

计算机视觉

立体视觉



中国传媒大学
COMMUNICATION UNIVERSITY OF CHINA



本节主题：

三角测量

本节主题：

三角测量
立体匹配

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三角测量
立体匹配
平面扫描

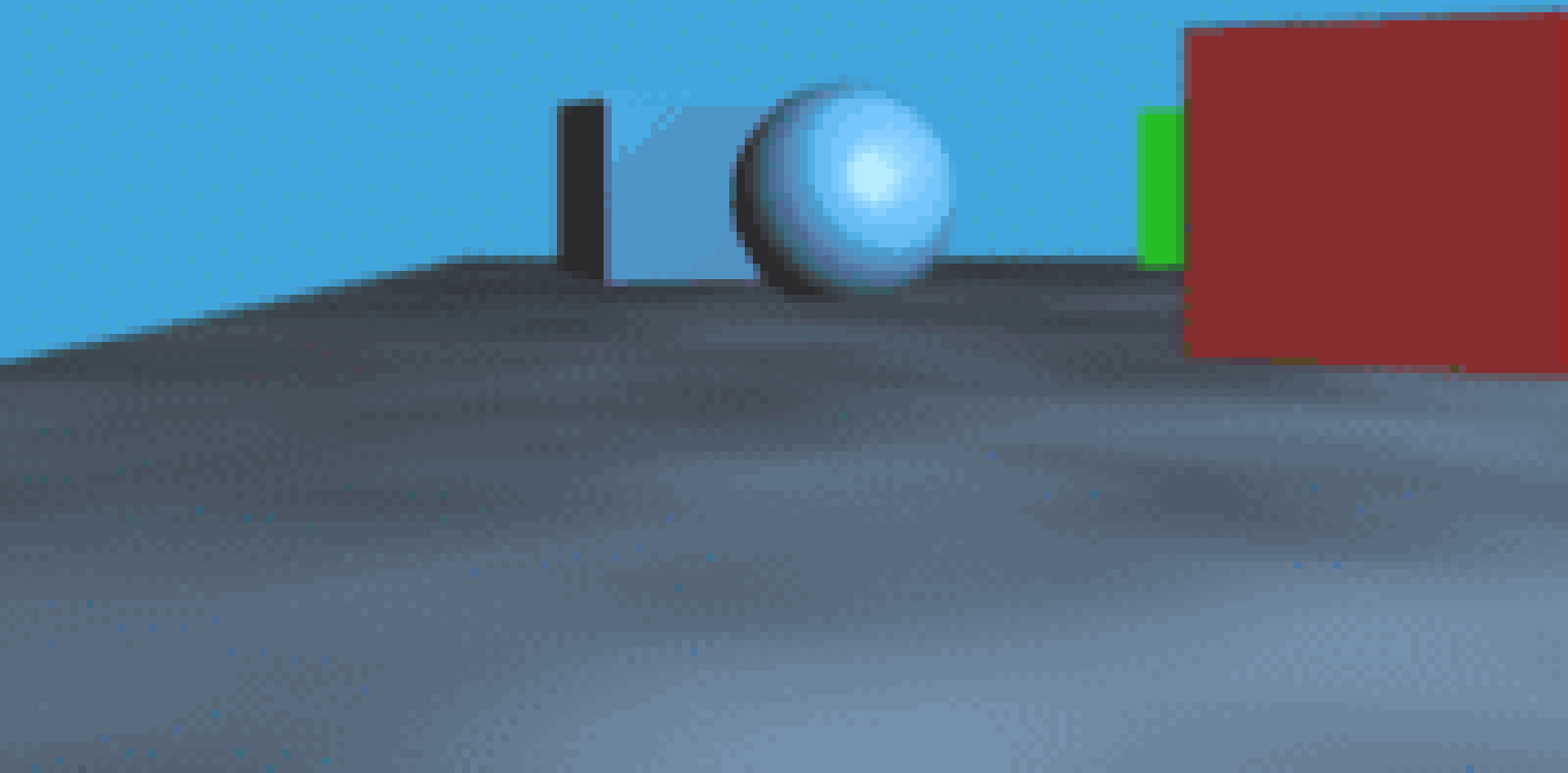
我们如何从图像中恢复3D几何结构？



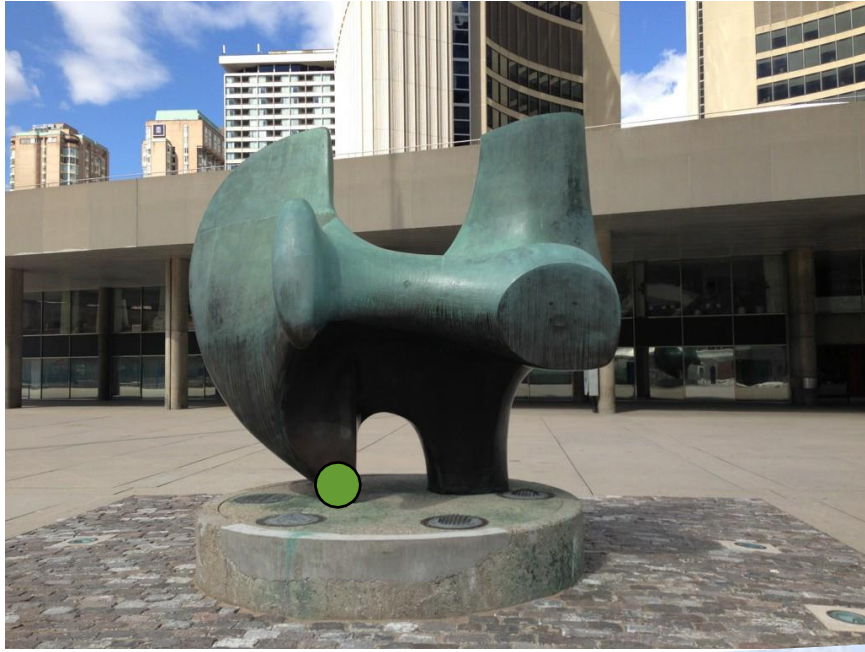
单视点是有歧义的



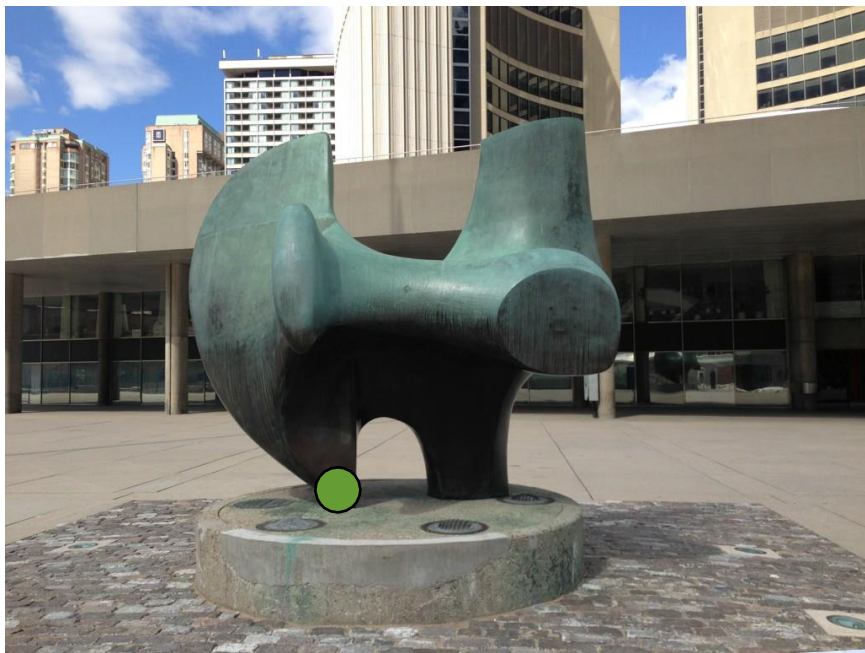
运动视差



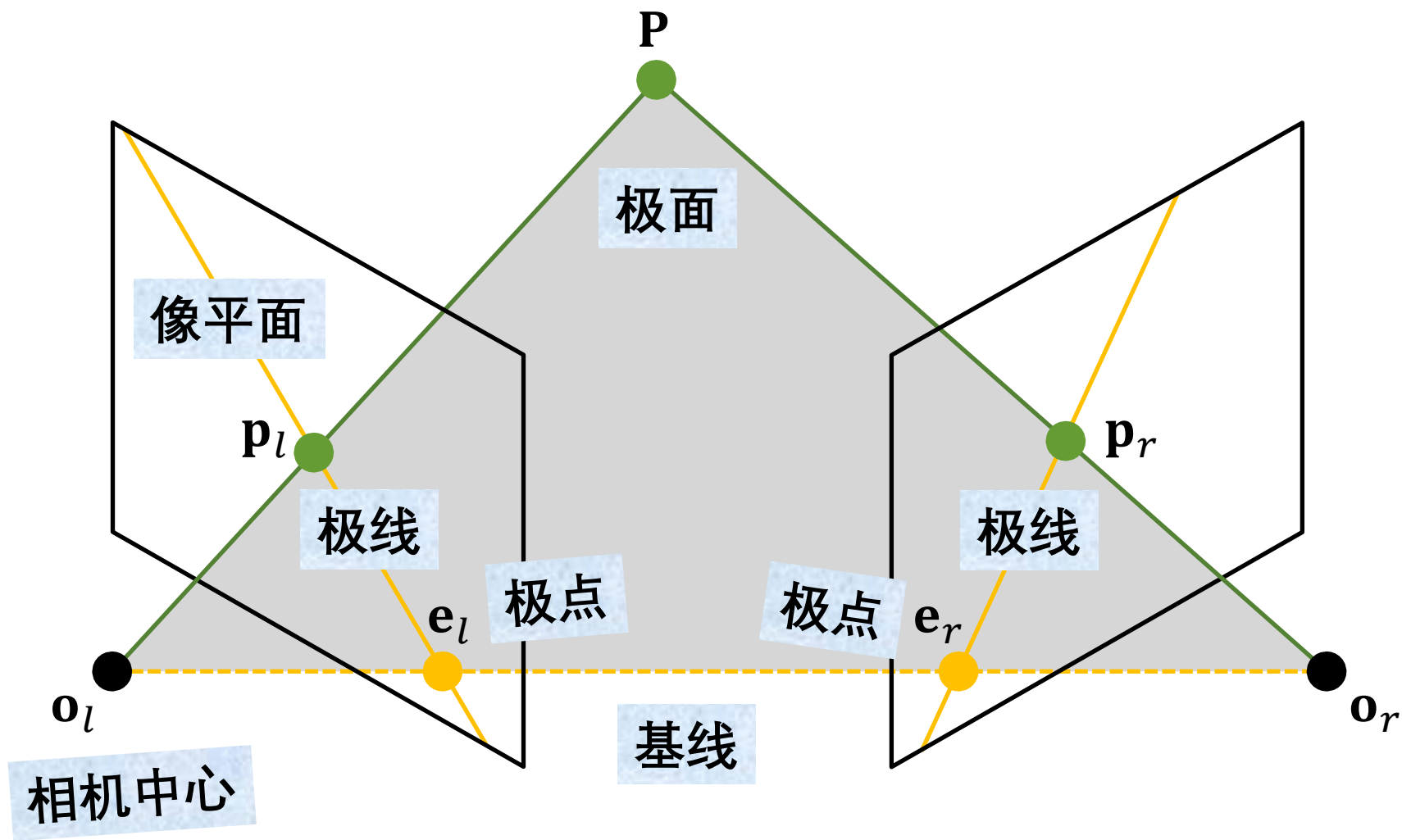


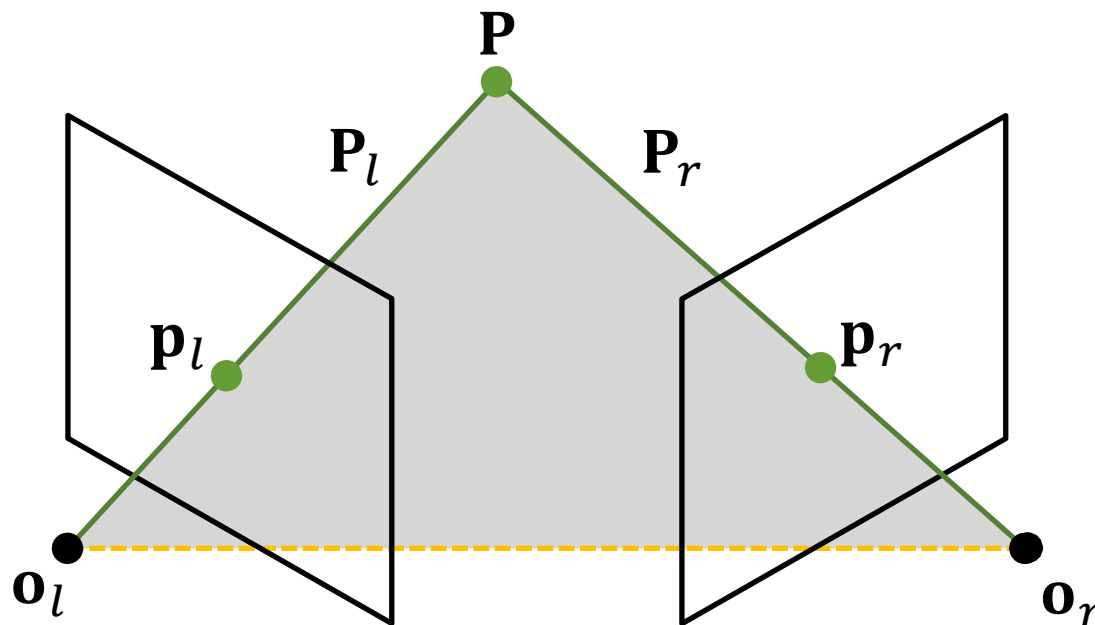


给定左图中的一点



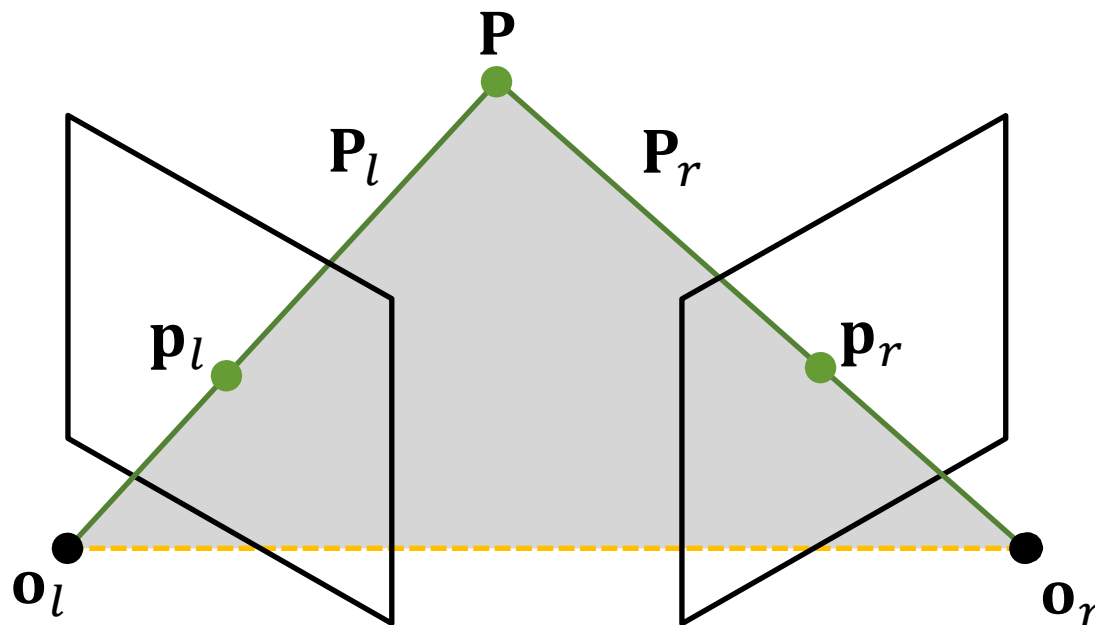
给定左图中的一点
如何找出它在右图中的对应点





基础矩阵： $\mathbf{F} = \mathbf{M}_{\text{int},r}^{-T} \mathbf{E} \mathbf{M}_{\text{int},l}^{-1}$

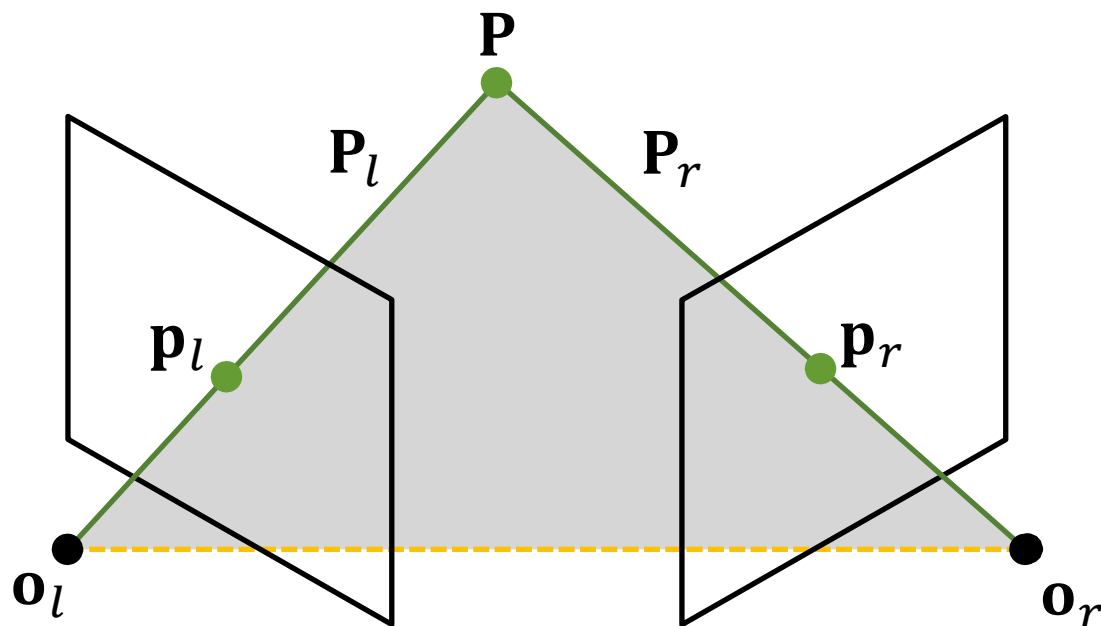
基础矩阵约束： $\tilde{\mathbf{p}}_r^T \mathbf{F} \tilde{\mathbf{p}}_l = 0$



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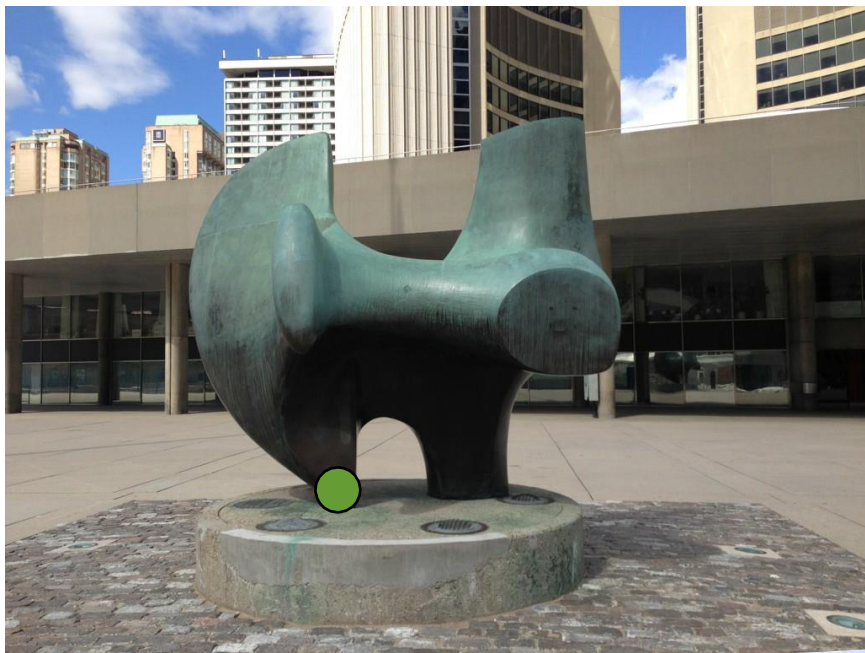
7个自由度



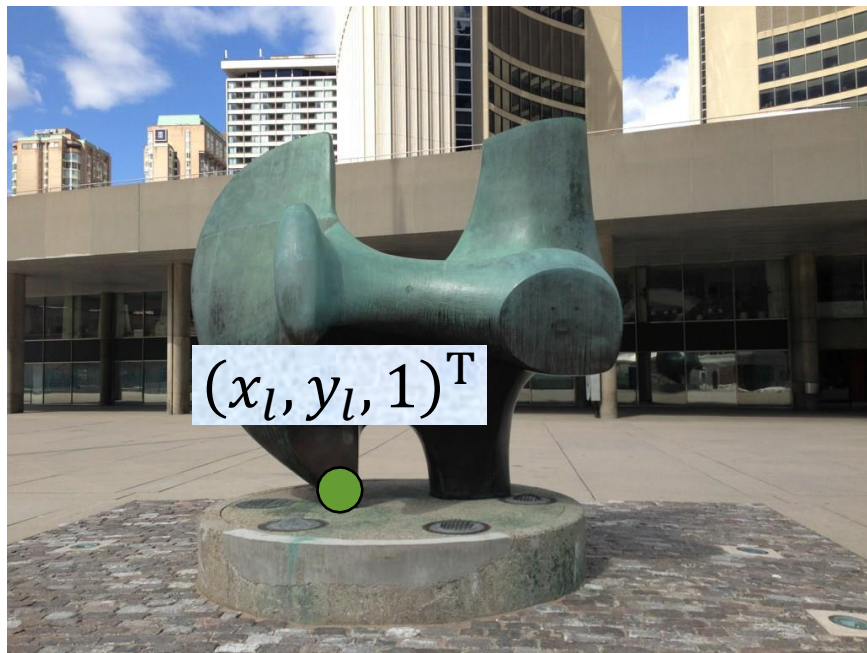
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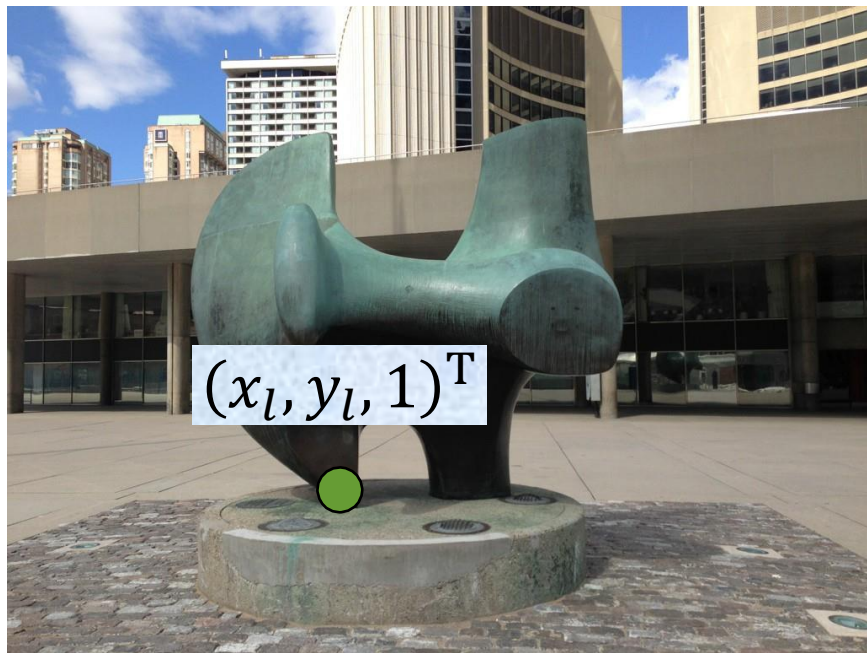
基础矩阵约束: $\tilde{\mathbf{p}}_r^T \mathbf{F} \tilde{\mathbf{p}}_l = 0$

P在左、右两个视点中的像素坐标之间的约束关系



给定左图中的一点
如何找出它在右图中的对应点





搜索空间被缩小到一条直线

H

单应矩阵

vs.

