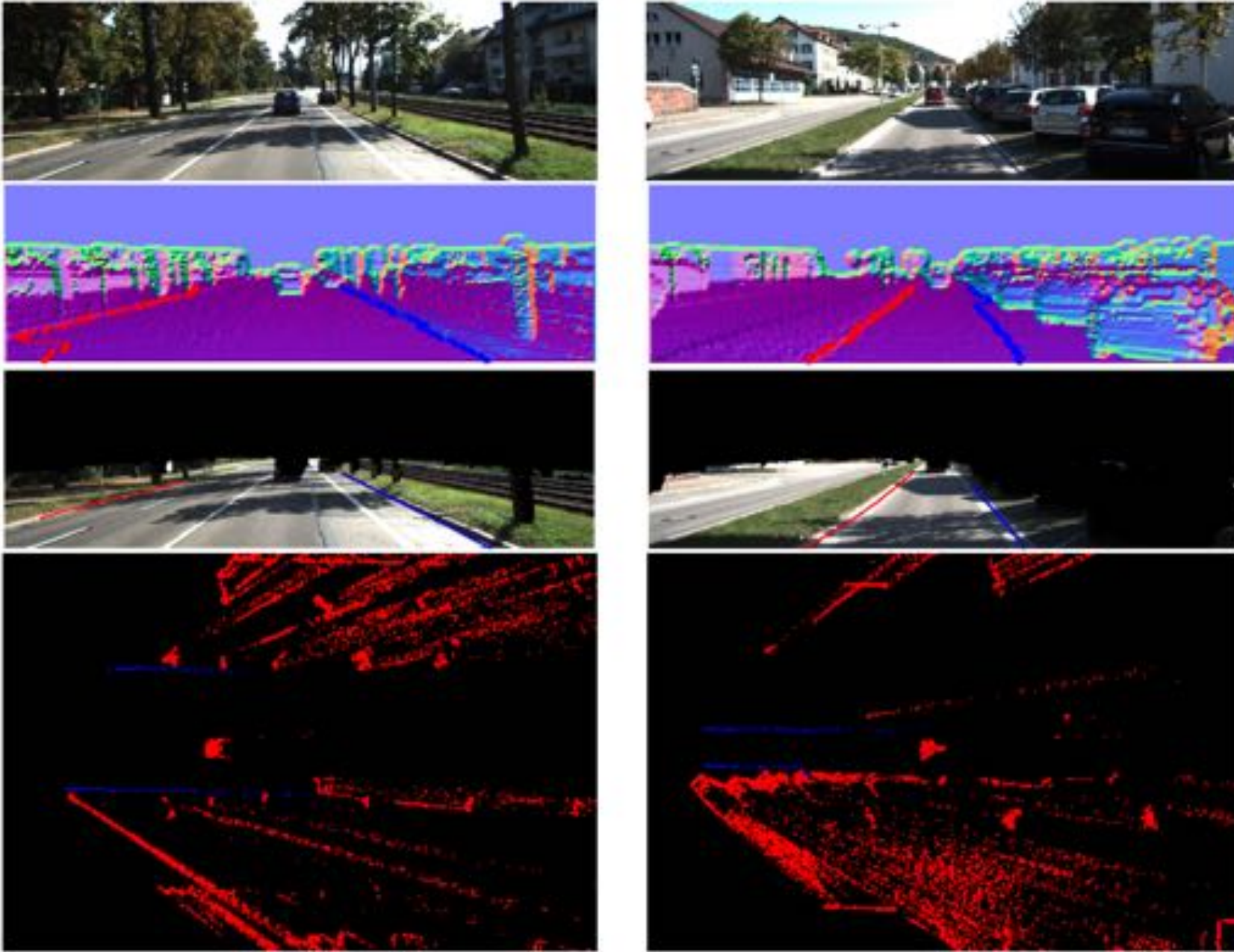
Right score = 12.7776

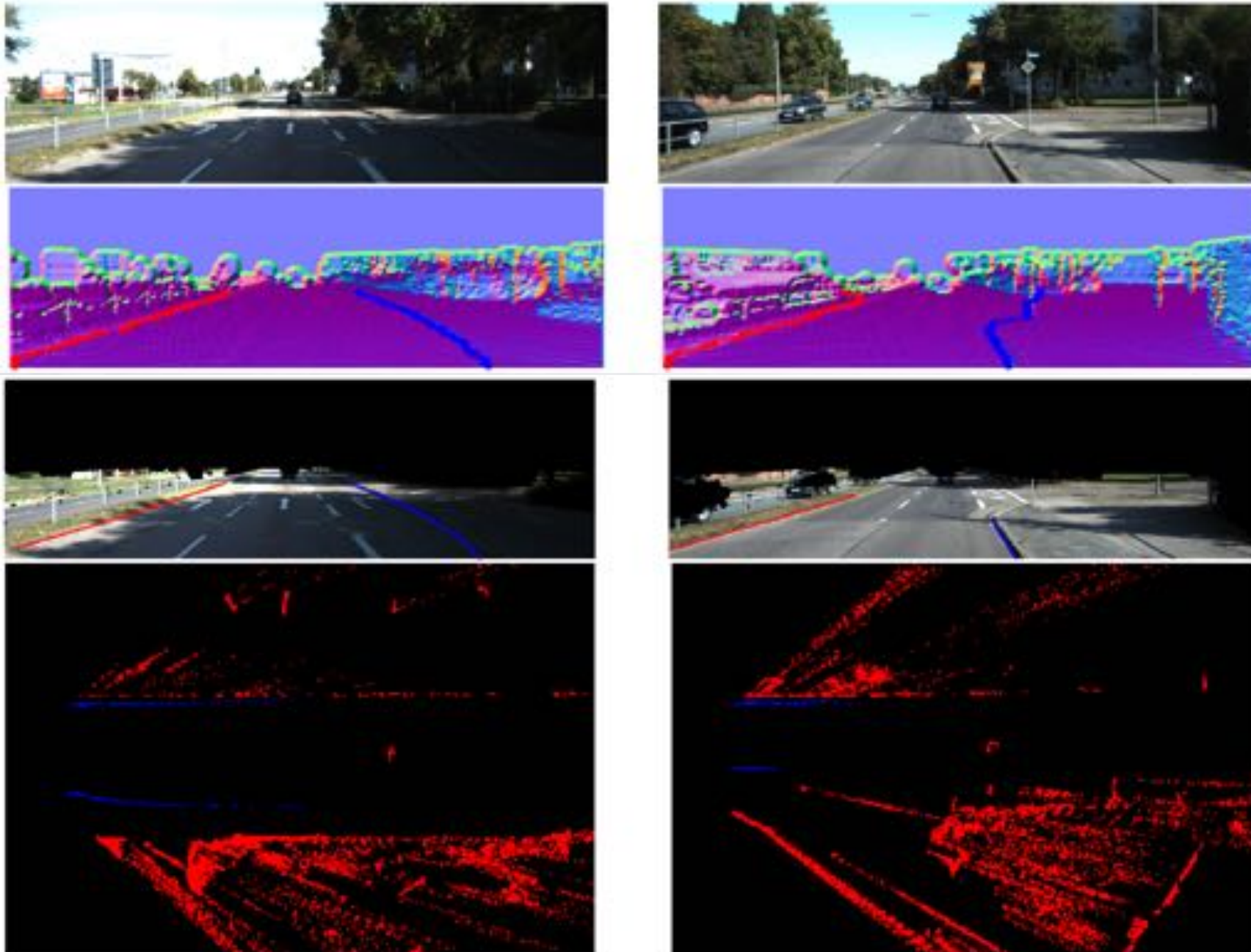