F

基础矩阵

$$\mathbf{x}' = \mathbf{H}\mathbf{x}$$

单应矩阵将一个点映射到一个点

$$\mathbf{l}' = \mathbf{F}\mathbf{x}$$

基础矩阵将一个点映射到一条直线

回顾：
8点算法

A computer algorithm for reconstructing a scene from two projections

H. C. Longuet-Higgins

Laboratory of Experimental Psychology, University of Sussex,
Brighton BN1 9QJ, UK

8点算法

A simple algorithm for reconstructing the three-dimensional structure of a scene from a correlated pair of perspective projections is described here, when the spatial relationship between the two projections is unknown. This problem is relevant not only to photographic surveying¹ but also to binocular vision², where the non-visual information available to the observer about the orientation and focal length of each eye is much less accurate than the optical information supplied by the retinal images.

Nature, 1981

回顾：
8点算法

$$\mathbf{p}_r^T \mathbf{F} \mathbf{p}_l = 0$$

$$\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix} = \mathbf{0}$$

n 对对应点

回顾：
8点算法

$$\mathbf{p}_r^T \mathbf{F} \mathbf{p}_l = 0$$

$$\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix} = \mathbf{0}$$

矩阵秩为8

回顾：
8点算法

$$\mathbf{p}_r^T \mathbf{F} \mathbf{p}_l = 0$$

$$\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix} = \mathbf{0}$$

矩阵秩为8

8对对应点可得一组非零解

回顾：
8点算法

$$\mathbf{p}_r^T \mathbf{F} \mathbf{p}_l = 0$$

$$\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix} = \mathbf{0}$$

矩阵秩为8

8对对应点可得一组非零解
解是零空间

SVD求解
基础矩阵

$$\mathbf{p}_r^T \mathbf{F} \mathbf{p}_l = 0$$

$$\underbrace{\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix}}_{\mathbf{A}} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix} = \mathbf{0}$$

SVD求解
基础矩阵

$$\mathbf{p}_r^T \mathbf{F} \mathbf{p}_l = 0$$

$$\underbrace{\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix}}_{\mathbf{A}} \underbrace{\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}}_{\mathbf{f}} = \mathbf{0}$$

$$\underset{\mathbf{A}}{\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix}} \underset{\mathbf{f}}{\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}} = \mathbf{0}$$

齐次最小二乘问题

$$\underset{\mathbf{A}}{\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix}} \underset{\mathbf{f}}{\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}} = \mathbf{0}$$

齐次最小二乘问题

$$\arg \min_{\mathbf{f}} \|\mathbf{A}\mathbf{f}\|^2$$

并服从如下约束

$$\|\mathbf{f}\| = 1$$

$$\underset{\mathbf{A}}{\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix}} \underset{\mathbf{f}}{\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}} = \mathbf{0}$$

计算A的SVD，解就是V的最后一列

$$\underset{\mathbf{A}}{\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix}} \underset{\mathbf{f}}{\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}} = \mathbf{0}$$

计算A的SVD，解就是V的最后一列

强制基础矩阵的秩必须为2

图像噪声

In Defense of the Eight-Point Algorithm

Richard I. Hartley

Abstract—The fundamental matrix is a basic tool in the analysis of scenes taken with two uncalibrated cameras, and the eight-point algorithm is a frequently cited method for computing the fundamental matrix from a set of eight or more point matches. It has the advantage of simplicity of implementation. The prevailing view is, however, that it is extremely susceptible to noise and hence virtually useless for most purposes. This paper challenges that view, by showing that by preceding the algorithm with a very simple normalization (translation and scaling) of the coordinates of the matched points, results are obtained comparable with the best iterative algorithms. This improved performance is justified by theory and verified by extensive experiments on real images.

IEEE Transactions on Pattern Analysis and Machine Intelligence, 1997

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解决数值计算问题

$$\mathbf{p}_r^T \mathbf{F} \mathbf{p}_l = 0$$

$$\underbrace{\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix}}_{\mathbf{A}} \underbrace{\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}}_{\mathbf{f}} = \mathbf{0}$$

$$\mathbf{p}_r^T \mathbf{F} \mathbf{p}_l = 0$$

$$\underbrace{\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix}}_{\mathbf{A}} \underbrace{\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}}_{\mathbf{f}} = \mathbf{0}$$

A是病态的

$$\mathbf{p}_r^T \mathbf{F} \mathbf{p}_l = 0$$

$$\underbrace{\begin{pmatrix} x_{r1}x_{l1}, x_{r1}y_{l1}, x_{r1}, y_{r1}x_{l1}, y_{r1}y_{l1}, y_{r1}, x_{l1}, y_{l1}, 1 \\ \vdots \\ x_{rn}x_{ln}, x_{rn}y_{ln}, x_{rn}, y_{rn}x_{ln}, y_{rn}y_{ln}, y_{rn}, x_{ln}, y_{ln}, 1 \end{pmatrix}}_{\mathbf{A}} \underbrace{\begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix}}_{\mathbf{f}} = \mathbf{0}$$

变换对应点的坐标改善A的状态

4

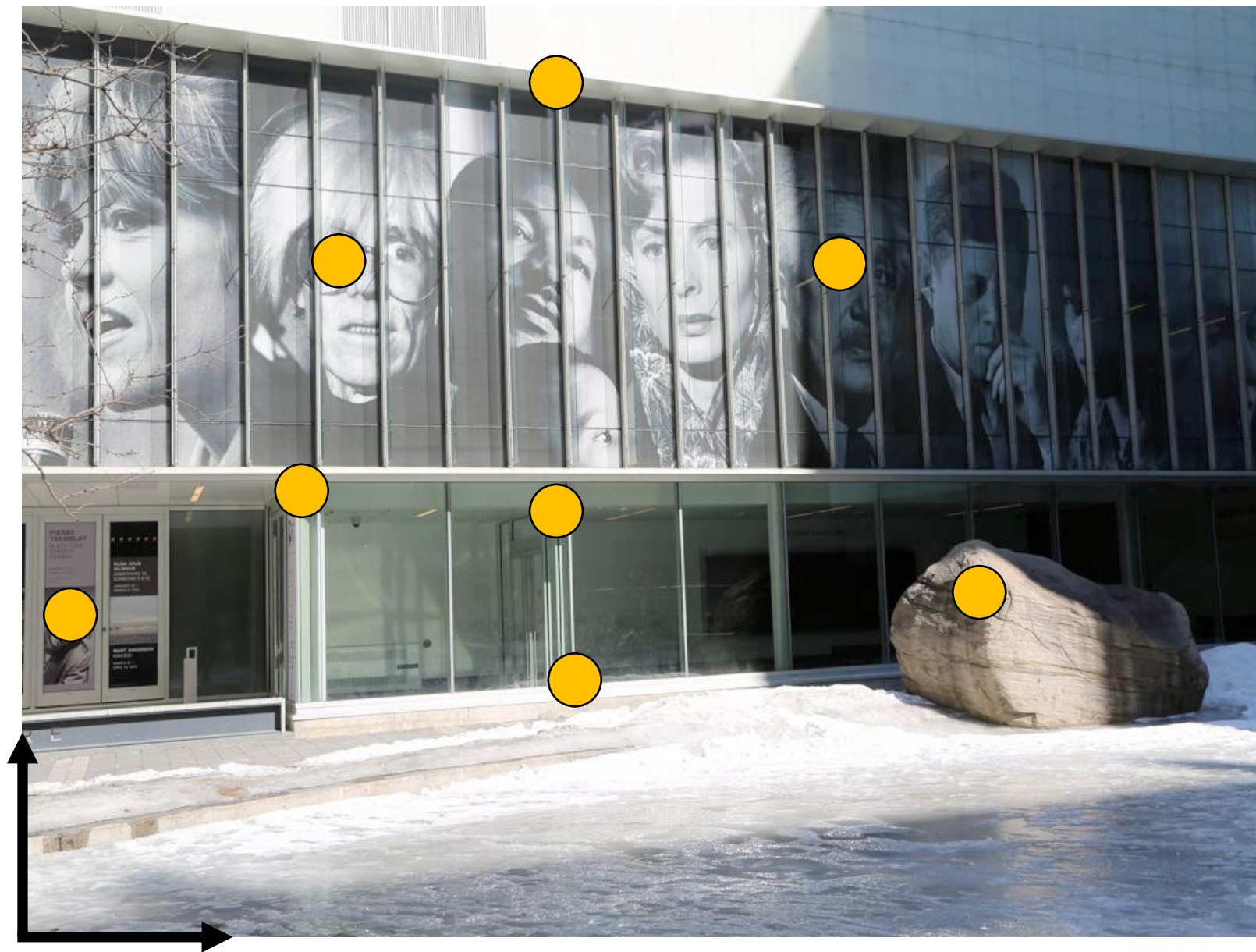
主要步骤

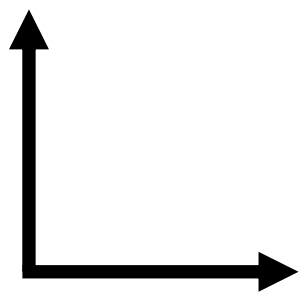
步骤1

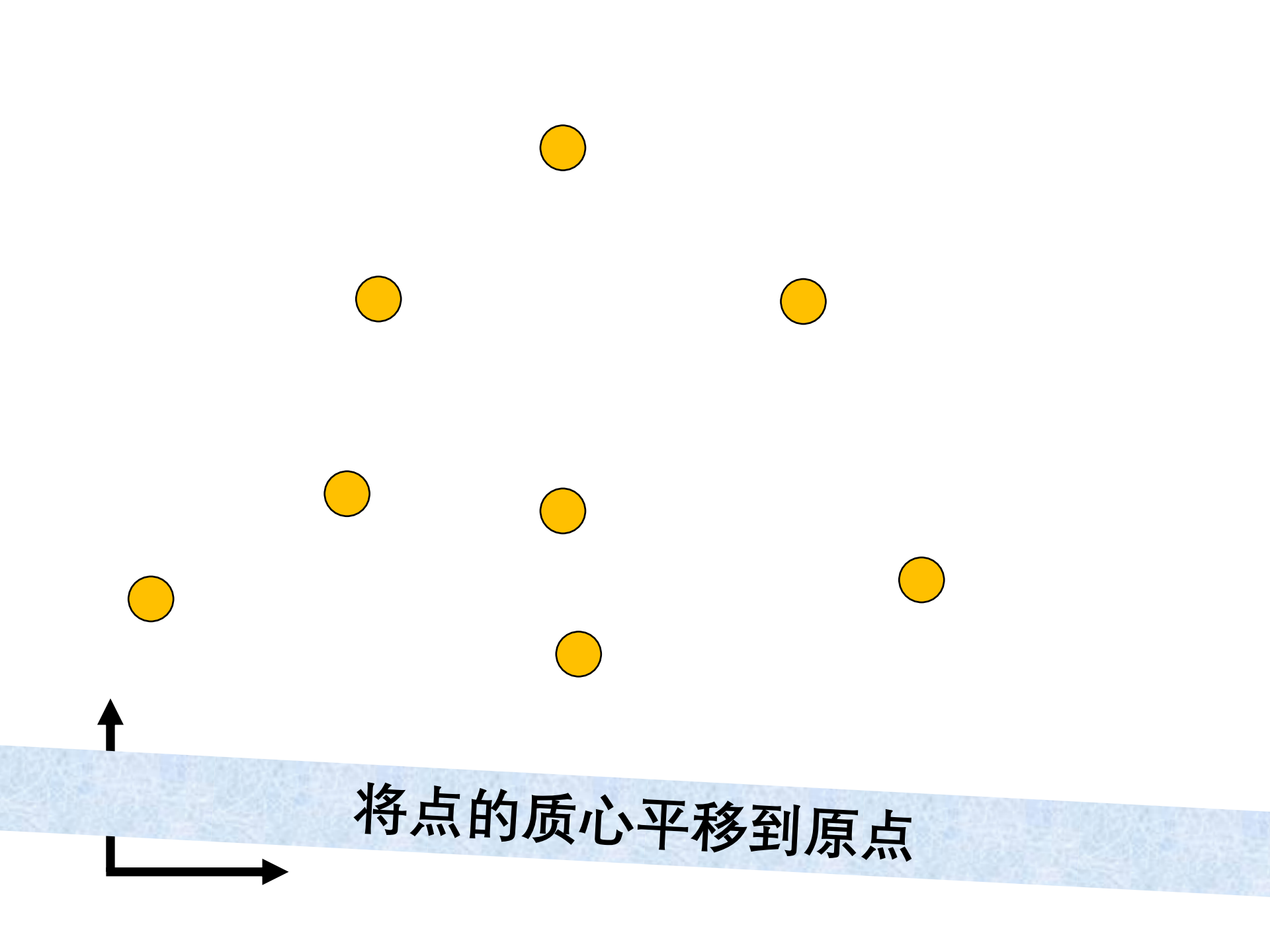
将数据点中心化

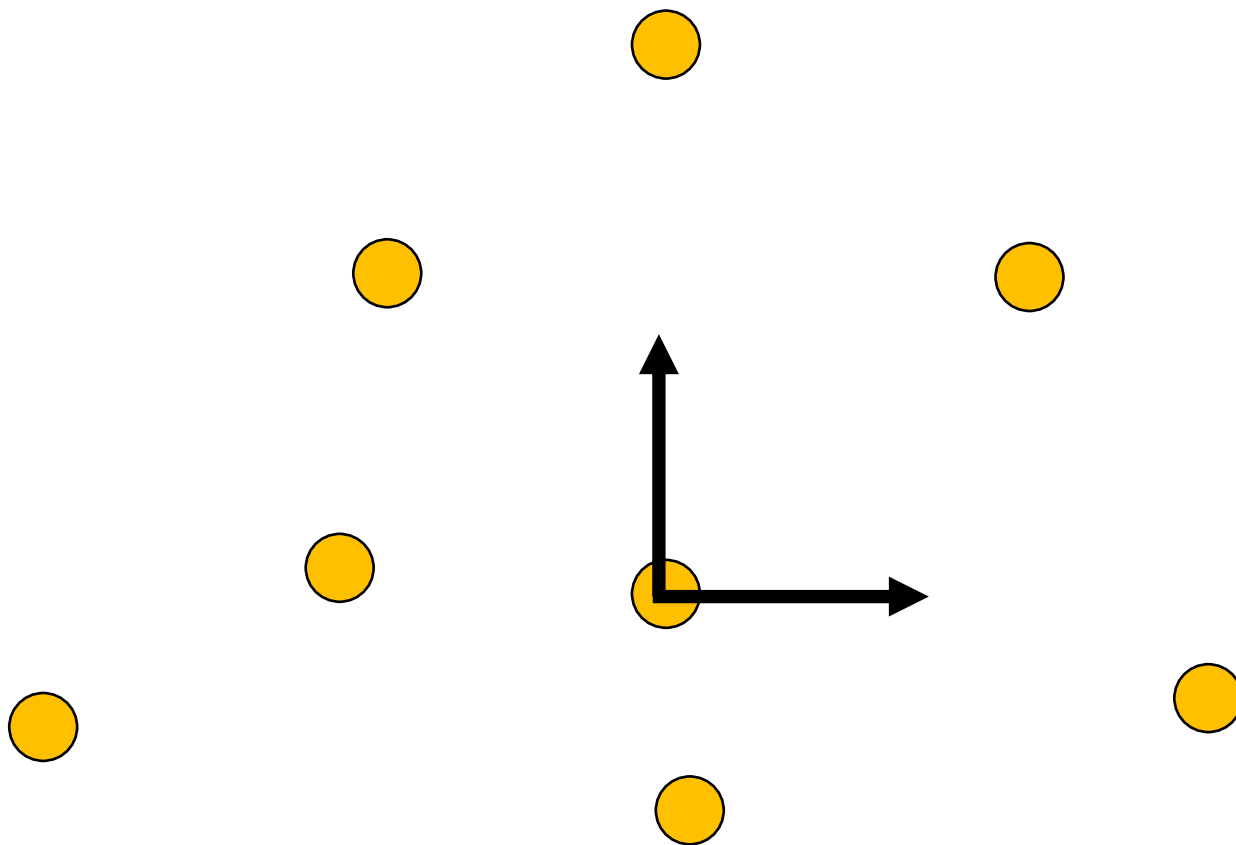








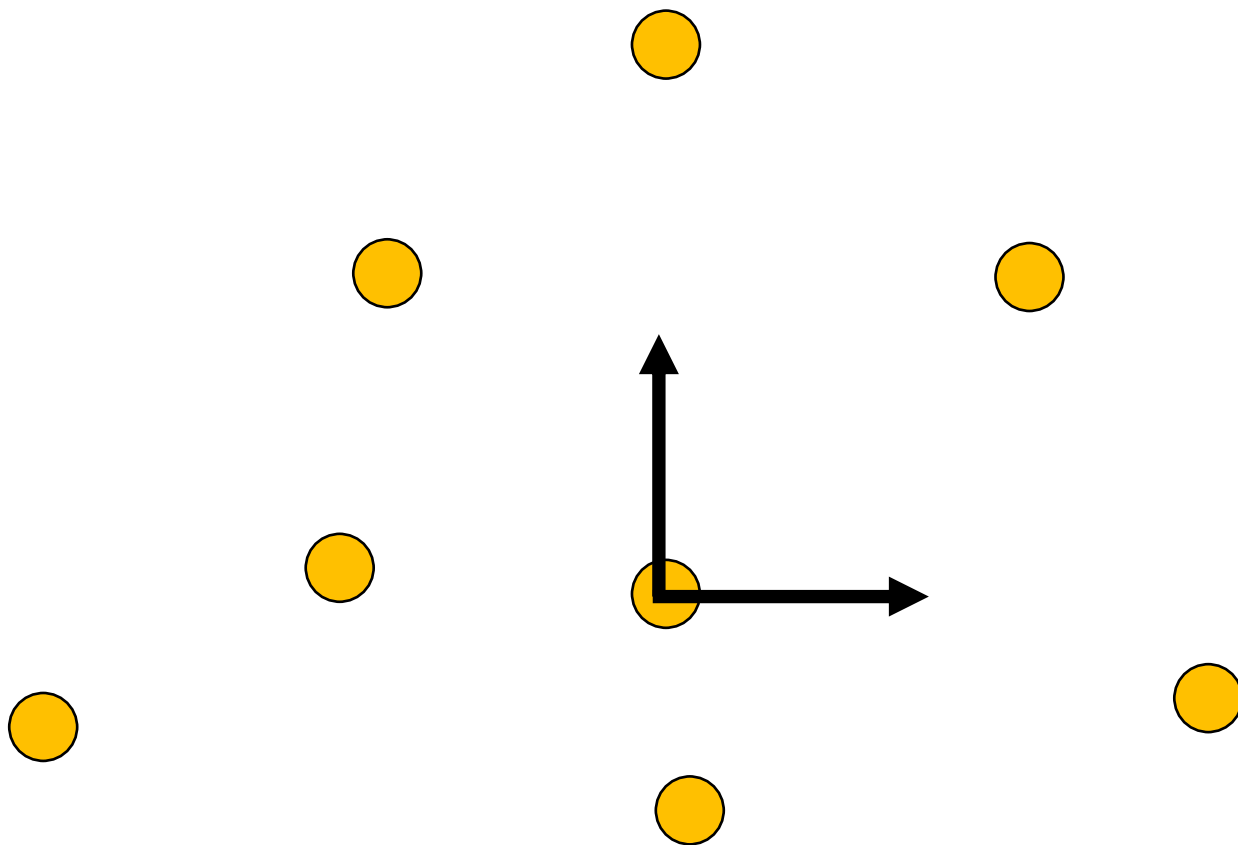


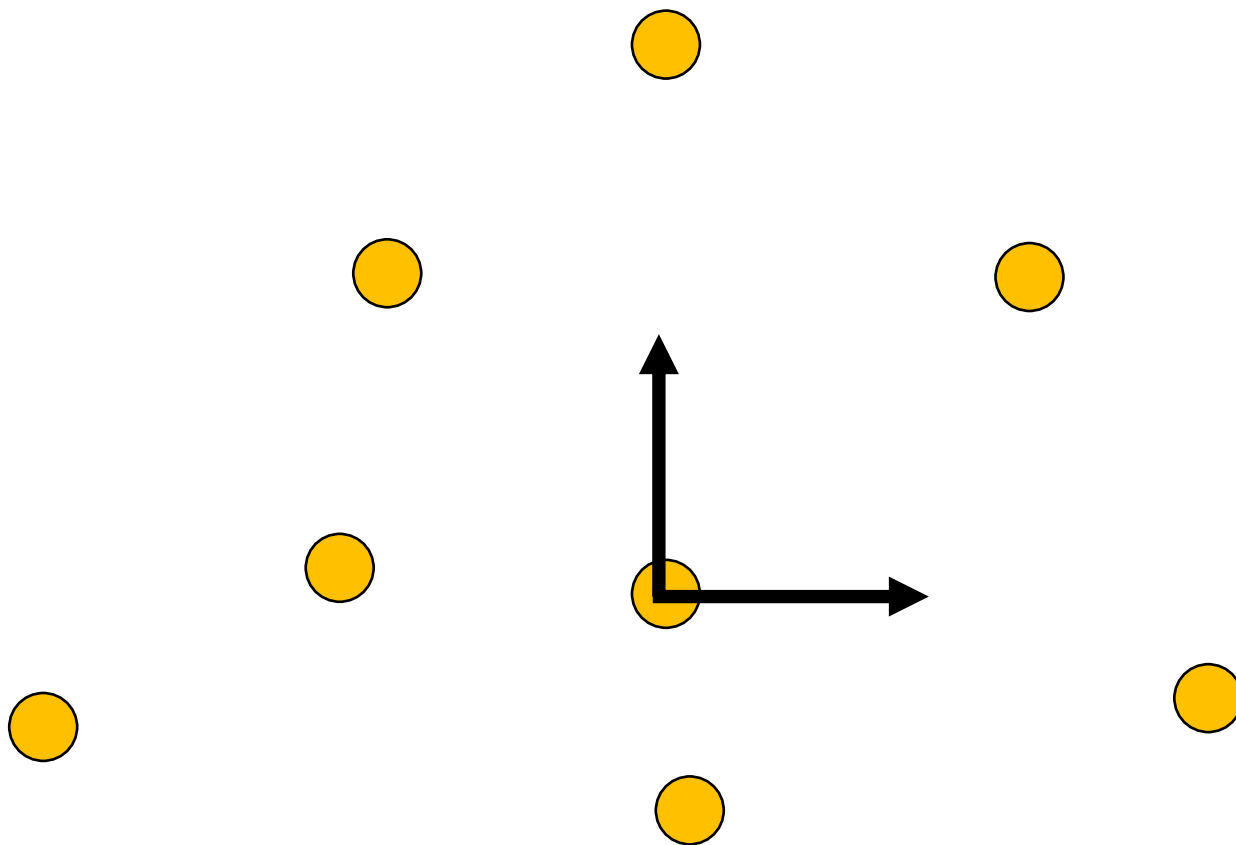


将点的质心平移到原点

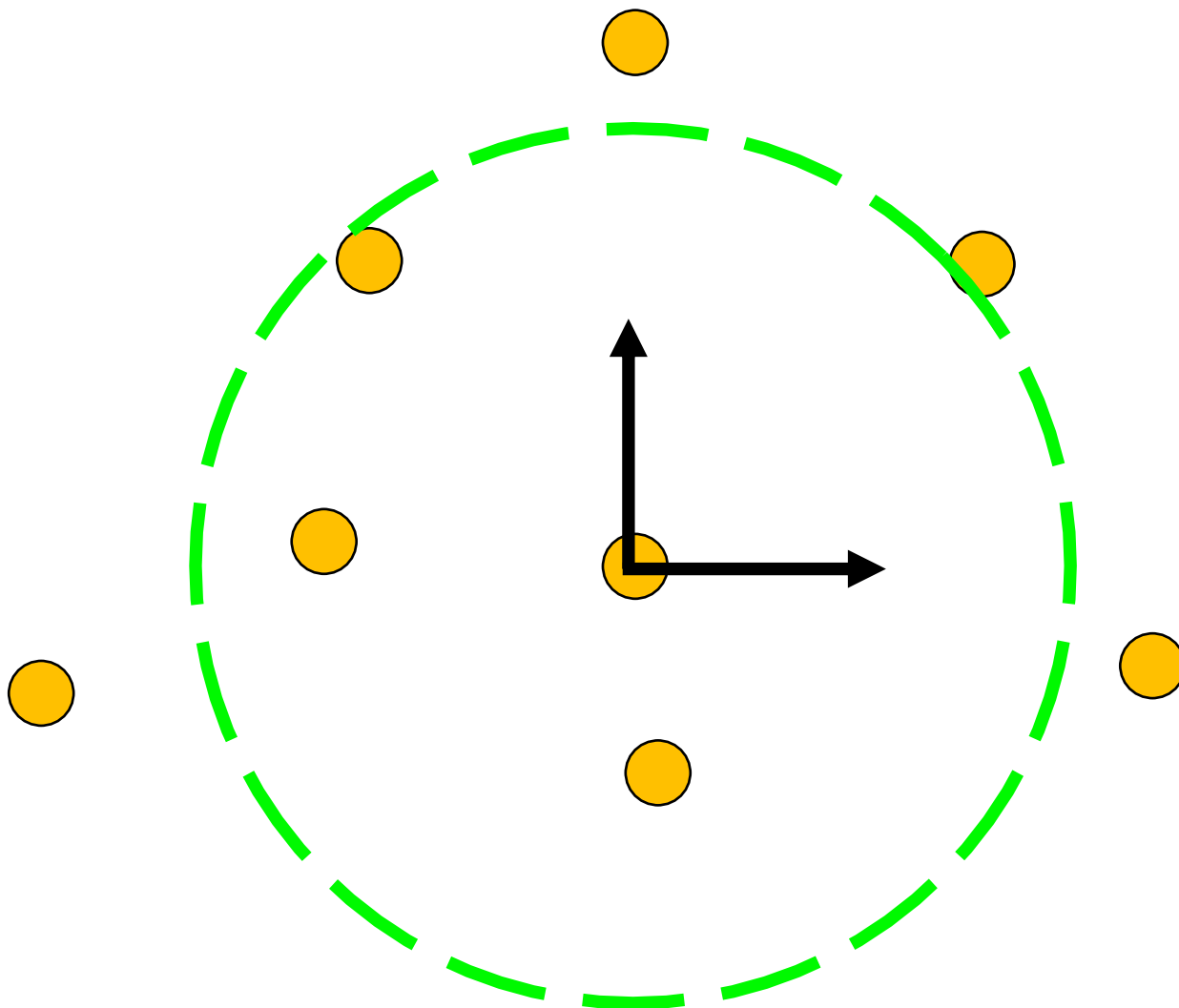
步骤2

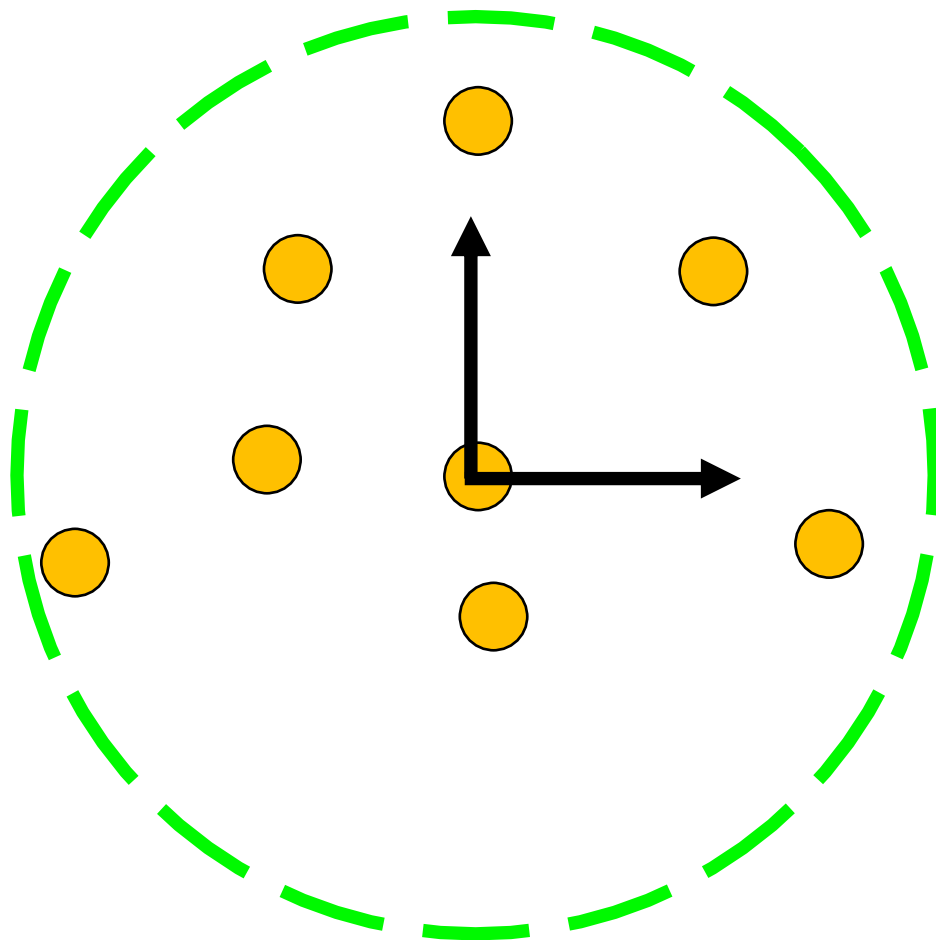
缩放数据





缩放点的坐标使得它们到原点的平均距离等于2像素





步骤3

计算基础矩阵

$$(\mathbf{T}_r \mathbf{p}_r)^T \mathbf{F} (\mathbf{T}_l \mathbf{p}_l) = 0$$

$$(\mathbf{T}_r \mathbf{p}_r)^T \mathbf{F} (\mathbf{T}_l \mathbf{p}_l) = 0$$

利用归一化后的对应点对求解基础矩阵

$$(\mathbf{T}_r \mathbf{p}_r)^T \mathbf{F} (\mathbf{T}_l \mathbf{p}_l) = 0$$

强制估计的基础矩阵秩为2

步骤4

去归一化基础矩阵

$$(\mathbf{T}_r \mathbf{p}_r)^T \mathbf{F} (\mathbf{T}_l \mathbf{p}_l) = 0$$

$$(\mathbf{T}_r \mathbf{p}_r)^T \mathbf{F} (\mathbf{T}_l \mathbf{p}_l) = 0$$

展开

$$\mathbf{p}_r^T \mathbf{T}_r^T \mathbf{F} \mathbf{T}_l \mathbf{p}_l = 0$$

$$(\mathbf{T}_r \mathbf{p}_r)^T \mathbf{F} (\mathbf{T}_l \mathbf{p}_l) = 0$$

展开

$$\mathbf{p}_r^T \mathbf{T}_r^T \mathbf{F} \mathbf{T}_l \mathbf{p}_l = 0$$

$$\mathbf{F} = \mathbf{T}_r^{\mathbf{T}} \hat{\mathbf{F}} \mathbf{T}_l$$

归一化8点
算法总结

归一化8点 算法总结

1. 将数据点的质心平移到原点

归一化8点 算法总结

1. 将数据点的质心平移到原点
2. 缩放点的坐标使得它们到原点的平均距离等于2像素

归一化8点 算法总结

1. 将数据点的质心平移到原点
2. 缩放点的坐标使得它们到原点的平均距离等于2像素
3. 按照步骤1、2分别独立处理两张图像，并估计基础矩阵

归一化8点 算法总结

1. 将数据点的质心平移到原点
2. 缩放点的坐标使得它们到原点的平均距离等于2像素
3. 按照步骤1、2分别独立处理两张图像，并估计基础矩阵
4. 对所估计的基础矩阵去归一化

**如果没有已知的对应关系，
我们如何估计基本矩阵？**

Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography

Martin A. Fischler and Robert C. Bolles
SRI International

A new paradigm, Random Sample Consensus (RANSAC), for fitting a model to experimental data is introduced. RANSAC is capable of interpreting/smoothing data containing a significant percentage of gross errors, and is thus ideally suited for applications in automated image analysis where interpretation is based on the data provided by error-prone feature detectors. A major portion of this paper describes the application of RANSAC to the Location Determination Problem (LDP): Given an image depicting a set of landmarks, determine a set of points that best fit a model in space. In response to a RANSAC requirement, new results are derived on the minimum number of landmarks needed to obtain a solution, and algorithms are presented for

I. Introduction

We introduce a new paradigm, Random Sample Consensus (RANSAC), for fitting a model to experimental data; and illustrate its use in scene analysis and automated cartography. The application discussed, the location determination problem (LDP), is treated not only beyond that of a mere example of the use of the RANSAC paradigm, but new basic findings concerning the conditions under which the LDP can be solved are presented and a comprehensive approach to the solution of this problem that we anticipate to be of broad interest in practical applications is described.

To a large extent, scene analysis (and, in fact, science in general) is concerned with the interpretation of sensed data in terms of a set of predefined models. Conceptually, the interpretation problem can be stated as follows: First, there is the problem of finding the best match between the data and one of the available models (the classification problem); Second, there is the problem of computing the best values for the free parameters of the selected model (the parameter estimation problem). In practice, these two problems are not independent—a solution to the parameter estimation problem is often required to solve the classification problem.

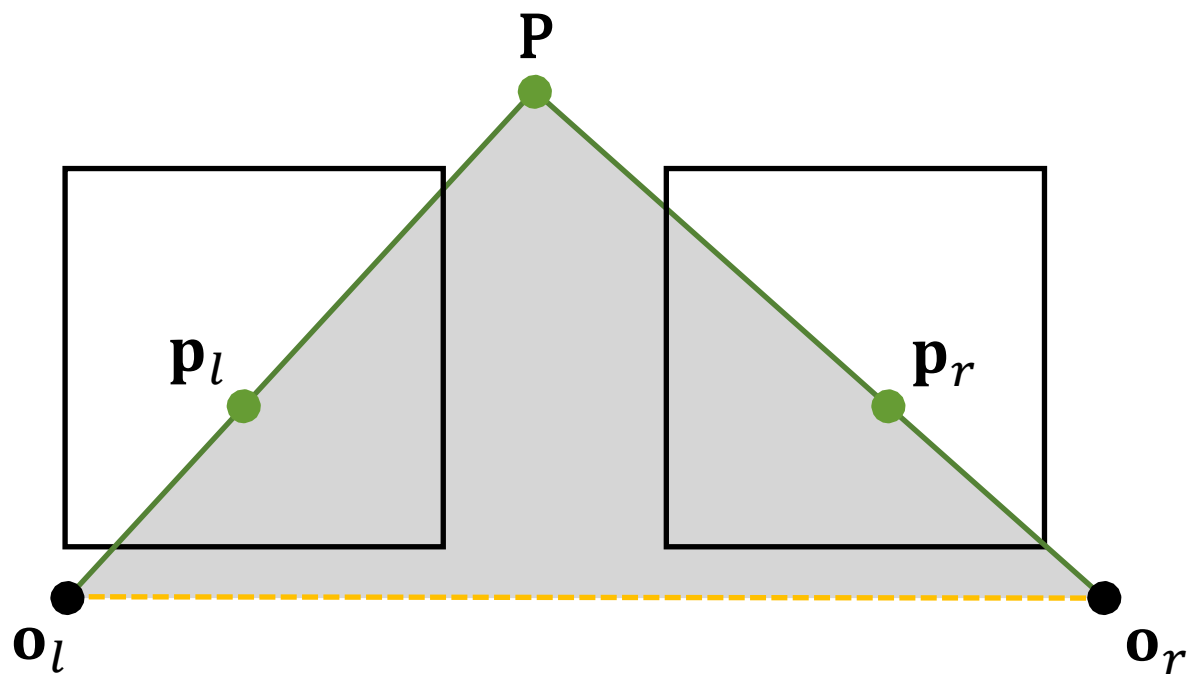
Classical techniques for parameter estimation, such as least squares, optimize (according to a specified objective function) the fit of a functional description (model) to *all* of the presented data. These techniques have no internal mechanisms for detecting and rejecting gross errors. They are a *naïve* technique that rely on the assumption that the data are *good* (that the maximum expected deviation of any datum from the assumed model is a direct function of the size of the data set, and thus regardless of the size of the data set, there will always be enough good values to smooth out any

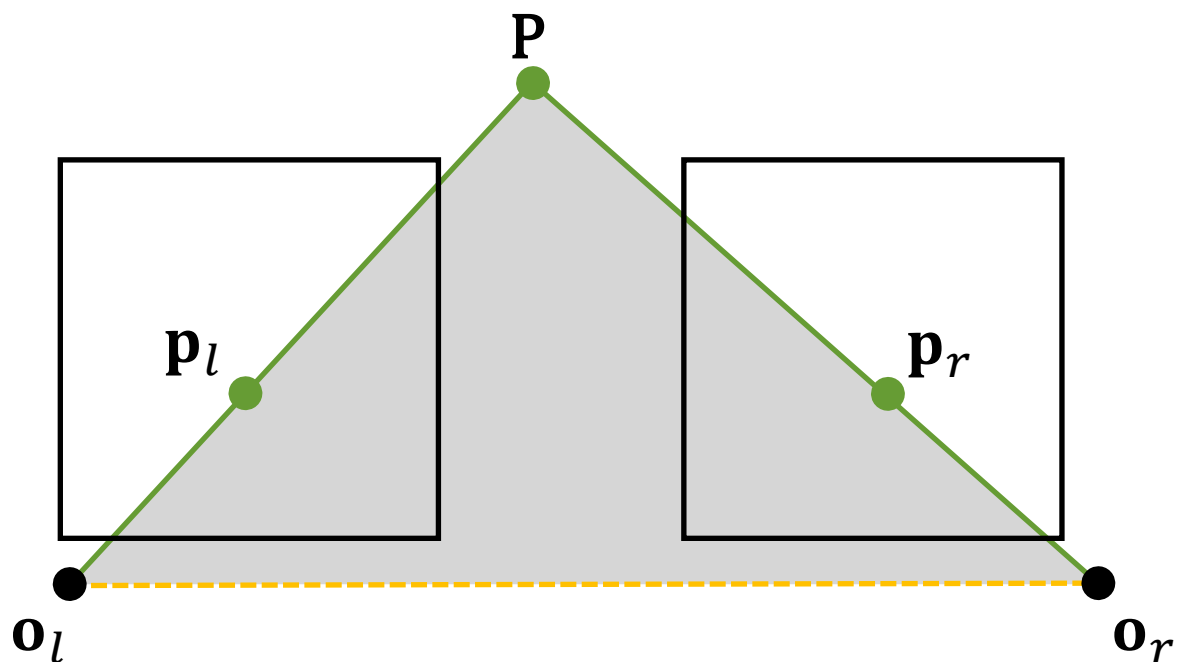
Random Sample Consensus

随机抽样一致

Communications of the ACM, 1981

图像矫正





$$\mathbf{R} = \mathbf{I}_{3 \times 3}$$

$$\mathbf{T} = (B, 0, 0)^T$$

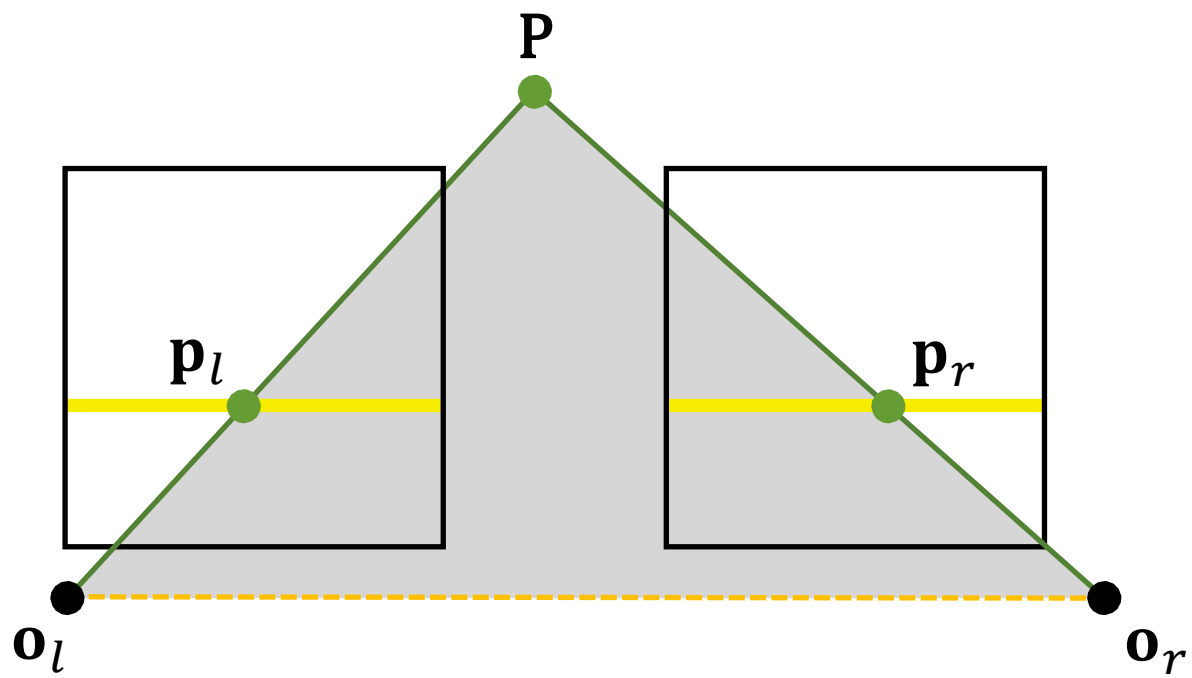
$$\mathbf{p}_r^T \mathbf{E} \mathbf{p}_l = 0$$

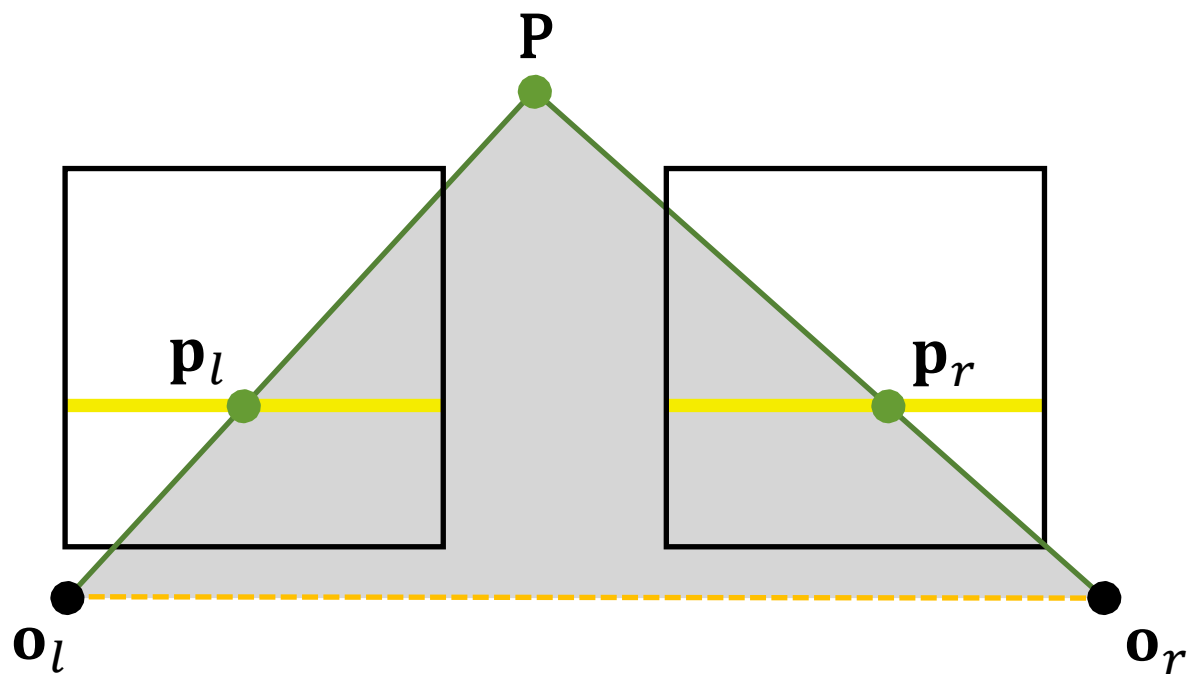
$$(x_r, y_r, 1) [\mathbf{T}_\times] (x_l, y_l, 1)^T = 0$$