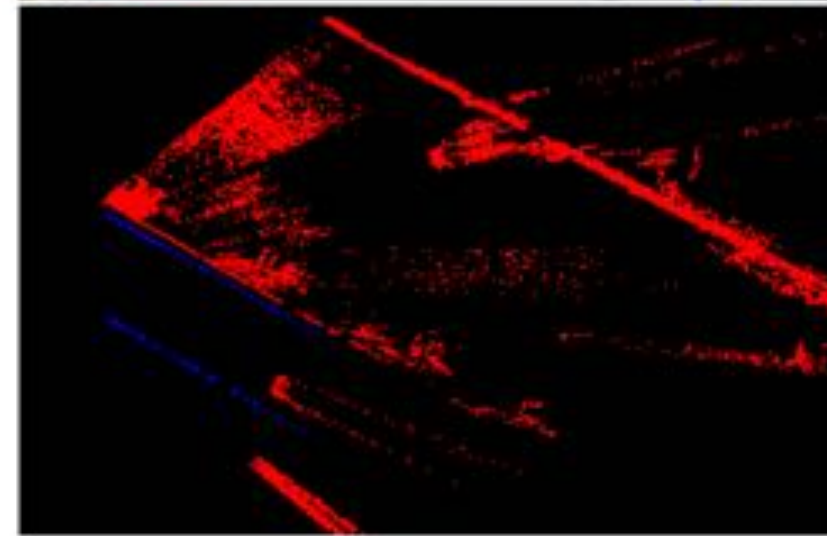
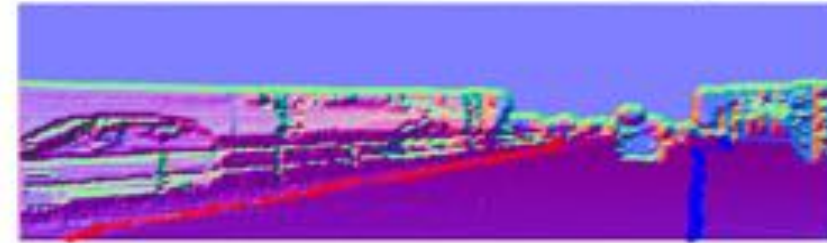