展开并化简

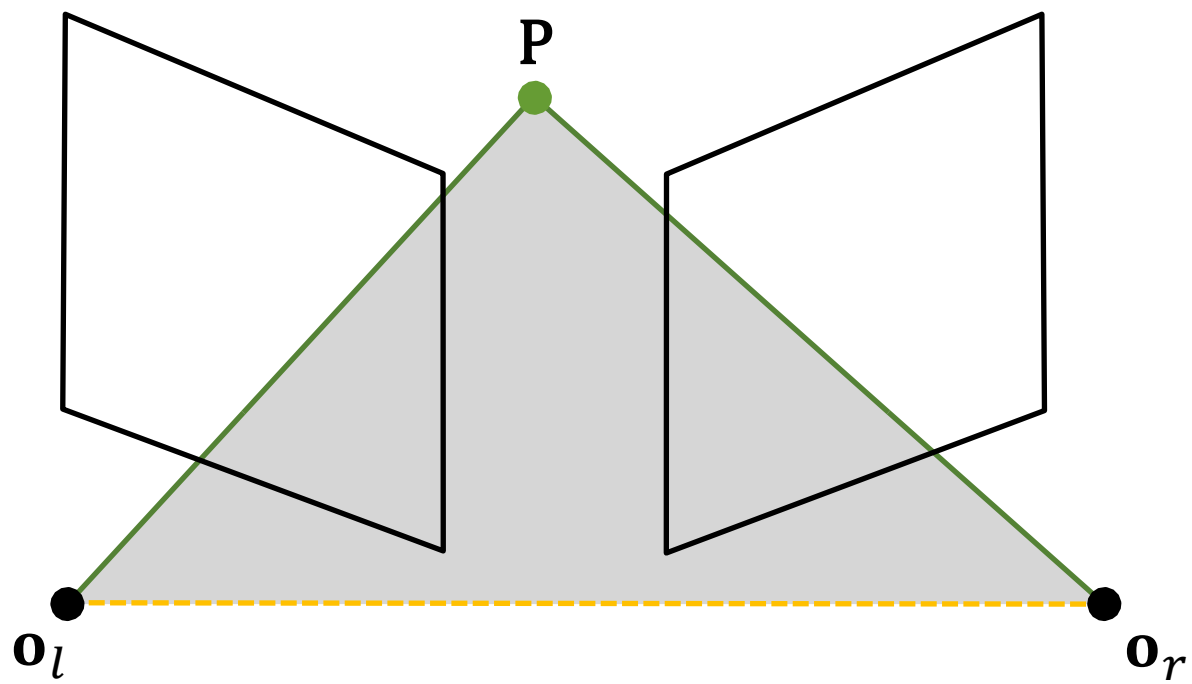
$$y_r = y_l$$

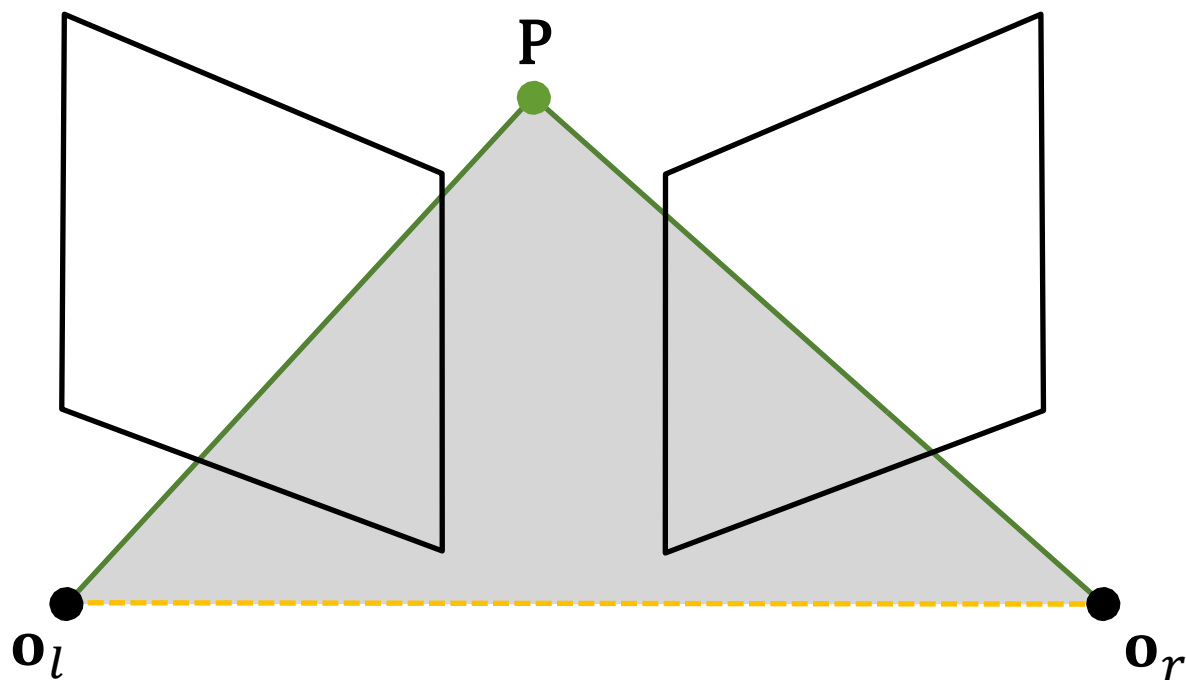
对应点位于同一条水平直线上



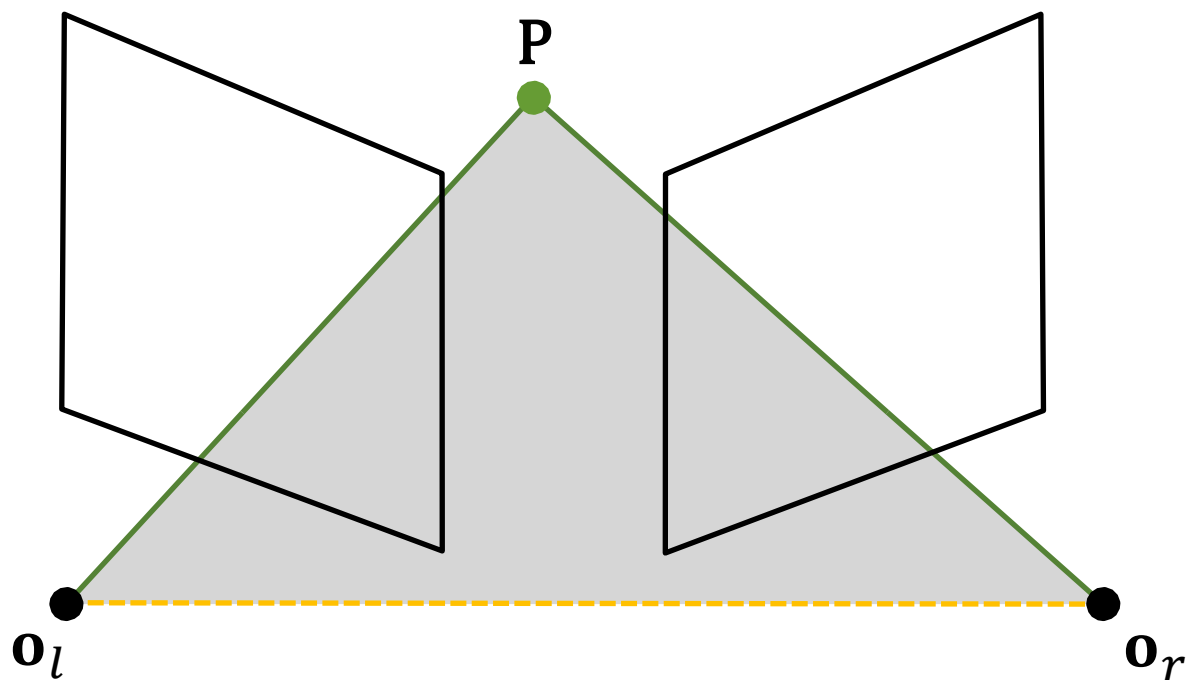


平行的像平面可以简化立体匹配问题



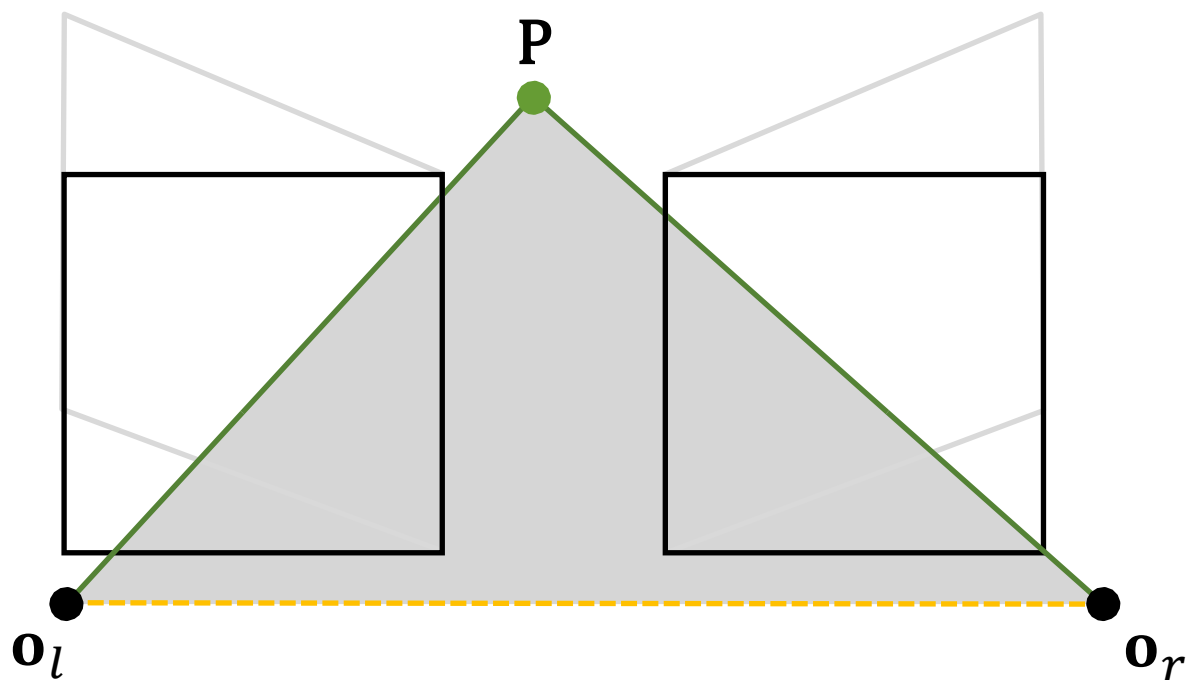


将图像重投影到与基线平行的公共平面上



将图像重投影到与基线平行的公共平面上

对每幅图像应用单应变换



将图像重投影到与基线平行的公共平面上

对每幅图像应用单应变换

原始
图像对



原始
图像对



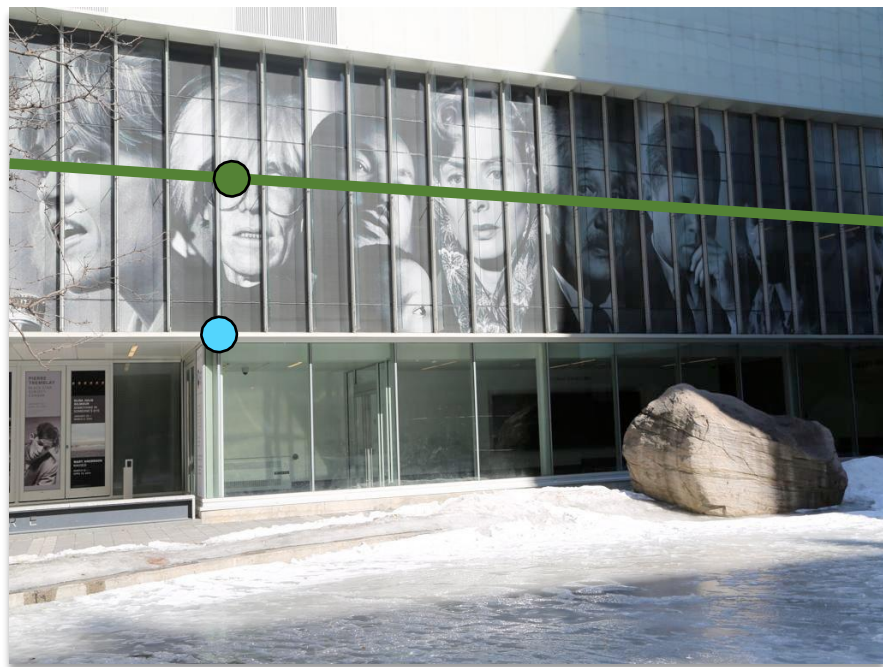
原始
图像对



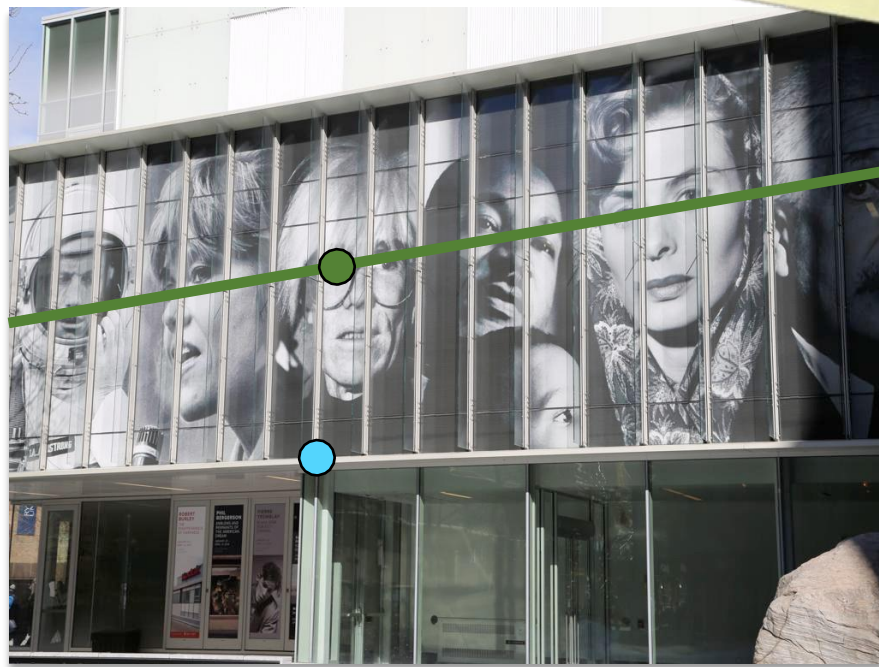
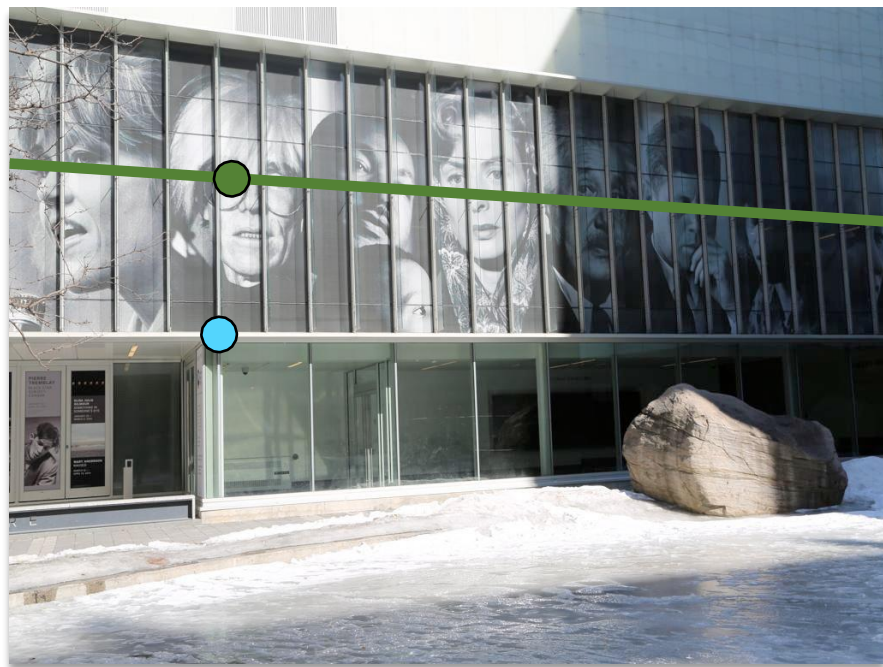
原始
图像对



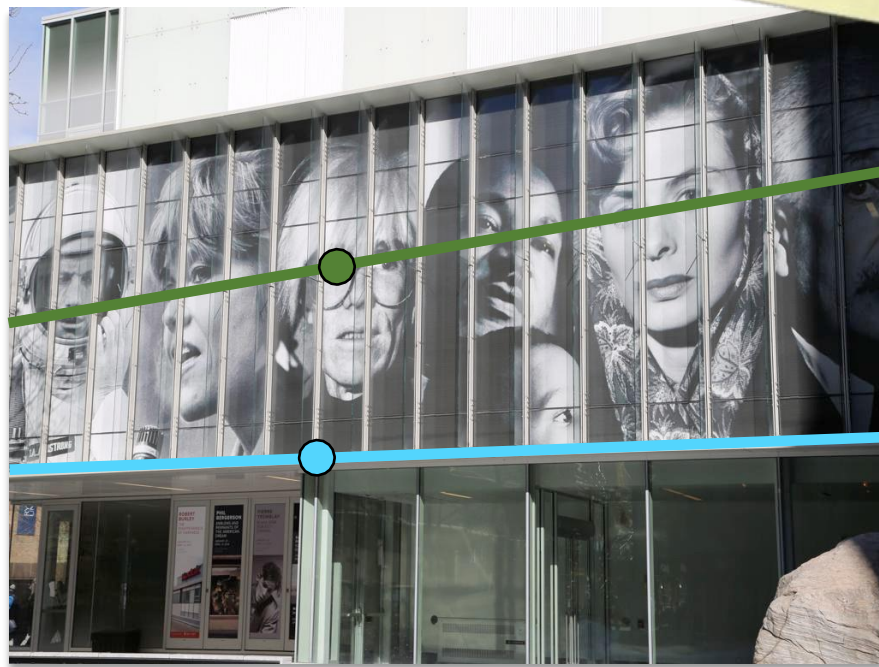
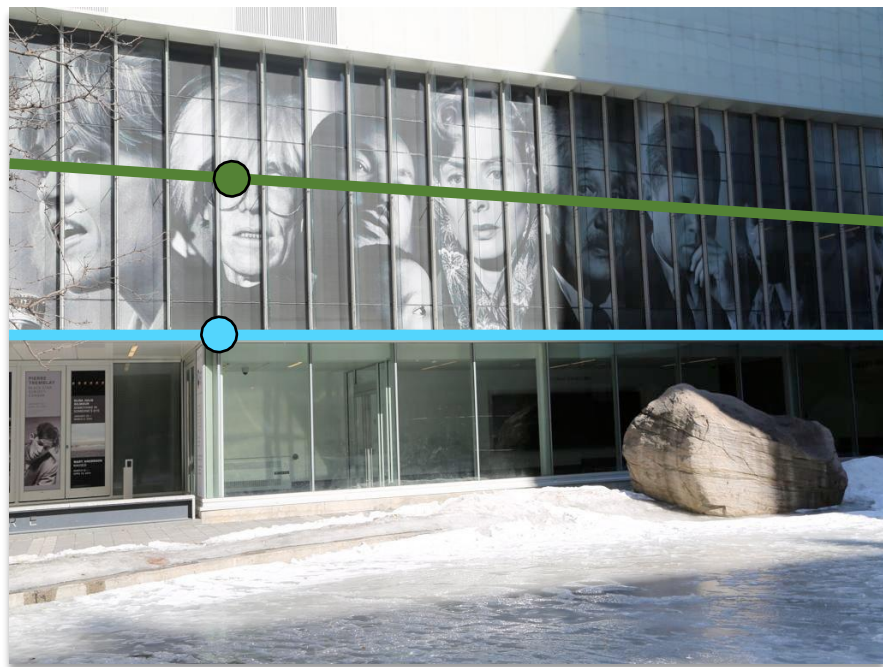
原始
图像对



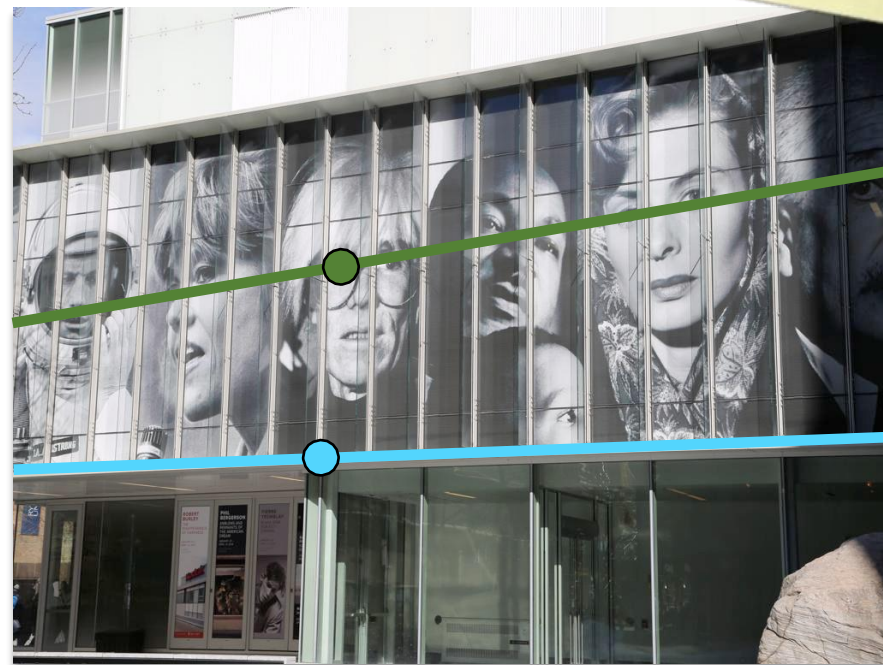
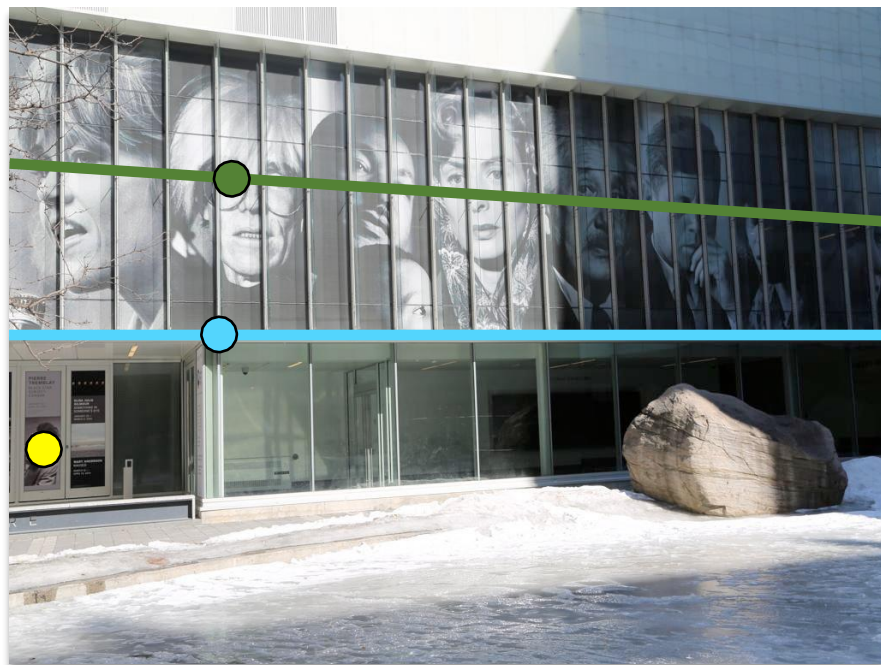
原始
图像对



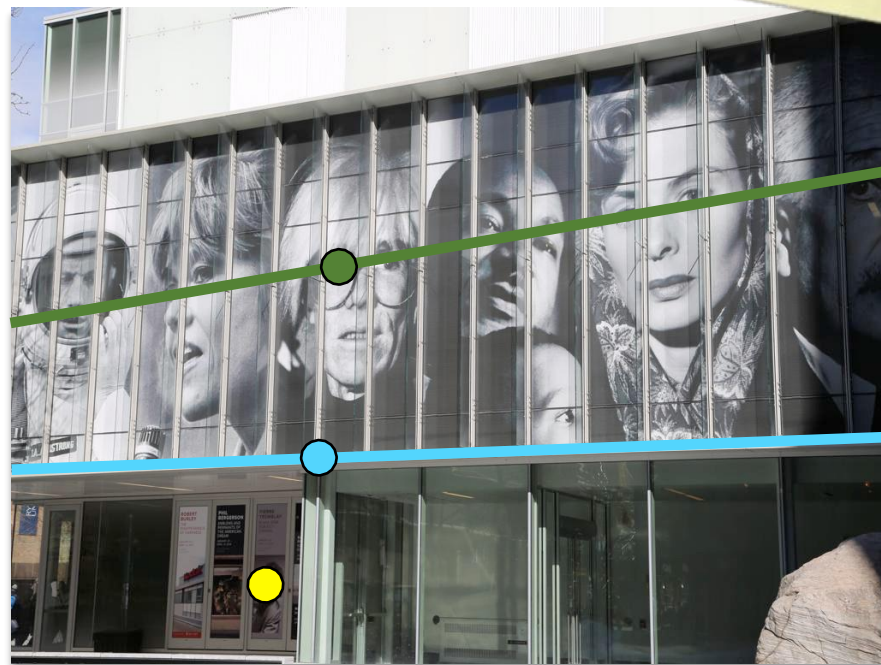
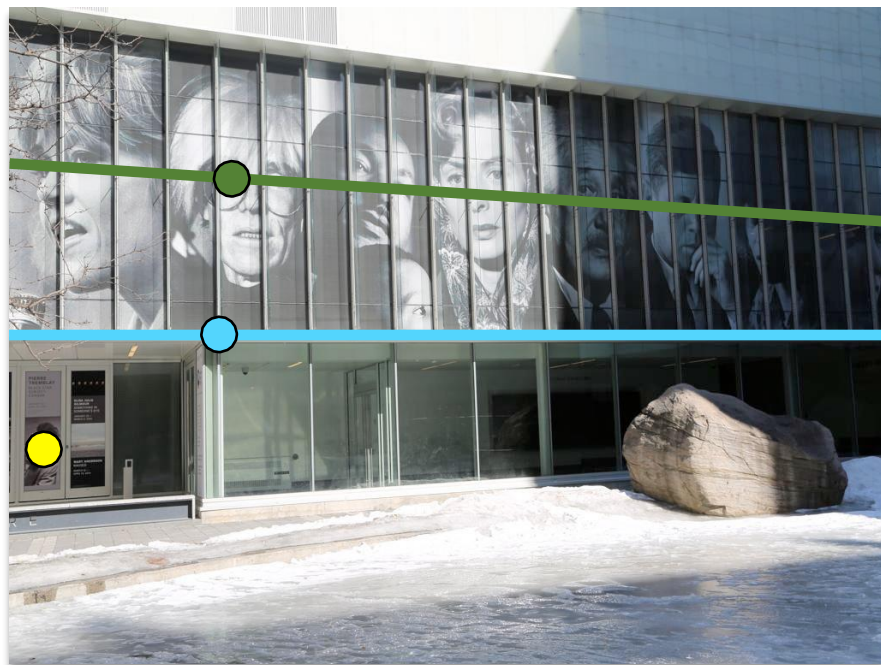
原始
图像对