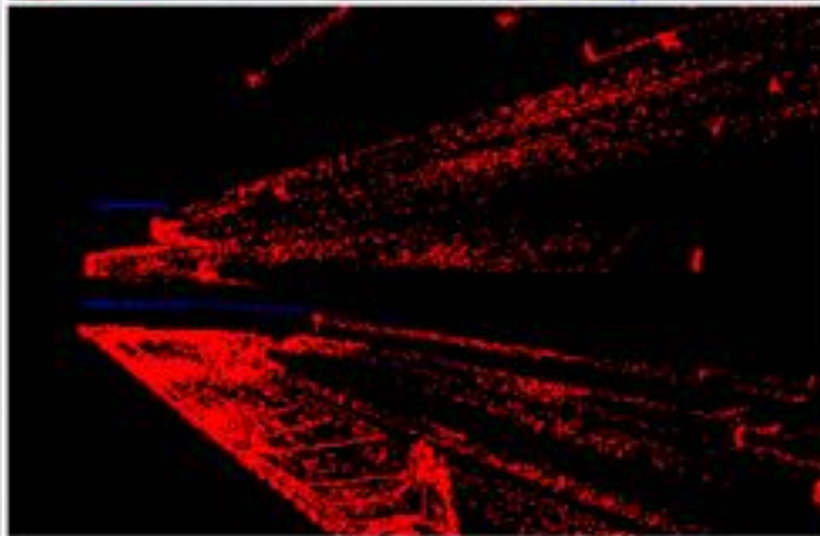
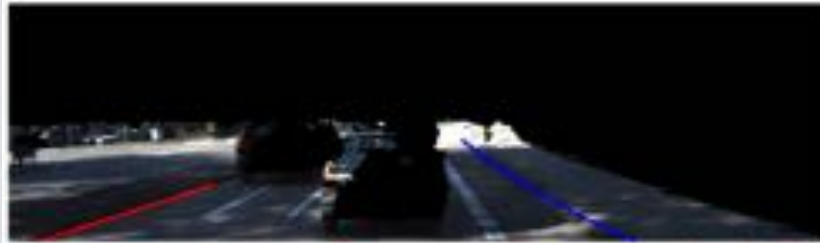