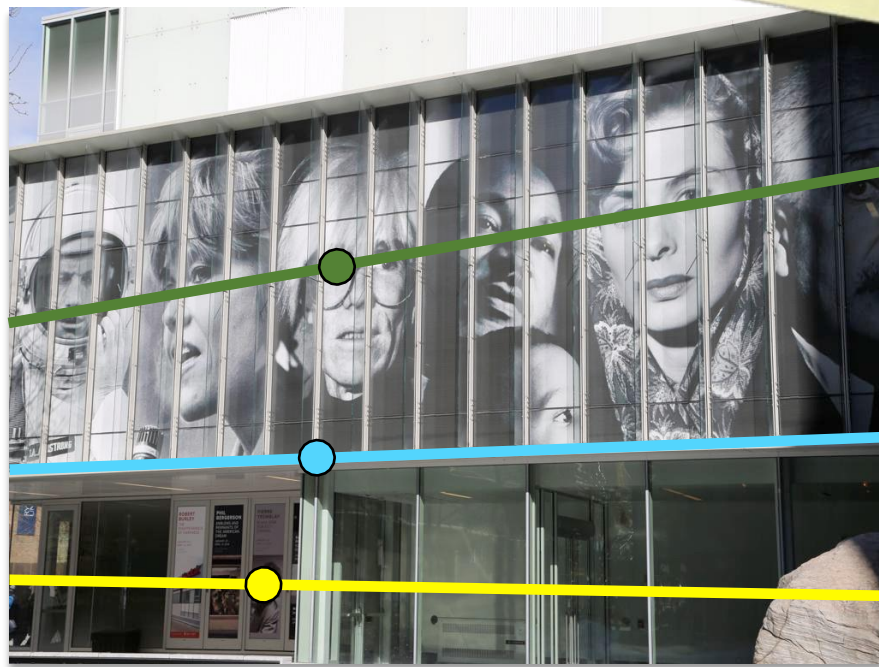
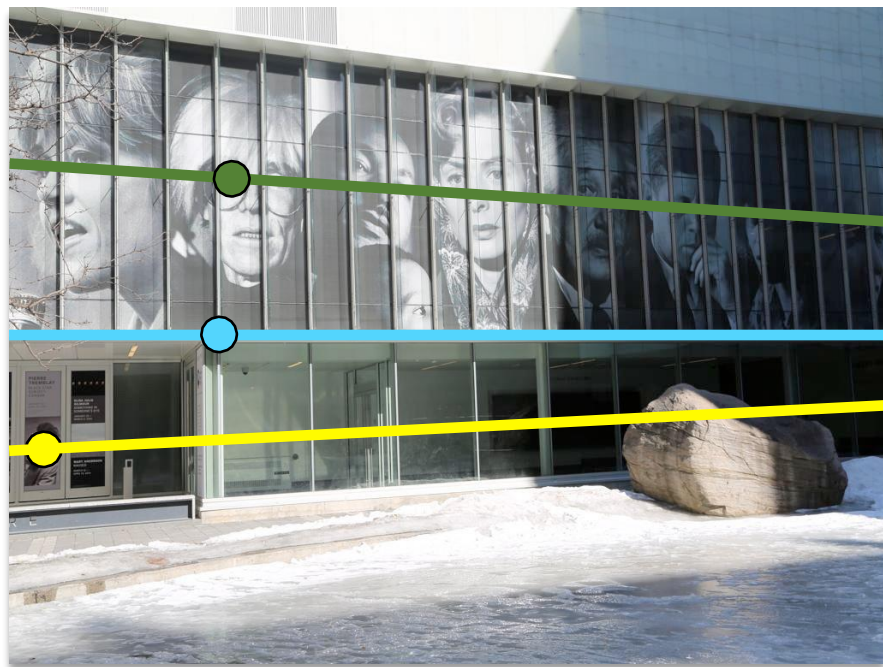
原始
图像对



原始
图像对



原始
图像对



矫正后
图像对

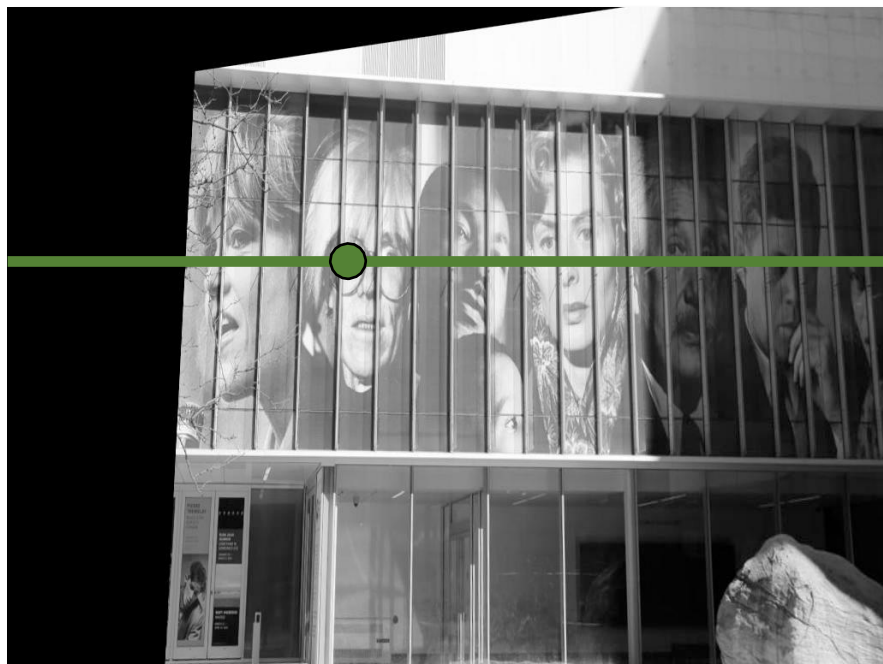


矫正后
图像对



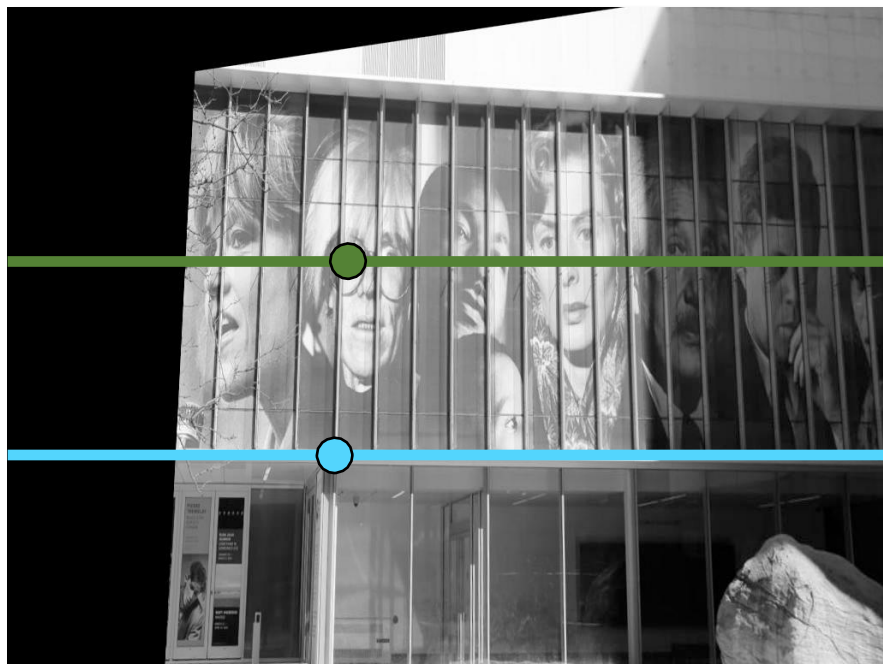
对应点在**同一条扫描线**上

矫正后
图像对



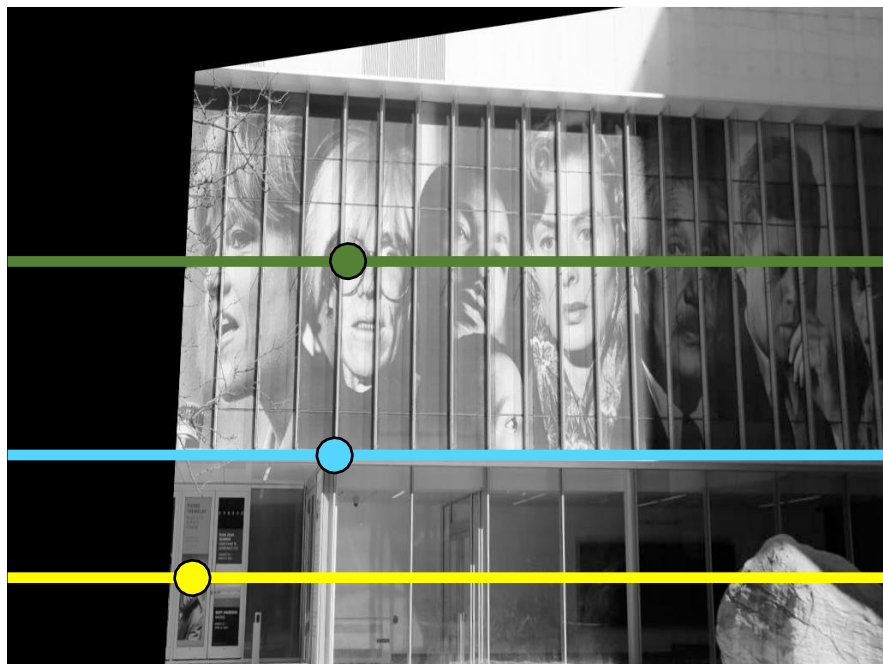
对应点在**同一条扫描线**上

矫正后
图像对



对应点在**同一条扫描线**上

矫正后
图像对



对应点在**同一条扫描线**上

Python时间

图像矫正

Load stereo image pair and convert to grayscale

```
I1 = cv2.imread('left.png', cv2.IMREAD_GRAYSCALE)
```

```
I2 = cv2.imread('right.png', cv2.IMREAD_GRAYSCALE)
```

Find the keypoints and descriptors with SIFT

```
sift = cv2.SIFT_create()
```

```
kp1, des1 = sift.detectAndCompute(I1, None)
```

```
kp2, des2 = sift.detectAndCompute(I2, None)
```

Visualize keypoints

```
I1_sift = cv2.drawKeypoints(I1, kp1, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I2_sift = cv2.drawKeypoints(I2, kp2, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I1_I2_sift = np.concatenate((I1_sift, I2_sift), axis=1)
```

```
cv2.imshow('Image SIFT keypoints', I1_I2_sift)
```

```
# Load stereo image pair and convert to grayscale
```

```
I1 = cv2.imread('left.png', cv2.IMREAD_GRAYSCALE)
```

```
I2 = cv2.imread('right.png', cv2.IMREAD_GRAYSCALE)
```

```
# Find the keypoints and descriptors with SIFT
```

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sift = cv2.SIFT_create()
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```
kp1, des1 = sift.detectAndCompute(I1, None)
```

```
kp2, des2 = sift.detectAndCompute(I2, None)
```

```
# Visualize keypoints
```

```
I1_sift = cv2.drawKeypoints(I1, kp1, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I2_sift = cv2.drawKeypoints(I2, kp2, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I1_I2_sift = np.concatenate((I1_sift, I2_sift), axis=1)
```

```
cv2.imshow('Image SIFT keypoints', I1_I2_sift)
```



```
# Load stereo image pair and convert to grayscale
```

```
I1 = cv2.imread('left.png', cv2.IMREAD_GRAYSCALE)
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I2 = cv2.imread('right.png', cv2.IMREAD_GRAYSCALE)
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```
# Find the keypoints and descriptors with SIFT
```

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kp1, des1 = sift.detectAndCompute(I1, None)
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```
kp2, des2 = sift.detectAndCompute(I2, None)
```

```
# Visualize keypoints
```

```
I1_sift = cv2.drawKeypoints(I1, kp1, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I2_sift = cv2.drawKeypoints(I2, kp2, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I1_I2_sift = np.concatenate((I1_sift, I2_sift), axis=1)
```

```
cv2.imshow('Image SIFT keypoints', I1_I2_sift)
```

```
# Load stereo image pair and convert to grayscale
```

```
I1 = cv2.imread('left.png', cv2.IMREAD_GRAYSCALE)
```

```
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```

```
# Find the keypoints and descriptors with SIFT
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sift = cv2.SIFT_create()
```

```
kp1, des1 = sift.detectAndCompute(I1, None)
```

```
kp2, des2 = sift.detectAndCompute(I2, None)
```

关键点

```
# visualize keypoints
```

```
I1_sift = cv2.drawKeypoints(I1, kp1, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I2_sift = cv2.drawKeypoints(I2, kp2, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I1_I2_sift = np.concatenate((I1_sift, I2_sift), axis=1)
```

```
cv2.imshow('Image SIFT keypoints', I1_I2_sift)
```

```
# Load stereo image pair and convert to grayscale
```

```
I1 = cv2.imread('left.png', cv2.IMREAD_GRAYSCALE)
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I2 = cv2.imread('right.png', cv2.IMREAD_GRAYSCALE)
```

```
# Find the keypoints and descriptors with SIFT
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sift = cv2.SIFT_create()
```

```
kp1, des1 = sift.detectAndCompute(I1, None)
```

```
kp2, des2 = sift.detectAndCompute(I2, None)
```

特征描述子

```
# Visualize keypoints
```

```
I1_sift = cv2.drawKeypoints(I1, kp1, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I2_sift = cv2.drawKeypoints(I2, kp2, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I1_I2_sift = np.concatenate((I1_sift, I2_sift), axis=1)
```

```
cv2.imshow('Image SIFT keypoints', I1_I2_sift)
```

```
# Load stereo image pair and convert to grayscale
```

```
I1 = cv2.imread('left.png', cv2.IMREAD_GRAYSCALE)
```

```
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```

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```
kp1, des1 = sift.detectAndCompute(I1, None)
```

```
kp2, des2 = sift.detectAndCompute(I2, None)
```

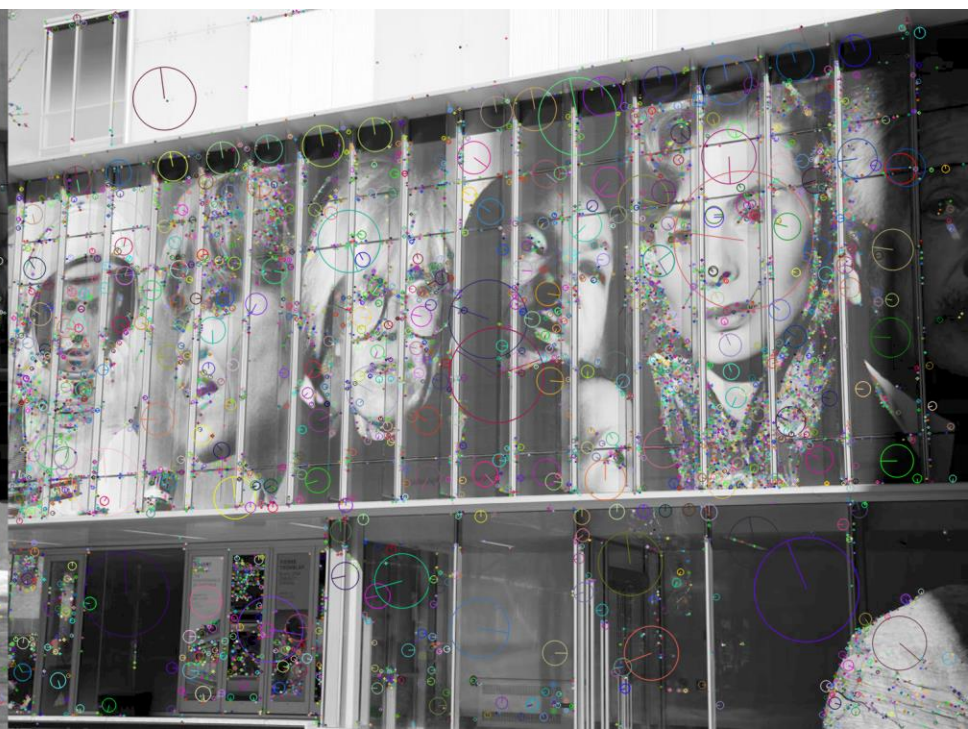
```
# Visualize keypoints
```

```
I1_sift = cv2.drawKeypoints(I1, kp1, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I2_sift = cv2.drawKeypoints(I2, kp2, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

```
I1_I2_sift = np.concatenate((I1_sift, I2_sift), axis=1)
```

```
cv2.imshow('Image SIFT keypoints', I1_I2_sift)
```



寻找
对应点

Match keypoints in both images

FLANN_INDEX_KDTREE = 1

index_params = dict(algorithm=FLANN_INDEX_KDTREE, trees=10)

flann = cv2.FlannBasedMatcher(index_params, {})

matches = flann.knnMatch(des1, des2, k=2)

Keep good matches: calculate distinctive image features

good, pts1, pts2 = [], [], []

for i, (m, n) in enumerate(matches):

if m.distance < 0.7 * n.distance:

good.append([m])

pts1.append(kp1[m.queryIdx].pt)

pts2.append(kp2[m.trainIdx].pt)

keypoint_matches = cv2.drawMatchesKnn(I1, kp1, I2, kp2, good, None,
flags=cv2.DRAW_MATCHES_FLAGS_NOT_DRAW_SINGLE_POINTS)

cv2.imshow('Keypoint matches', keypoint_matches)


```
# Match keypoints in both images
```

```
FLANN_INDEX_KDTREE = 1
```

```
index_params = dict(algorithm=FLANN_INDEX_KDTREE, trees=5)
```

```
flann = cv2.FlannBasedMatcher(index_params, {})
```

```
matches = flann.knnMatch(des1, des2, k=2)
```

```
# Keep good matches: calculate distinctive image features
```

```
good, pts1, pts2 = [], [], []
```

```
for i, (m, n) in enumerate(matches):
```

```
    if m.distance < 0.7 * n.distance:
```

```
        good.append([m])
```

```
        pts1.append(kp1[m.queryIdx].pt)
```

```
        pts2.append(kp2[m.trainIdx].pt)
```

```
keypoint_matches = cv2.drawMatchesKnn(I1, kp1, I2, kp2, good, None,  
    flags=cv2.DRAW_MATCHES_FLAGS_NOT_DRAW_SINGLE_POINTS)
```

```
cv2.imshow('Keypoint matches', keypoint_matches)
```

```
# Match keypoints in both images
```

```
FLANN_INDEX_KDTREE = 1
```

```
index_params = dict(algorithm=FLANN_INDEX_KDTREE, trees=5)
```

```
flann = cv2.FlannBasedMatcher(index_params, {})
```

```
matches = flann.knnMatch(des1, des2, k=2)
```

```
# Keep good matches: calculate distinctive image features
```

```
good, pts1, pts2 = [], [], []
```

```
for i, (m, n) in enumerate(matches):
```

```
    if m.distance < 0.7 * n.distance:
```

```
        good.append([m])
```

```
        pts1.append(kp1[m.queryIdx].pt)
```

```
        pts2.append(kp2[m.trainIdx].pt)
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```
keypoint_matches = cv2.drawMatchesKnn(I1, kp1, I2, kp2, good, None,  
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```

```
cv2.imshow('Keypoint matches', keypoint_matches)
```

```
# Match keypoints in both images
```

```
FLANN_INDEX_KDTREE = 1
```

```
index_params = dict(algorithm=FLANN_INDEX_KDTREE, trees=5)
```

```
flann = cv2.FlannBasedMatcher(index_params, {})
```

```
matches = flann.knnMatch(des1, des2, k=2)
```

```
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```
    if m.distance < 0.7 * n.distance:
```

```
        good.append([m])
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```
        pts1.append(kp1[m.queryIdx].pt)
```

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cv2.imshow('Keypoint matches', keypoint_matches)
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# Match keypoints in both images
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```
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    if m.distance < 0.7 * n.distance:
```

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        good.append([m])
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        pts1.append(kp1[m.queryIdx].pt)
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```

Match keypoints in both images

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index_params = dict(algorithm=FLANN_INDEX_KDTREE, trees=5)

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for i, (m, n) in enumerate(matches):

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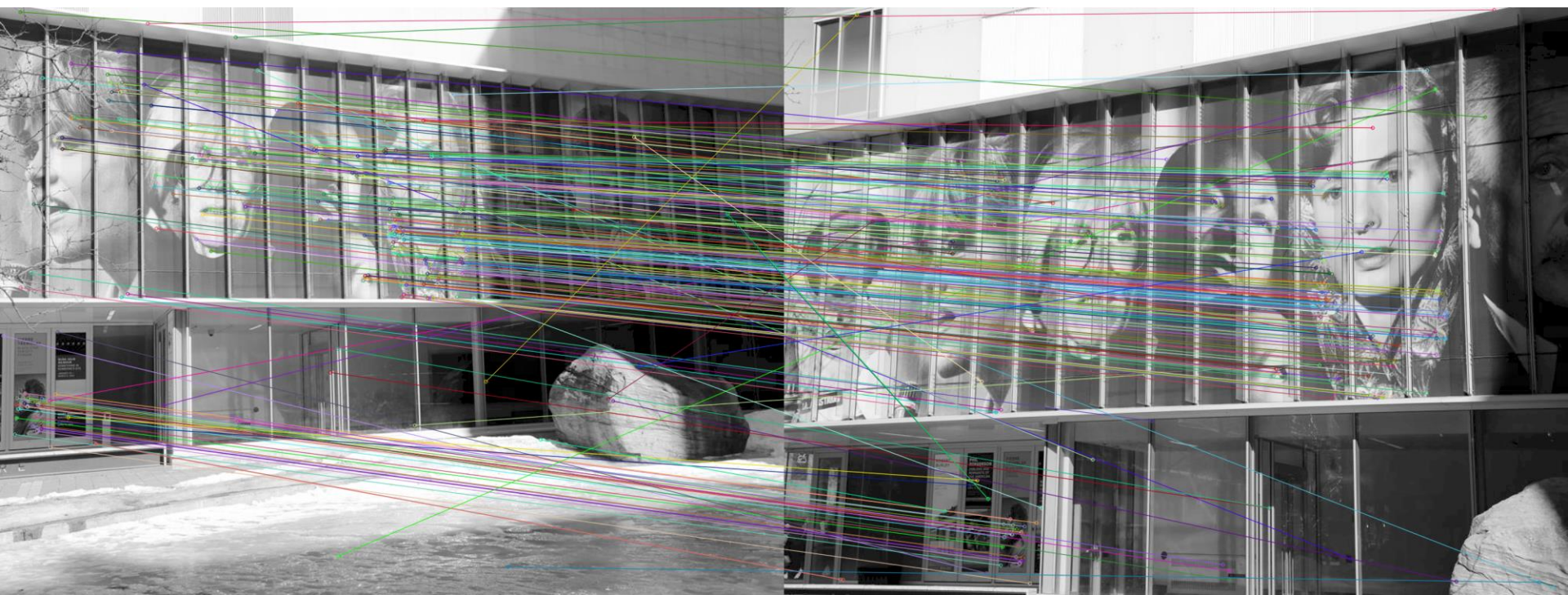
good.append([m])

pts1.append(kp1[m.queryIdx].pt)

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keypoint_matches = cv2.drawMatchesKnn(I1, kp1, I2, kp2, good, None,
 flags=cv2.DRAW_MATCHES_FLAGS_NOT_DRAW_SINGLE_POINTS)

cv2.imshow('Keypoint matches', keypoint_matches)



Calculate the fundamental matrix for the cameras

```
pts1 = np.float32(pts1)
```

```
pts2 = np.float32(pts2)
```

```
fundamental_matrix, inliers = cv2.findFundamentalMat(  
    pts1, pts2, cv2.FM_RANSAC,  
    ransacReprojThreshold=0.9, confidence=0.99  
)
```

Select only inlier points

```
pts1 = pts1[inliers.ravel() == 1]
```

```
pts2 = pts2[inliers.ravel() == 1]
```

计算
基础矩阵

Calculate the fundamental matrix for the cameras

```
pts1 = np.float32(pts1)
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fundamental_matrix, inliers = cv2.findFundamentalMat(  
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    pts1, pts2, cv2.FM_RANSAC,  
    ransacReprojThreshold=0.9, confidence=0.99  
)
```

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# Select only inlier points
```

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pts1 = pts1[inliers.ravel() == 1]
```

```
pts2 = pts2[inliers.ravel() == 1]
```

```
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```
# Select only inlier points
```

```
pts1 = pts1[inliers.ravel() == 1]
```

```
pts2 = pts2[inliers.ravel() == 1]
```

```
# Stereo rectification (uncalibrated variant)
```

```
h1, w1 = img1.shape
```

```
h2, w2 = img2.shape
```

```
_, H1, H2 = cv2.stereoRectifyUncalibrated(  
    pts1, pts2, fundamental_matrix, imgSize=(w1, h1)  
)
```

```
# Rectify the images
```

```
I1_rect = cv2.warpPerspective(I1, H1, (w1, h1))
```

```
I2_rect = cv2.warpPerspective(I2, H2, (w2, h2))
```

```
# Visualize rectified images
```

```
I1_I2_rect = np.concatenate((I1_rect, I2_rect), axis=1)
```

```
cv2.imshow('Rectified images', I1_I2_rect), cv2.waitKey(0)
```

矫正图像


```
# Stereo rectification (uncalibrated variant)
```

```
h1, w1 = img1.shape
```

```
h2, w2 = img2.shape
```

```
_, H1, H2 = cv2.stereoRectifyUncalibrated(  
    pts1, pts2, fundamental_matrix, imgSize=(w1, h1)  
)
```

```
# Rectify the images
```

```
I1_rect = cv2.warpPerspective(I1, H1, (w1, h1))
```

```
I2_rect = cv2.warpPerspective(I2, H2, (w2, h2))
```

```
# Visualize rectified images
```

```
I1_I2_rect = np.concatenate((I1_rect, I2_rect), axis=1)
```

```
cv2.imshow('Rectified images', I1_I2_rect), cv2.waitKey(0)
```

```
# Stereo rectification (uncalibrated variant)
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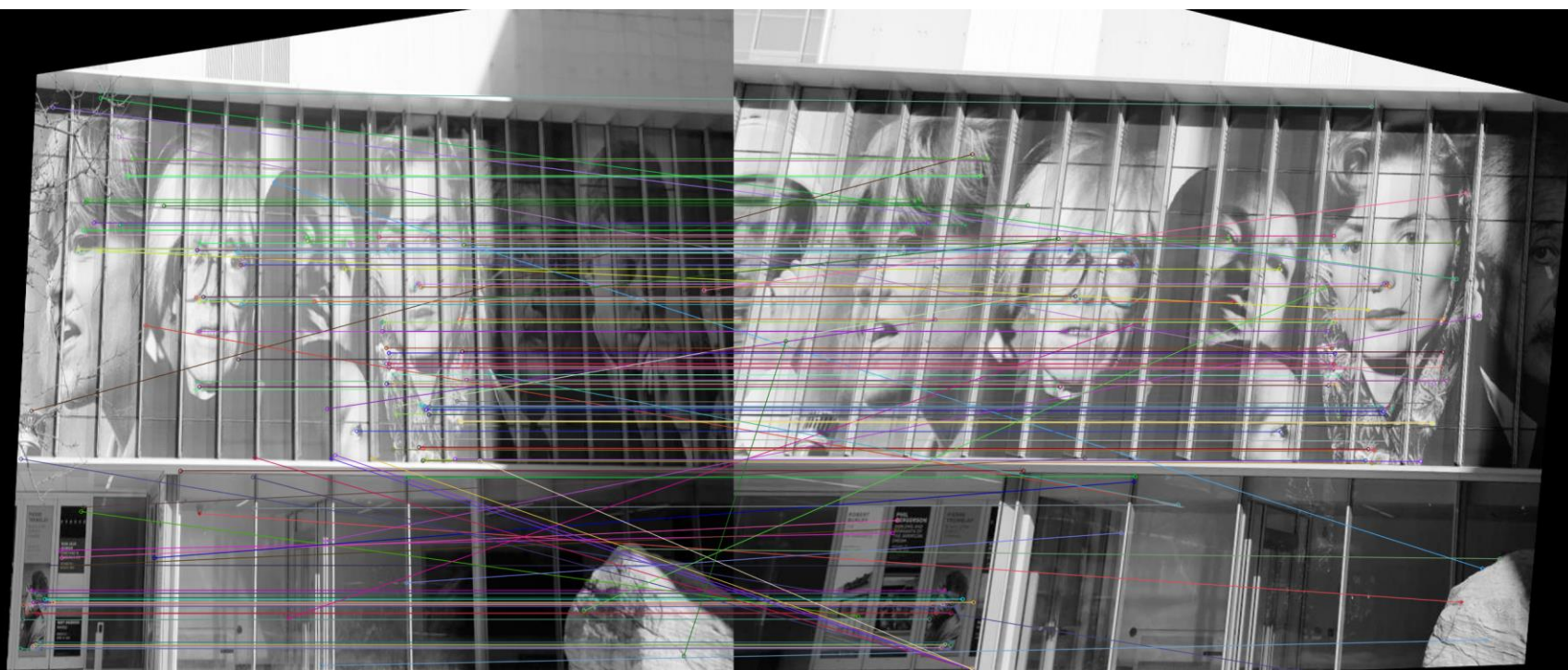
```
I2_rect = cv2.warpPerspective(I2, H2, (w2, h2))
```