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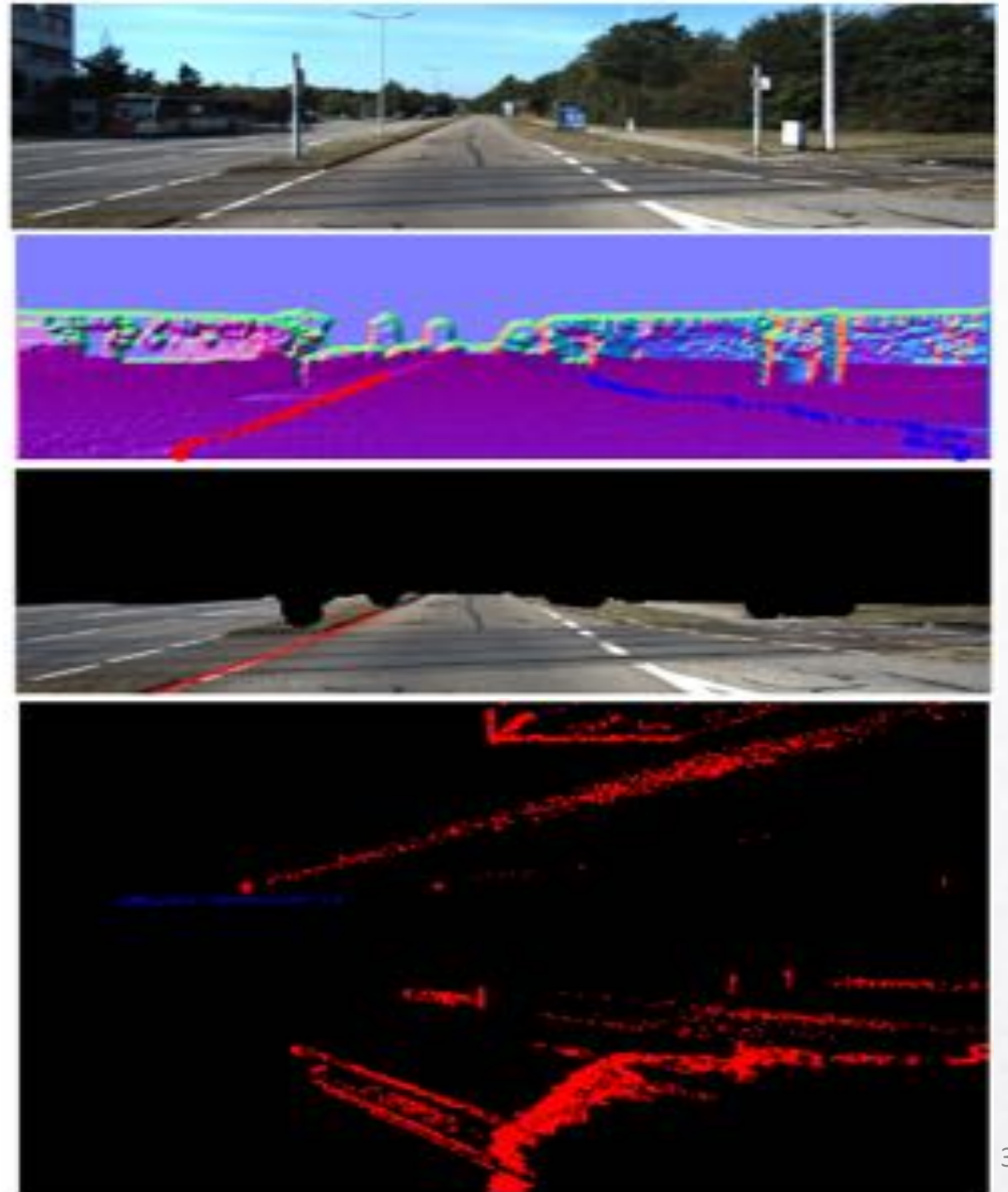