```
# Visualize rectified images
```

```
I1_I2_rect = np.concatenate((I1_rect, I2_rect), axis=1)
```

```
cv2.imshow('Rectified images', I1_I2_rect), cv2.waitKey(0)
```

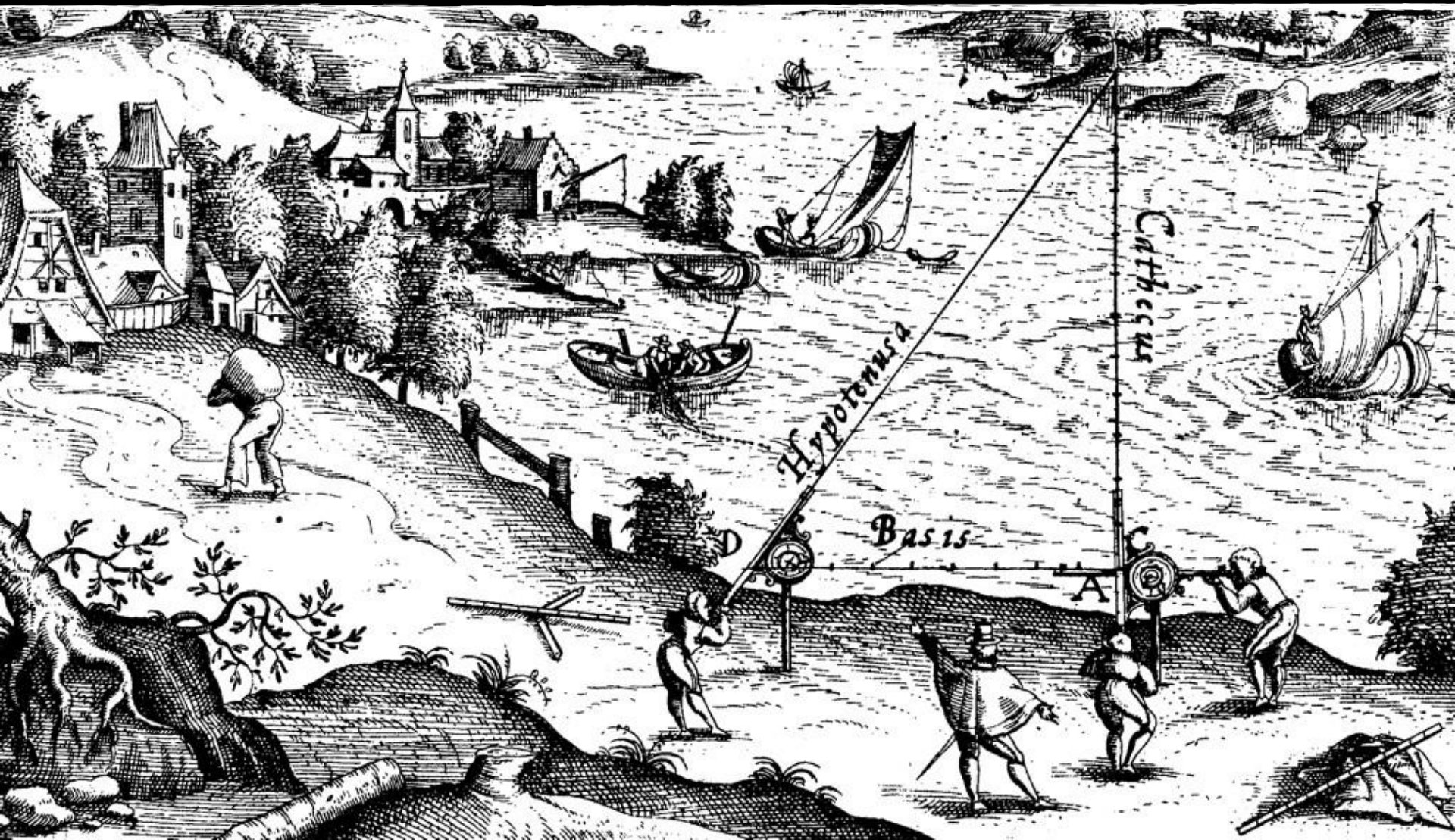


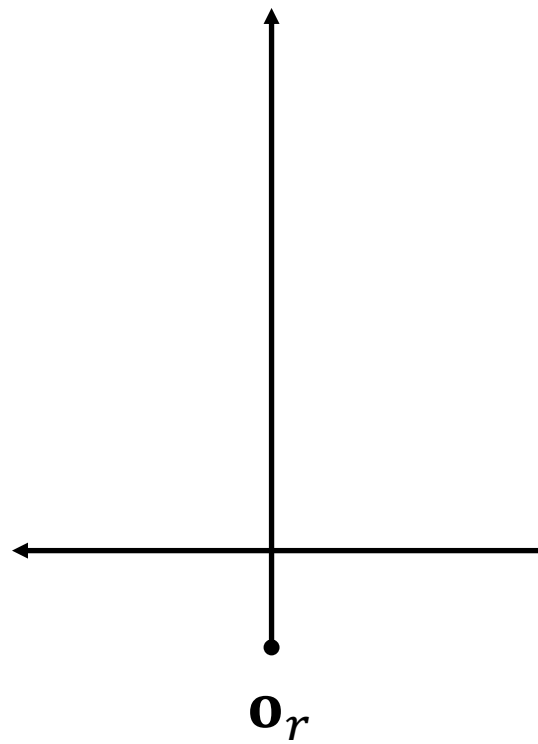
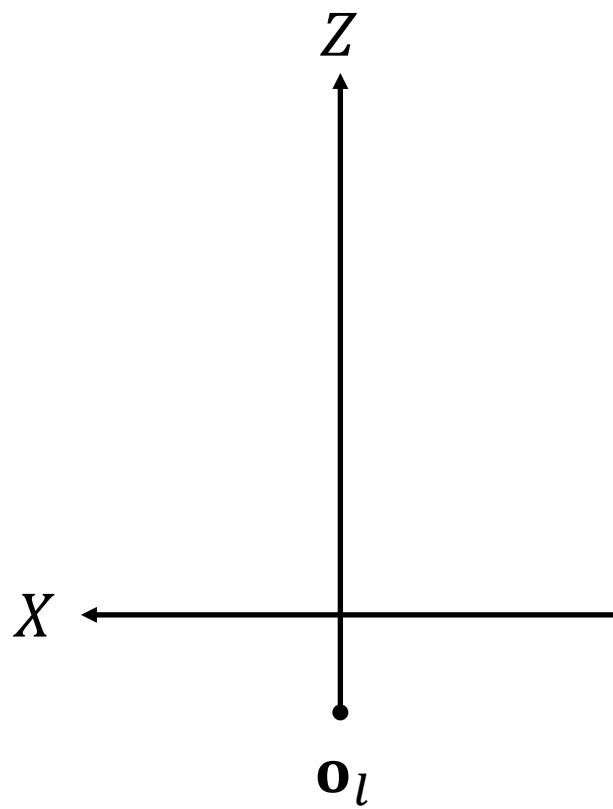


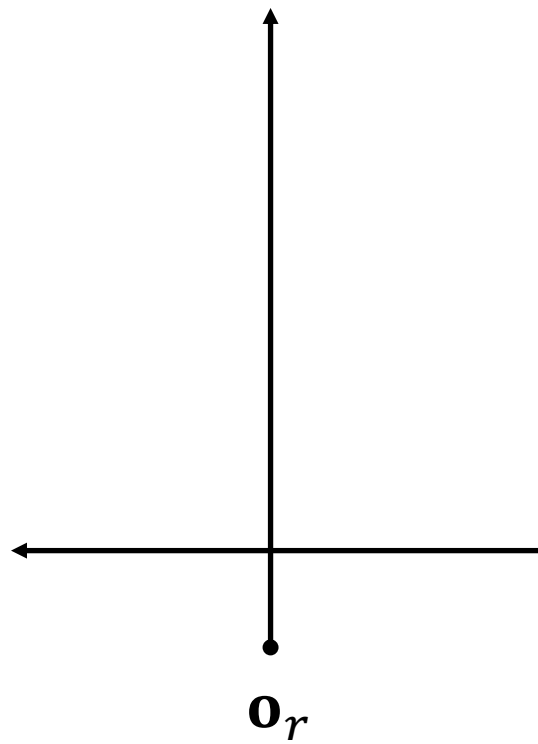
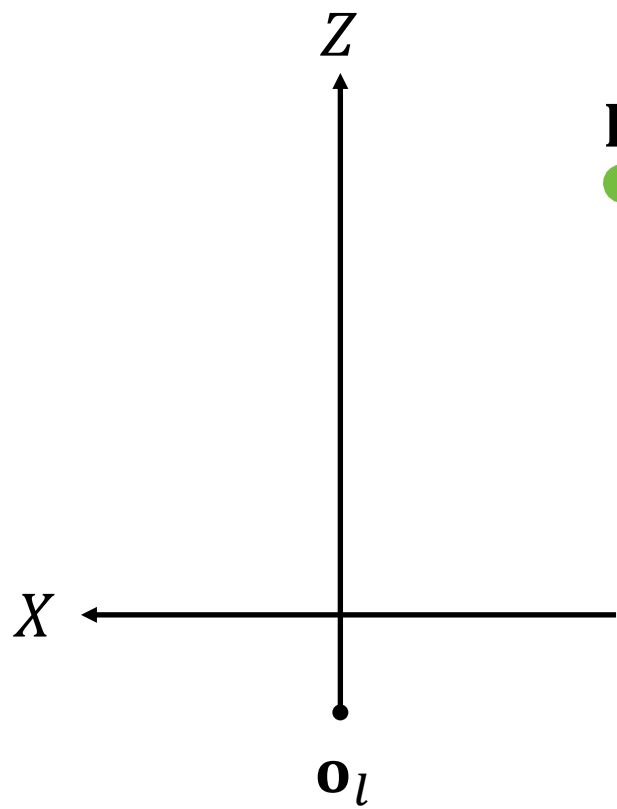
Python时间

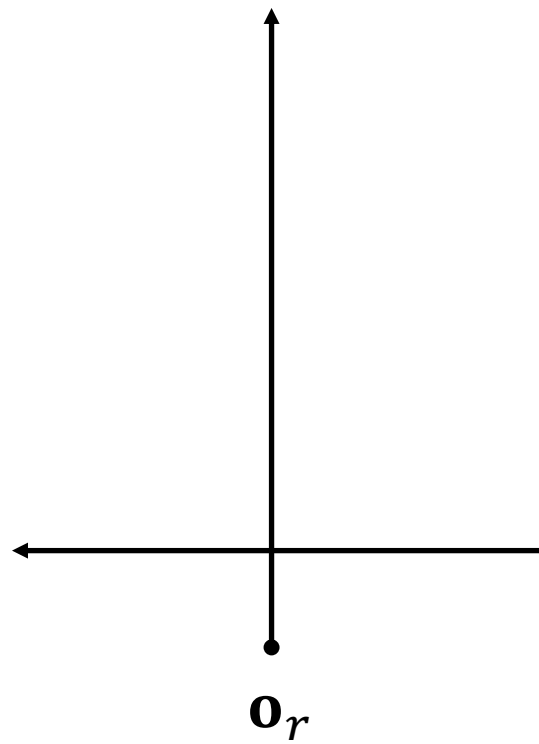
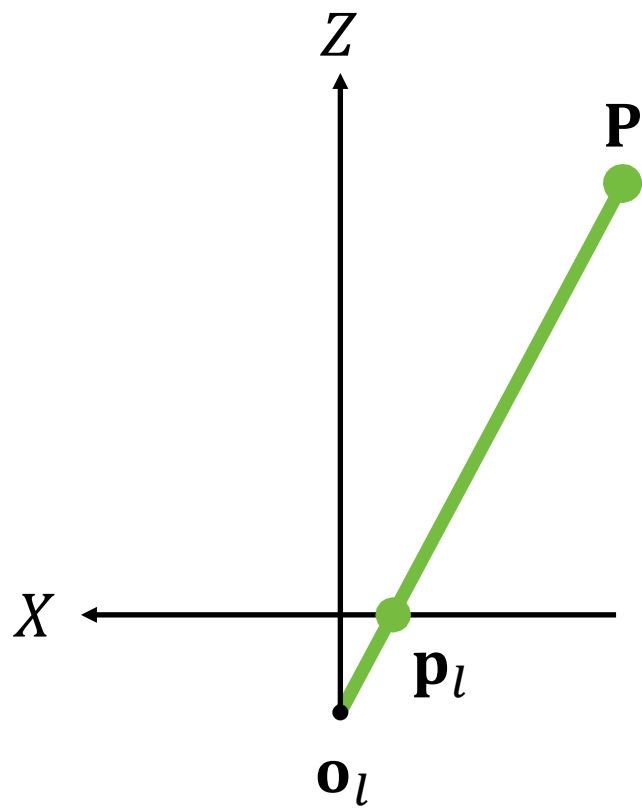


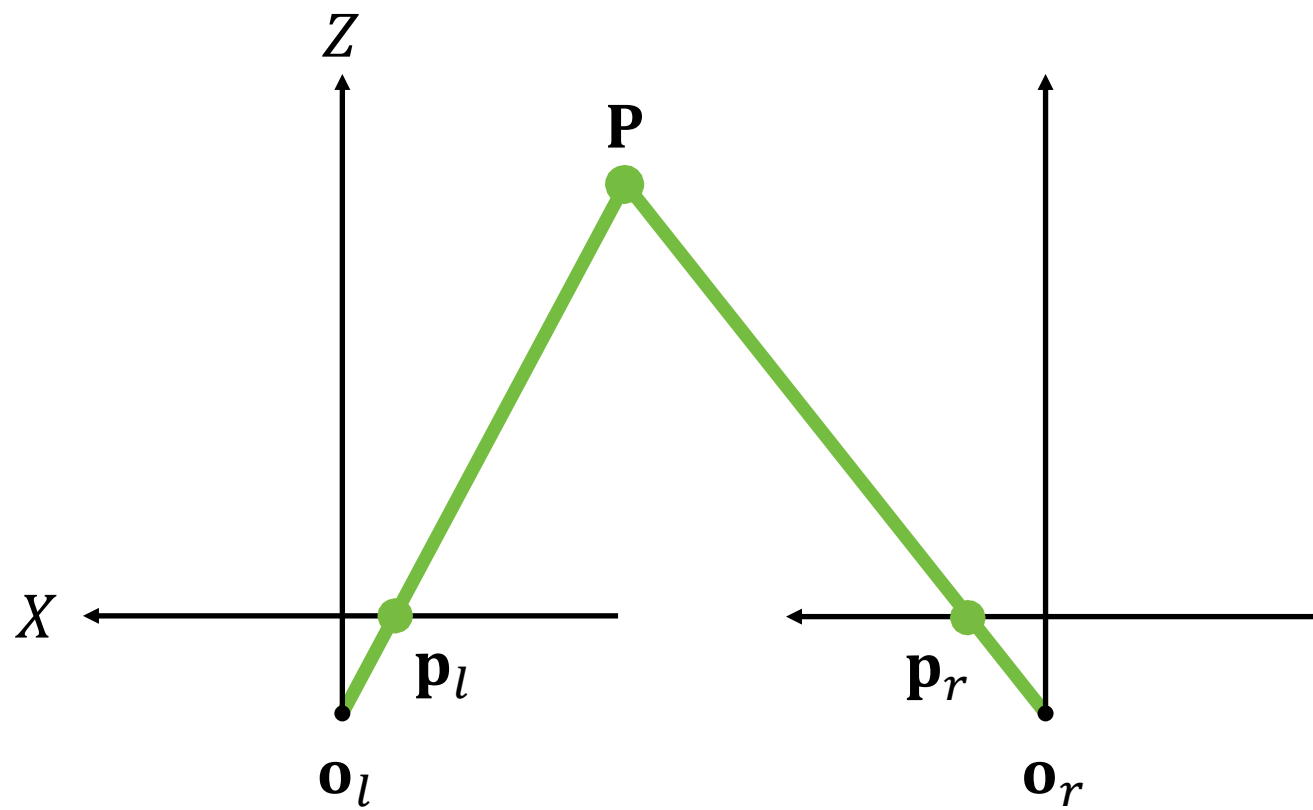
三角测量

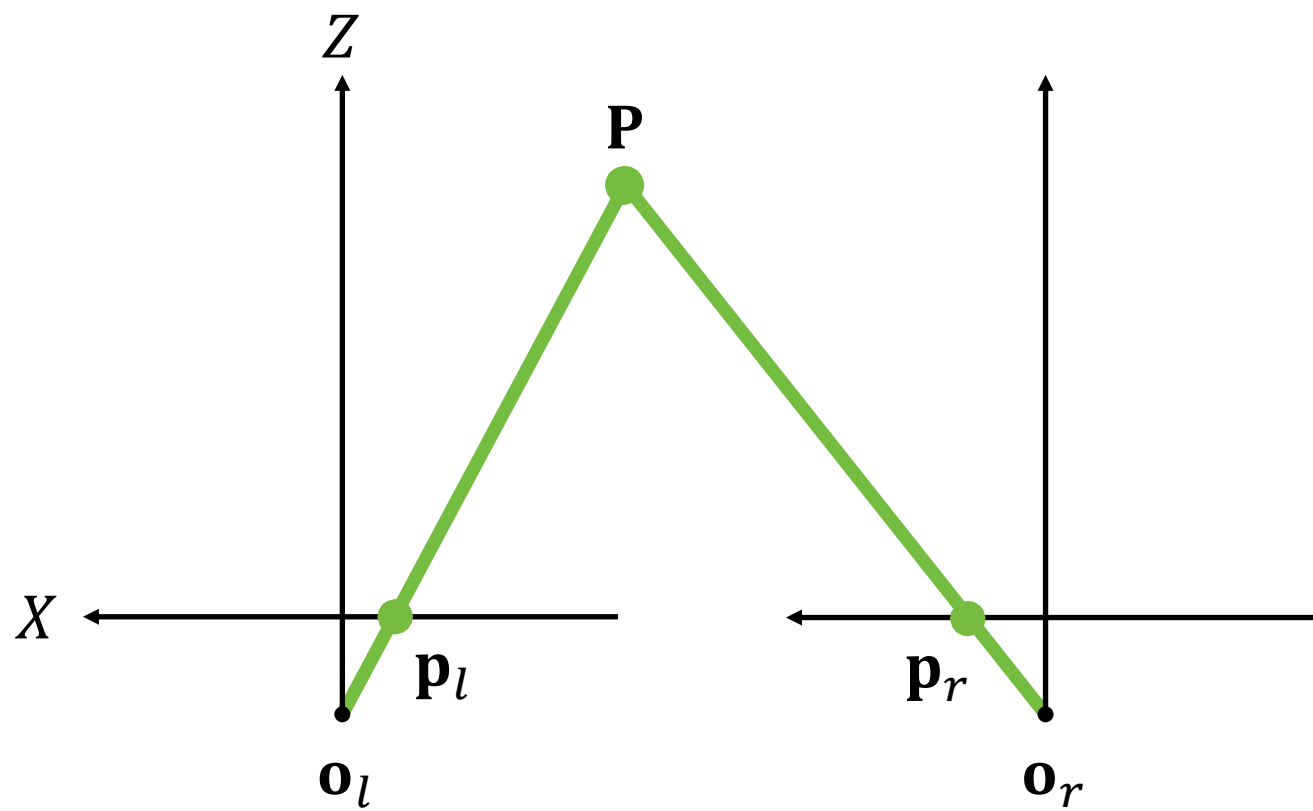


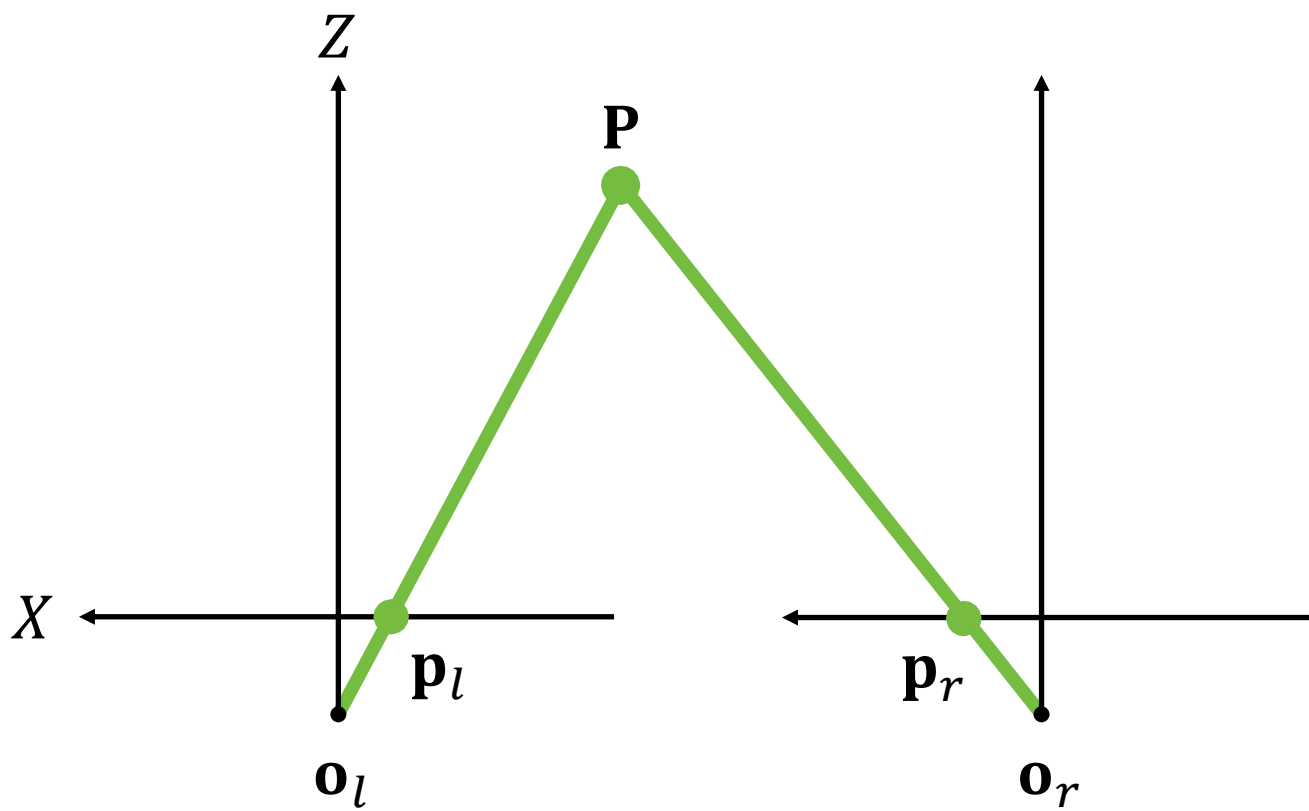




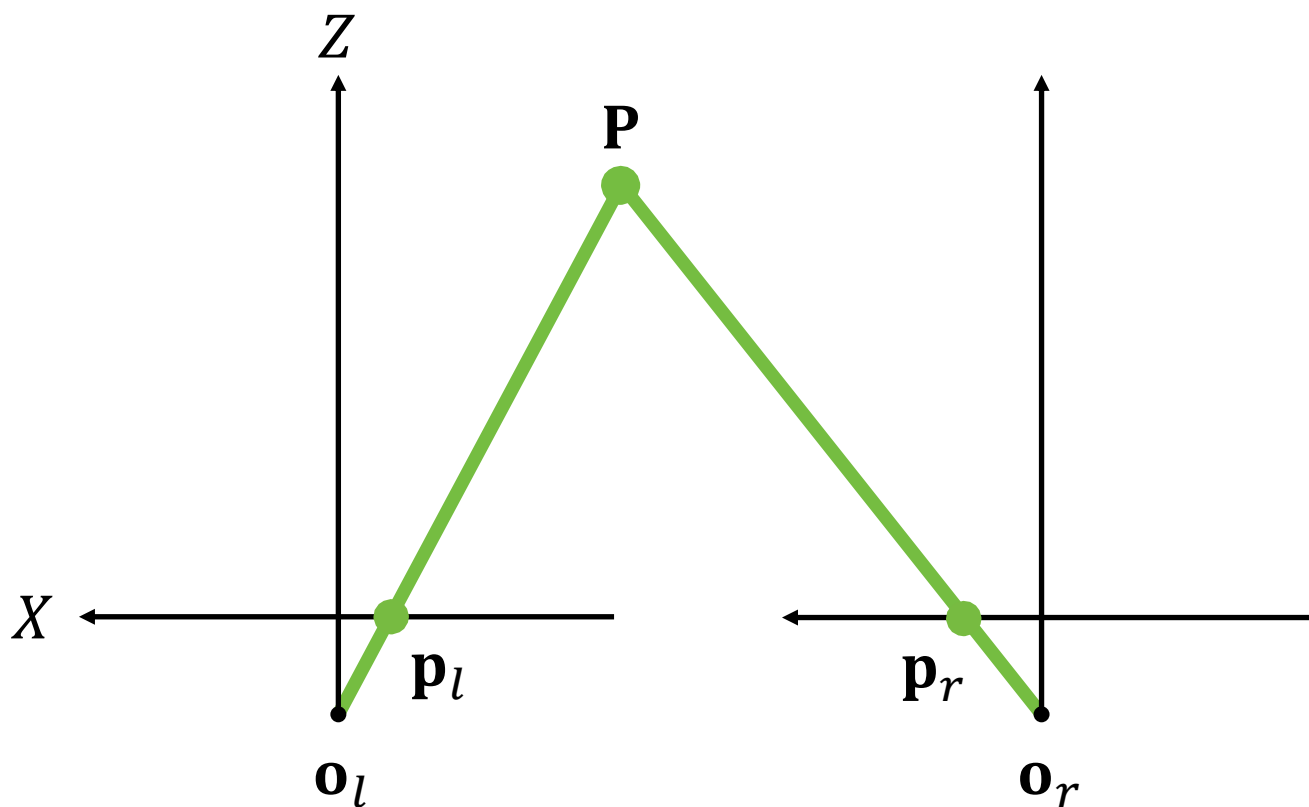








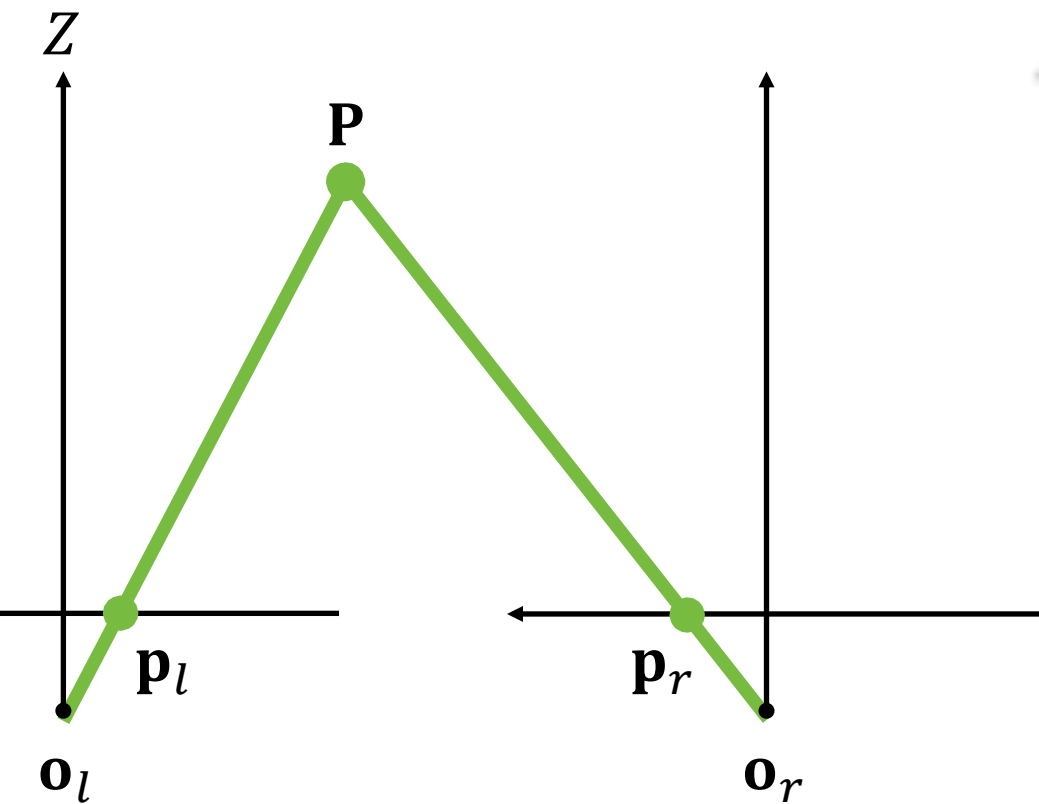
P的3D坐标可以通过射线的交点确定



P的3D坐标可以通过射线的交点确定

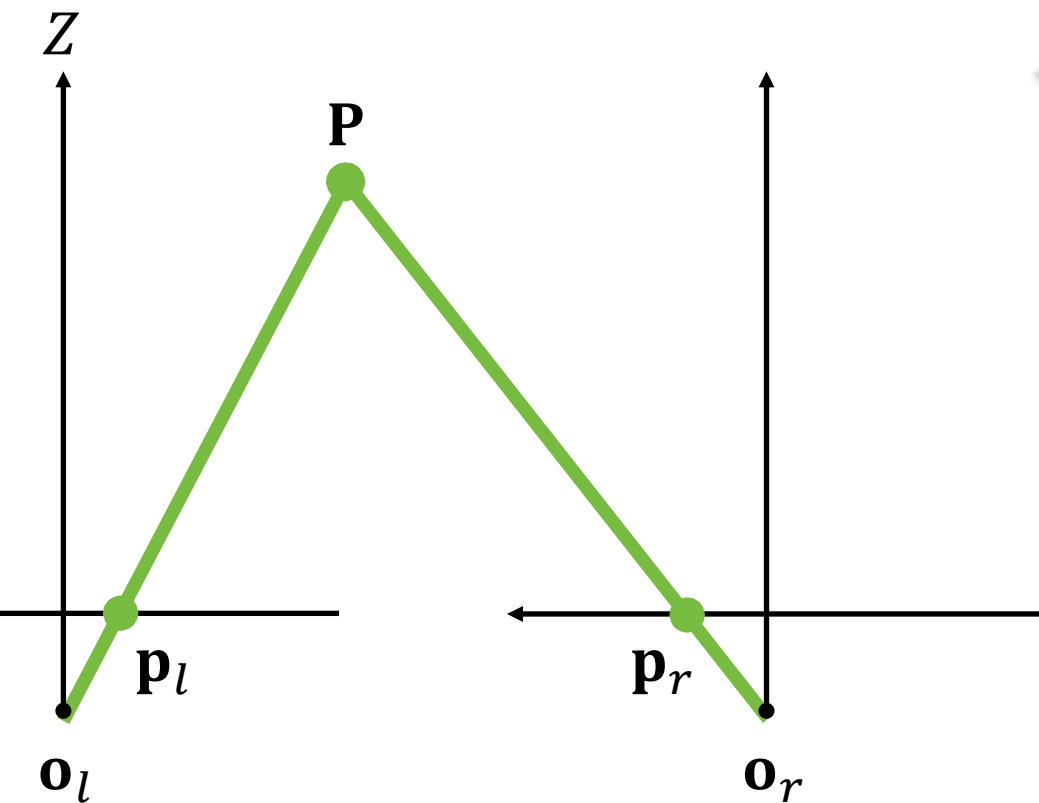
这个过程称为三角测量

三角测量推导



三角测量推导

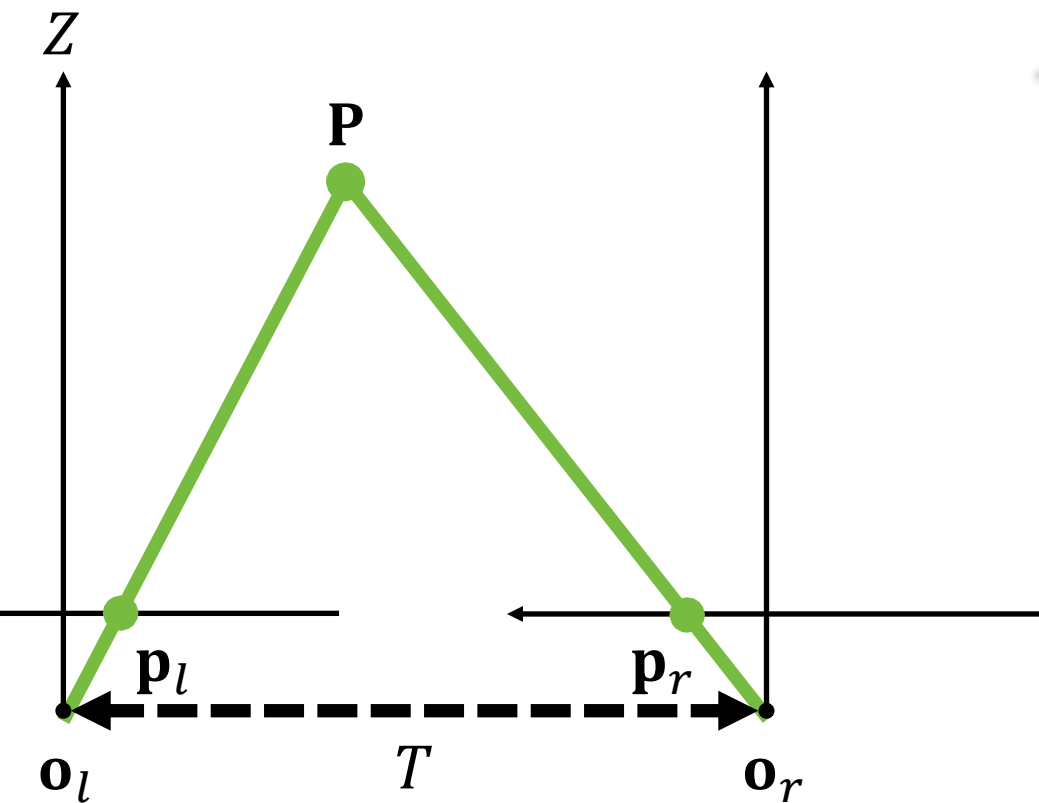
定义



三角测量推导

定义

T 相机中心距离

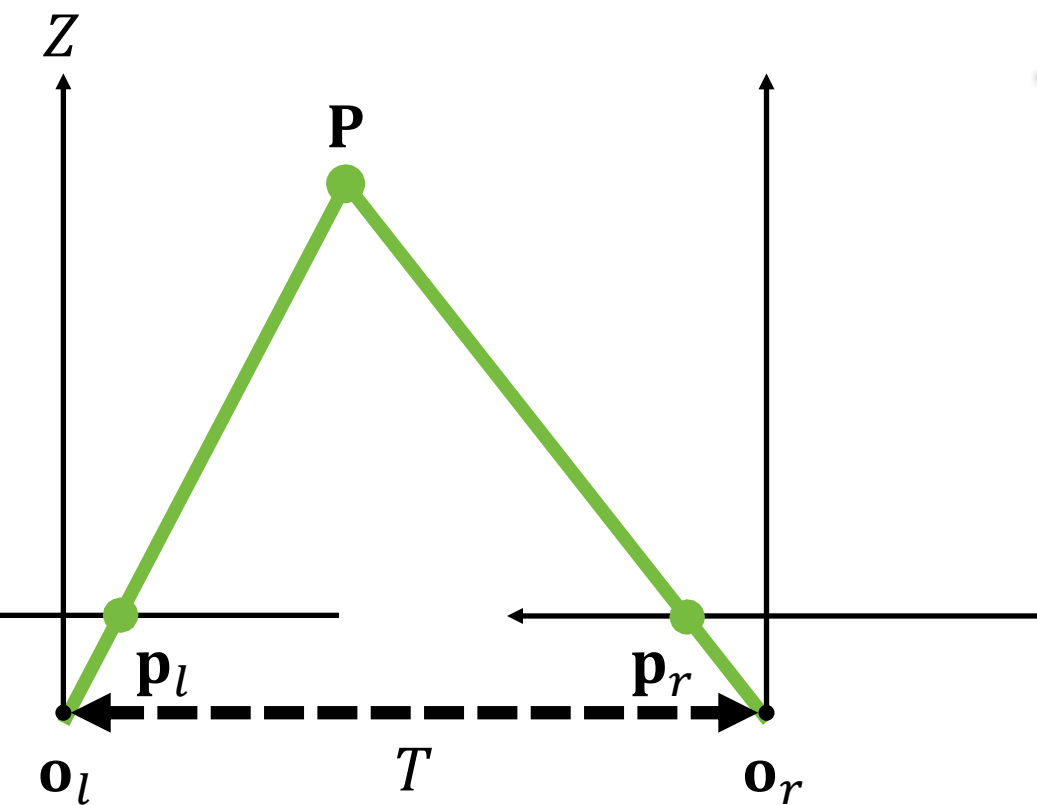


三角测量推导

定义

T 相机中心距离

基线宽度

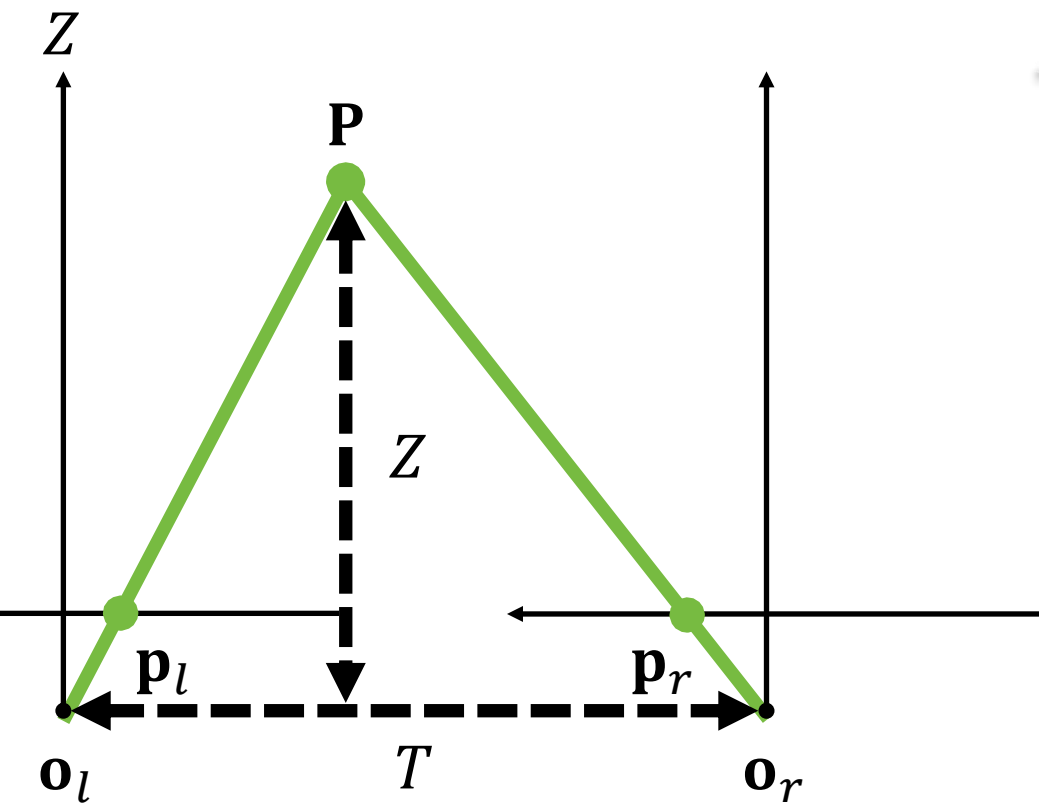


三角测量推导

定义