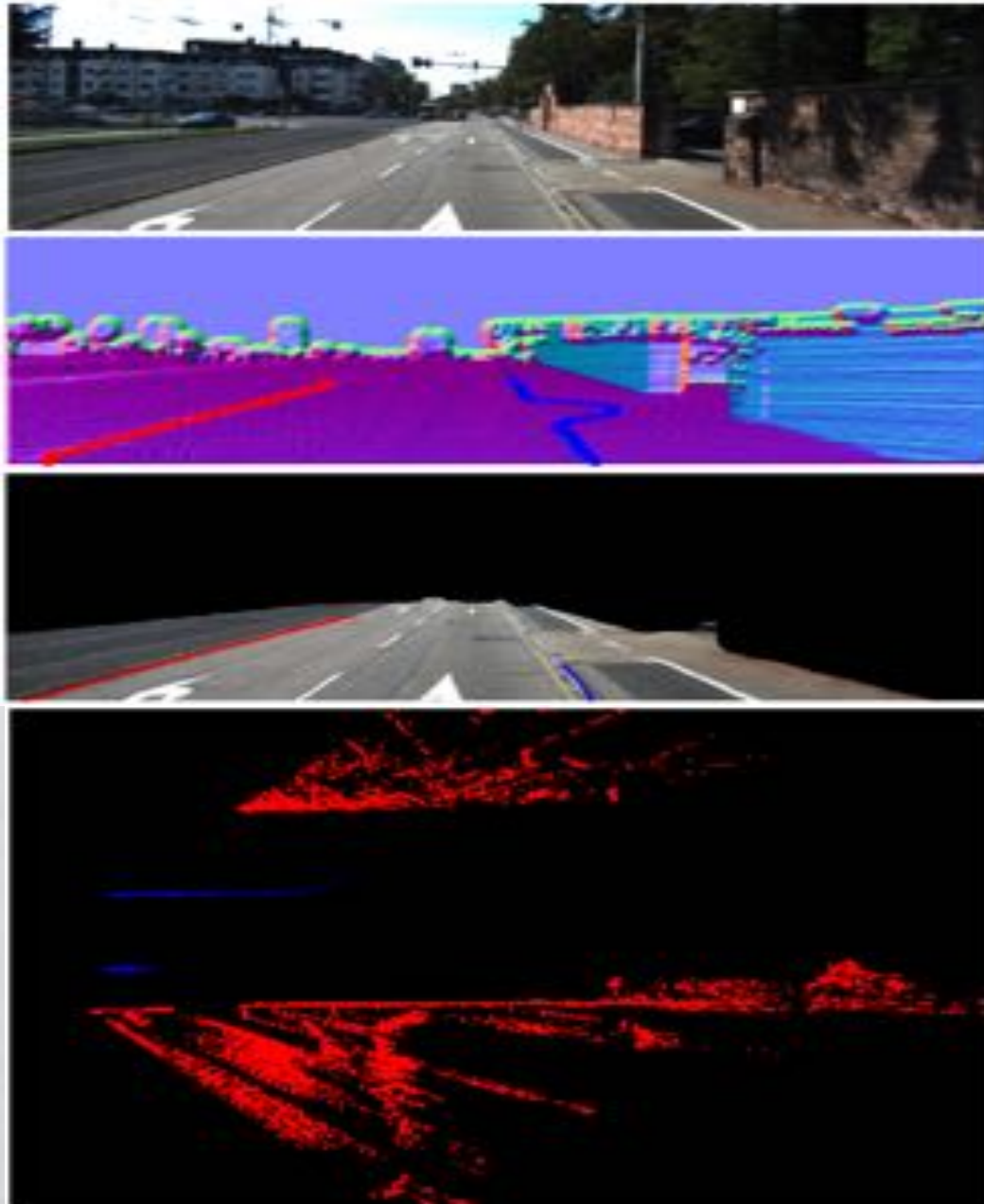
Discussion

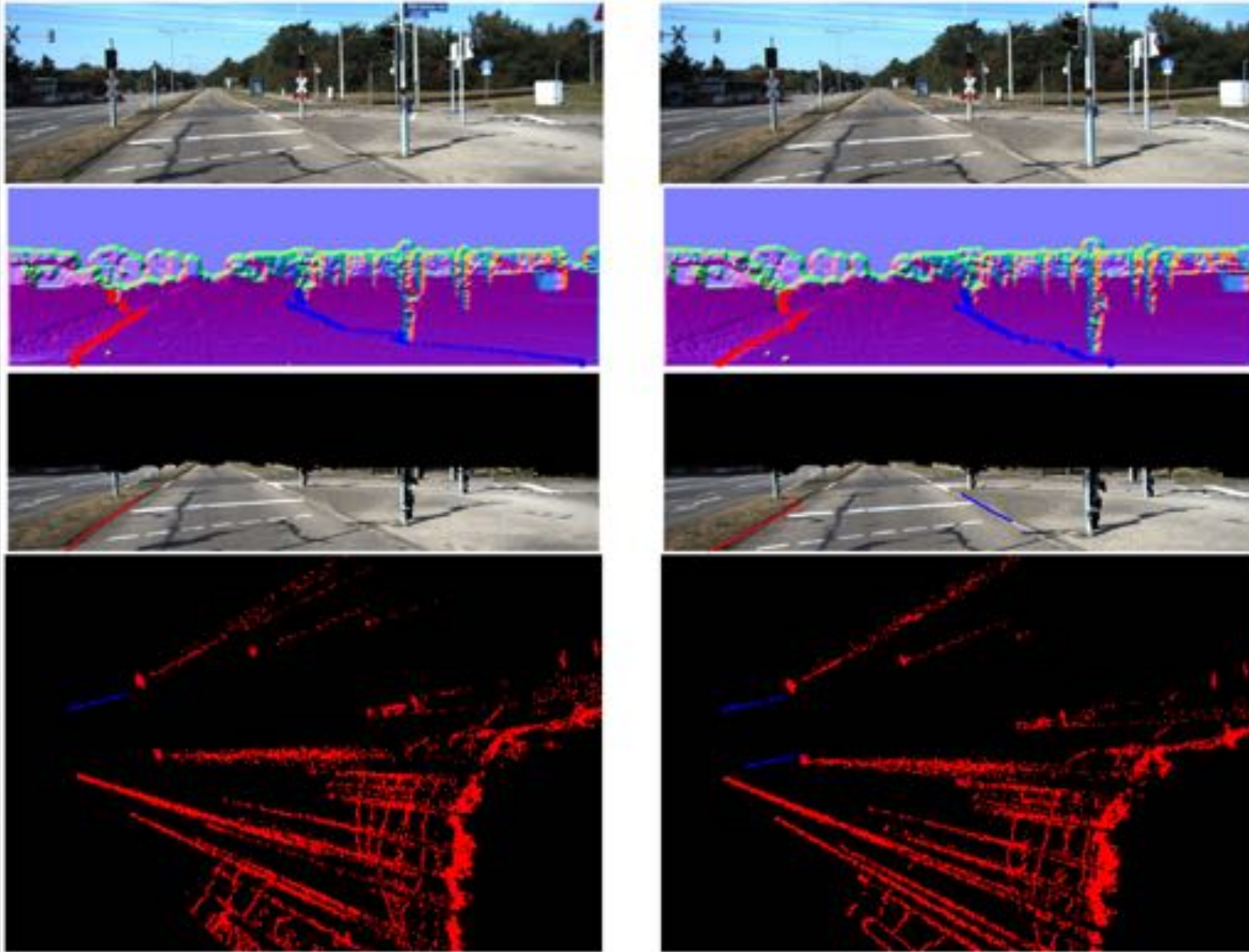














Map building
Vehicle localization
Fusion with more sensors

THANK YOU