T 相机中心距离

Z 到基线的距离



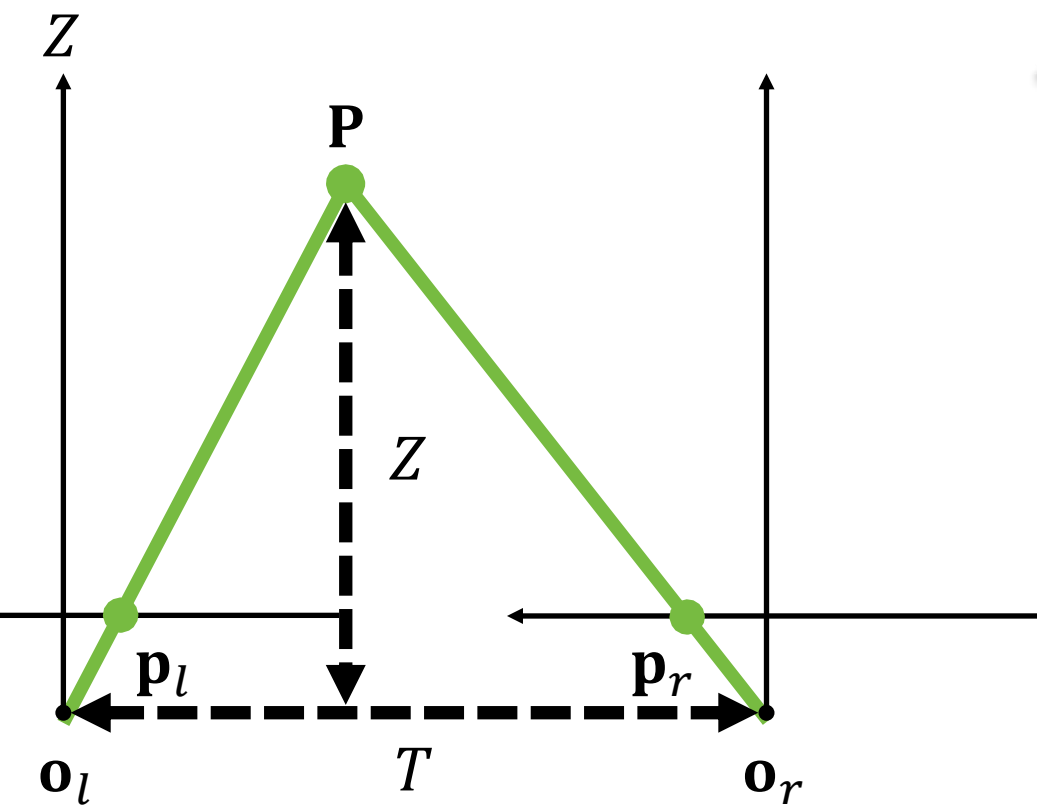
三角测量推导

定义

T 相机中心距离

Z 到基线的距离

深度



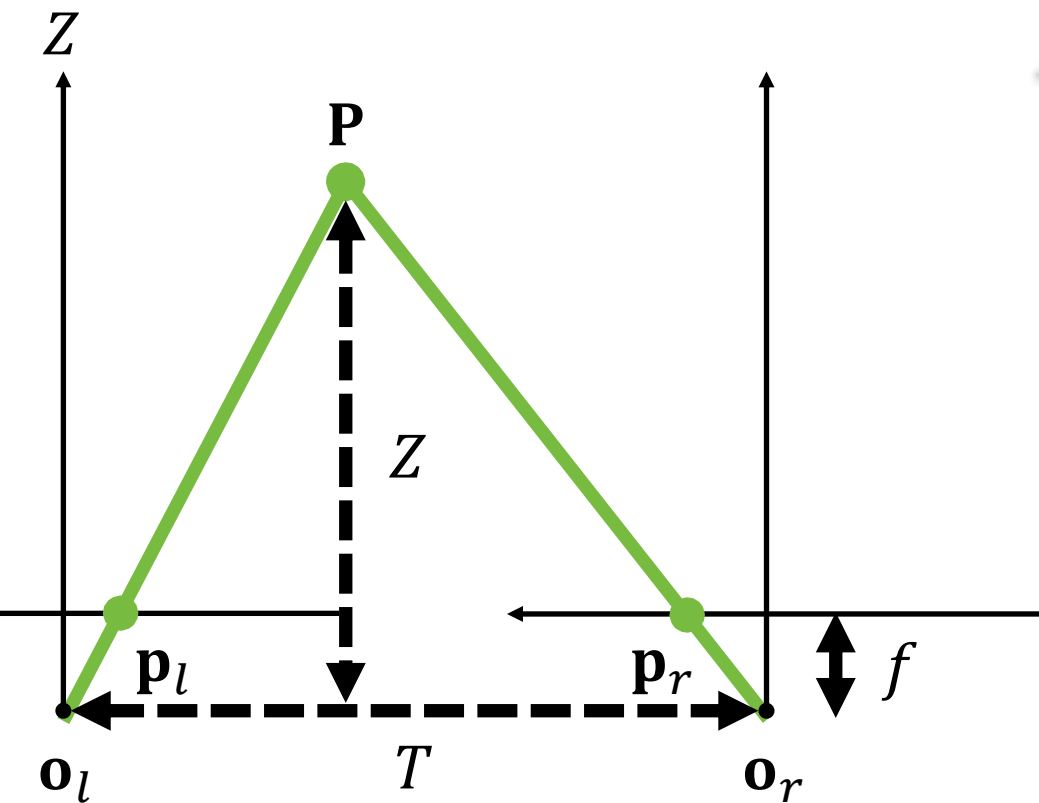
三角测量推导

定义

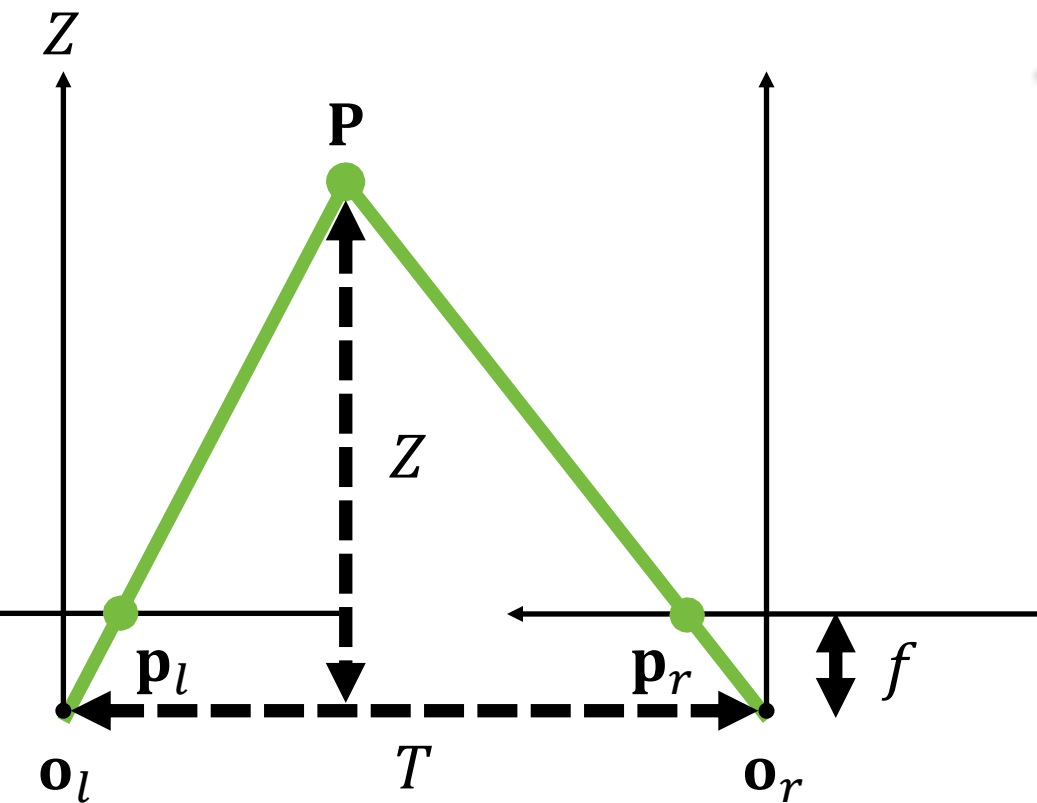
T 相机中心距离

Z 到基线的距离

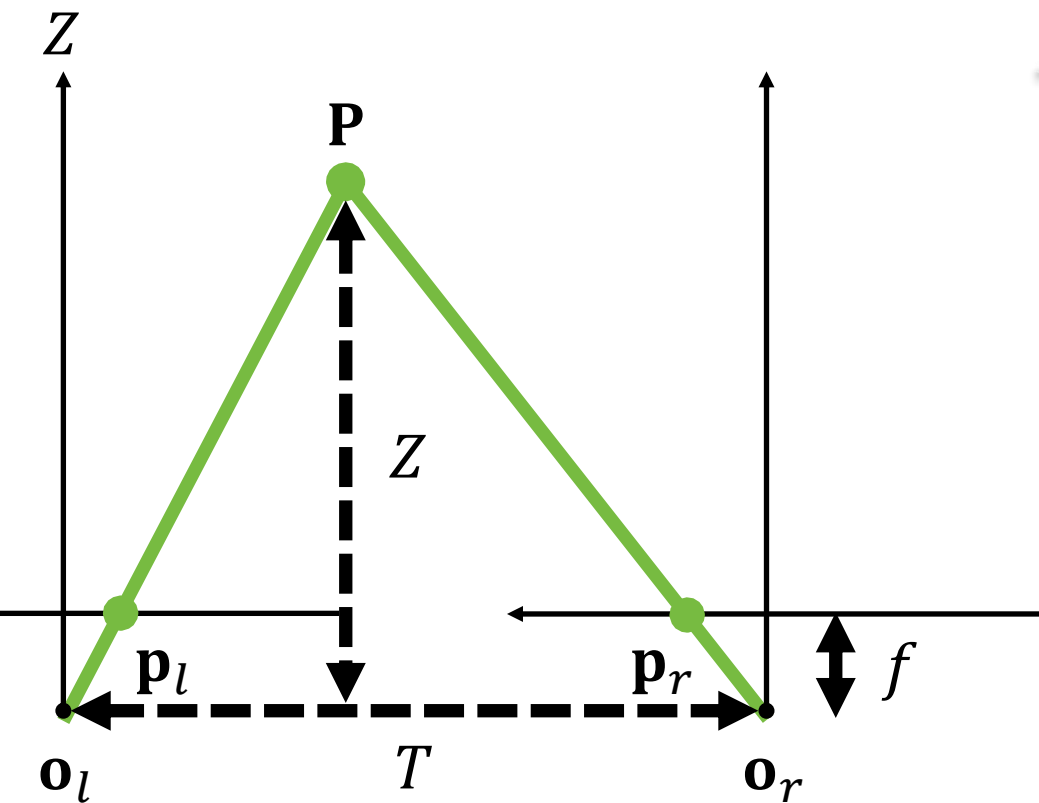
f 共同焦距



三角测量推导

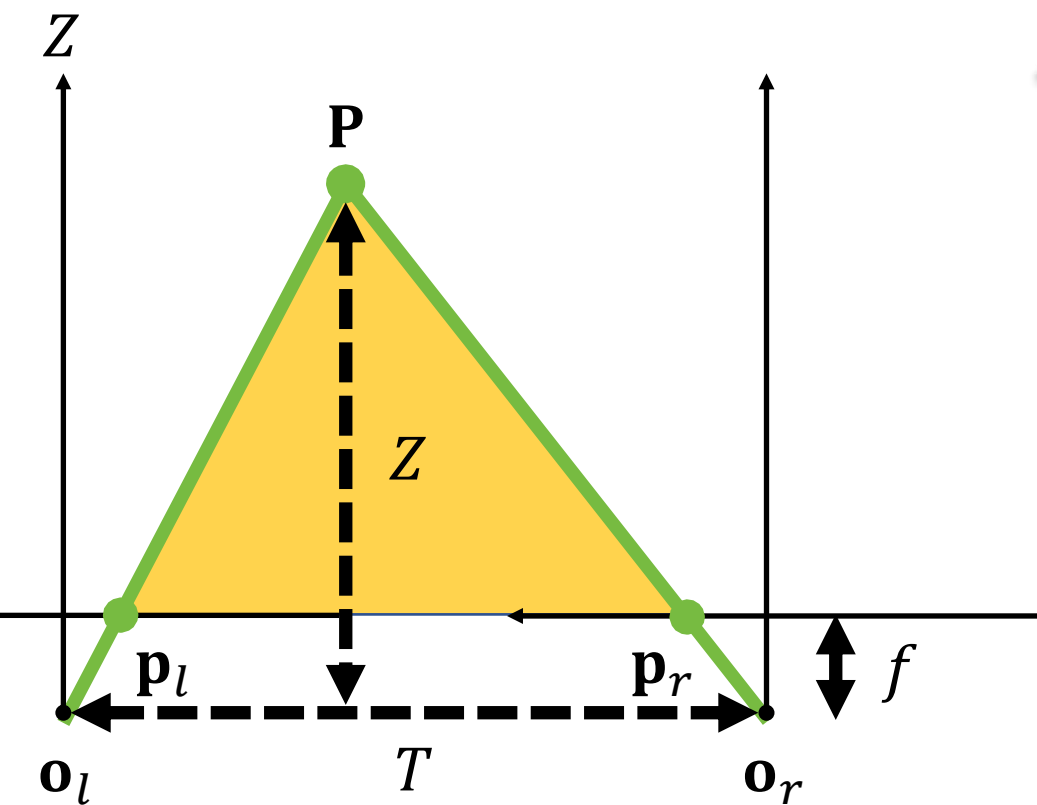


三角测量推导



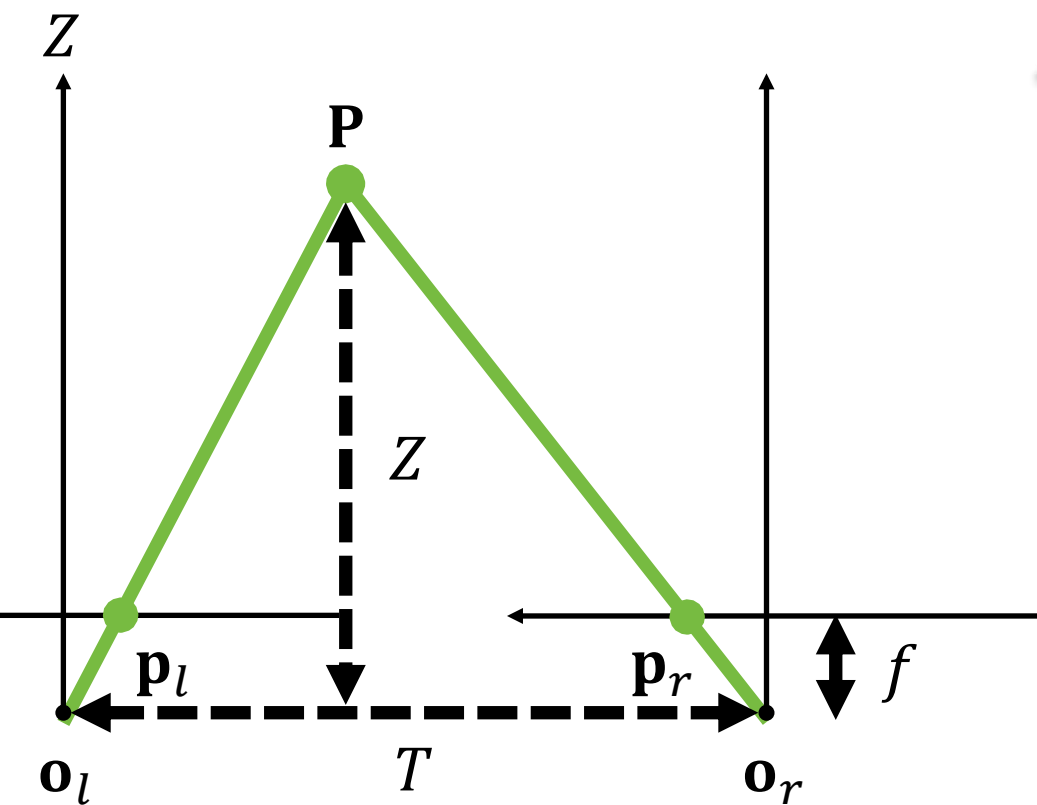
$$\Delta p_l P p_r$$

三角测量推导



$$\Delta p_l P p_r$$

三角测量推导

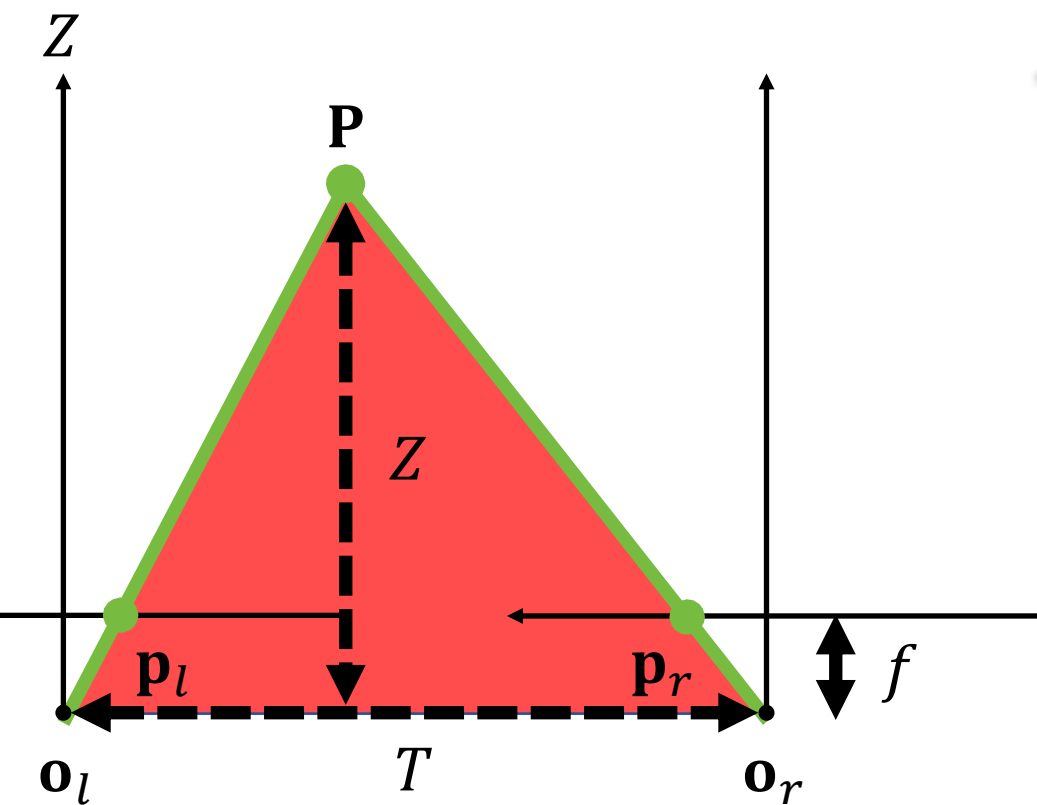


$$\Delta \mathbf{p}_l \mathbf{P} \mathbf{p}_r$$

和

$$\Delta \mathbf{o}_l \mathbf{P} \mathbf{o}_r$$

三角测量推导

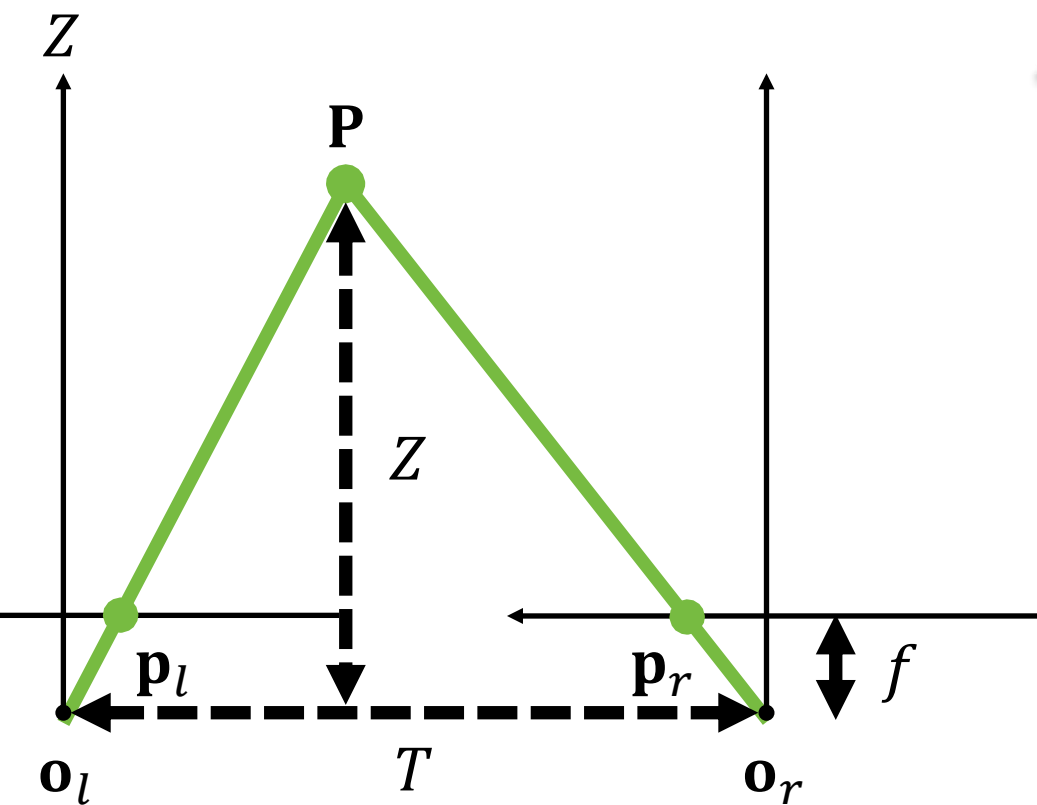


$$\Delta p_l P p_r$$

和

$$\Delta o_l P o_r$$

三角测量推导



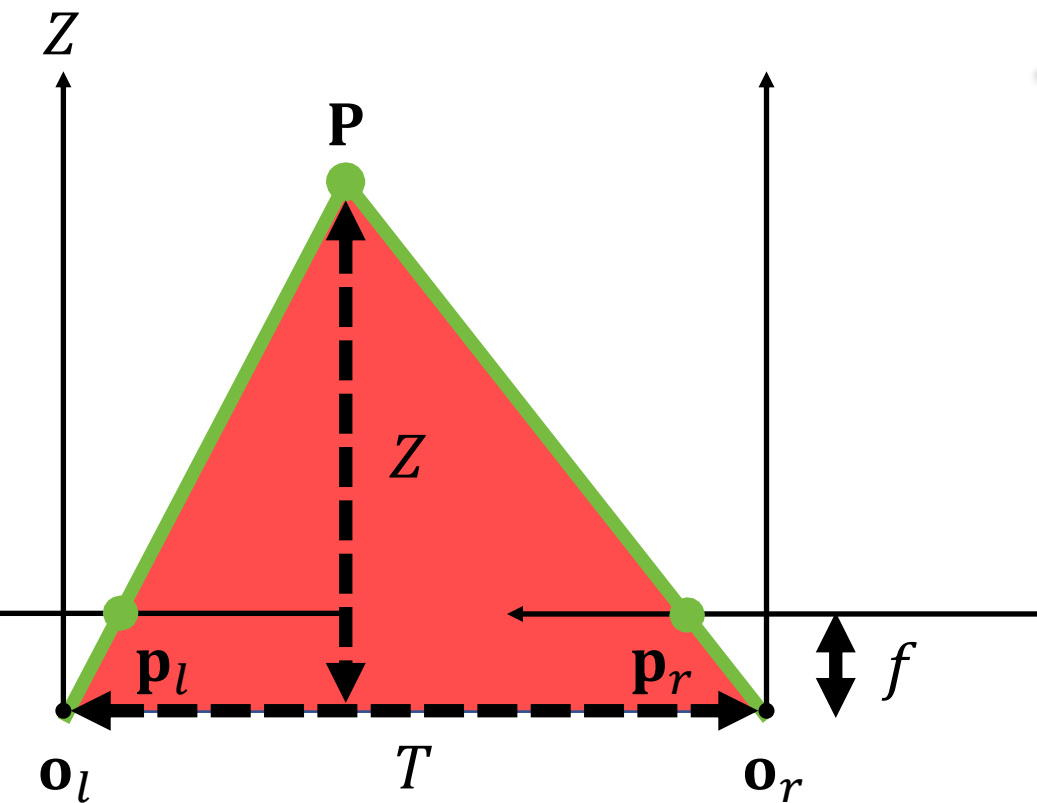
$$\Delta p_l P p_r$$

和

$$\Delta o_l P o_r$$

通过相似三角形

三角测量推导



$$\Delta p_l P p_r$$

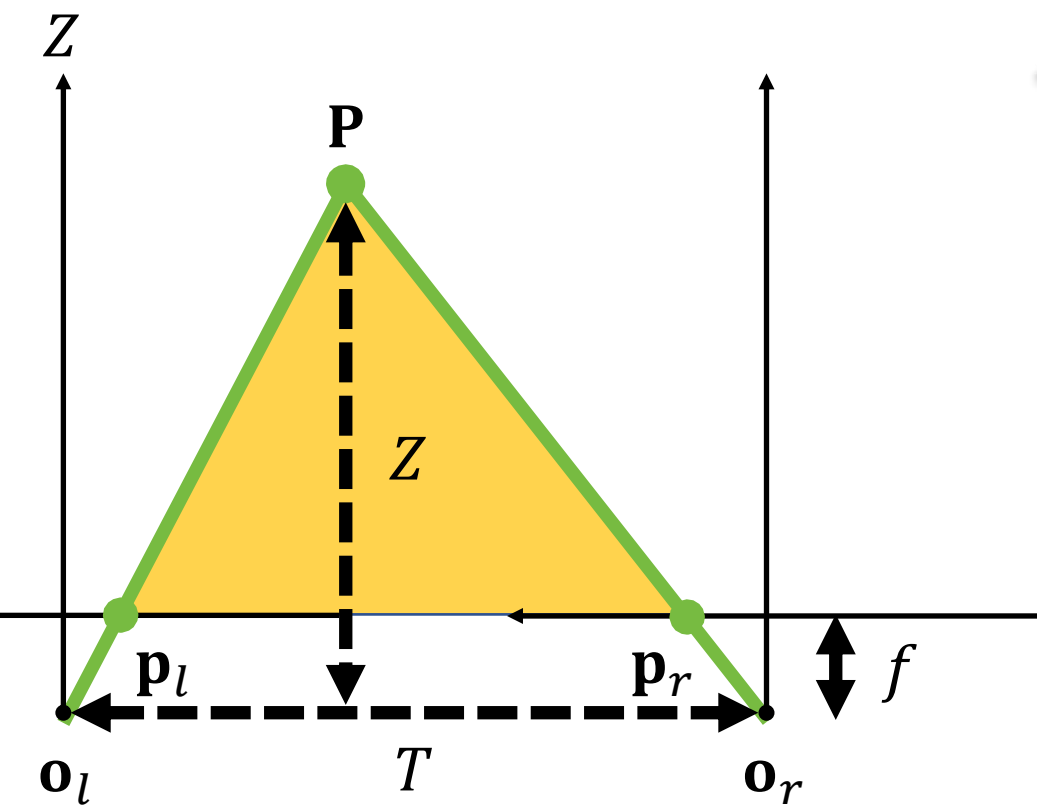
和

$$\Delta o_l P o_r$$

通过相似三角形

$$\frac{T}{Z}$$

三角测量推导



$\triangle p_l P p_r$

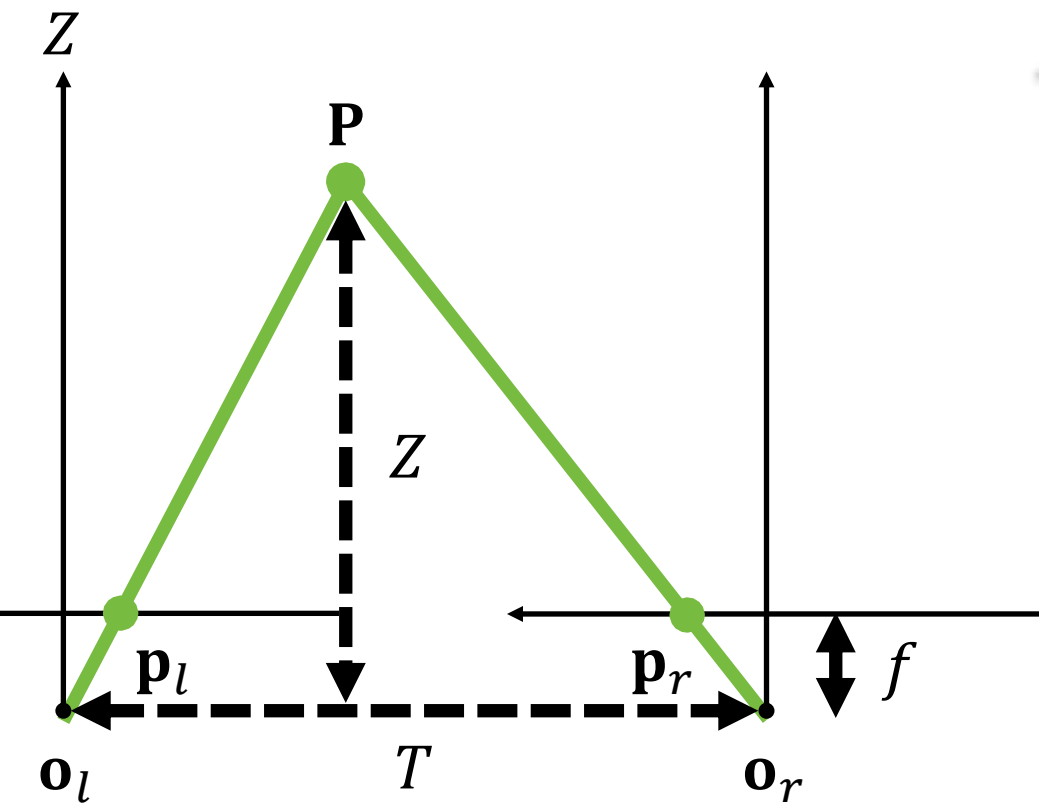
和

$\triangle o_l P o_r$

通过相似三角形

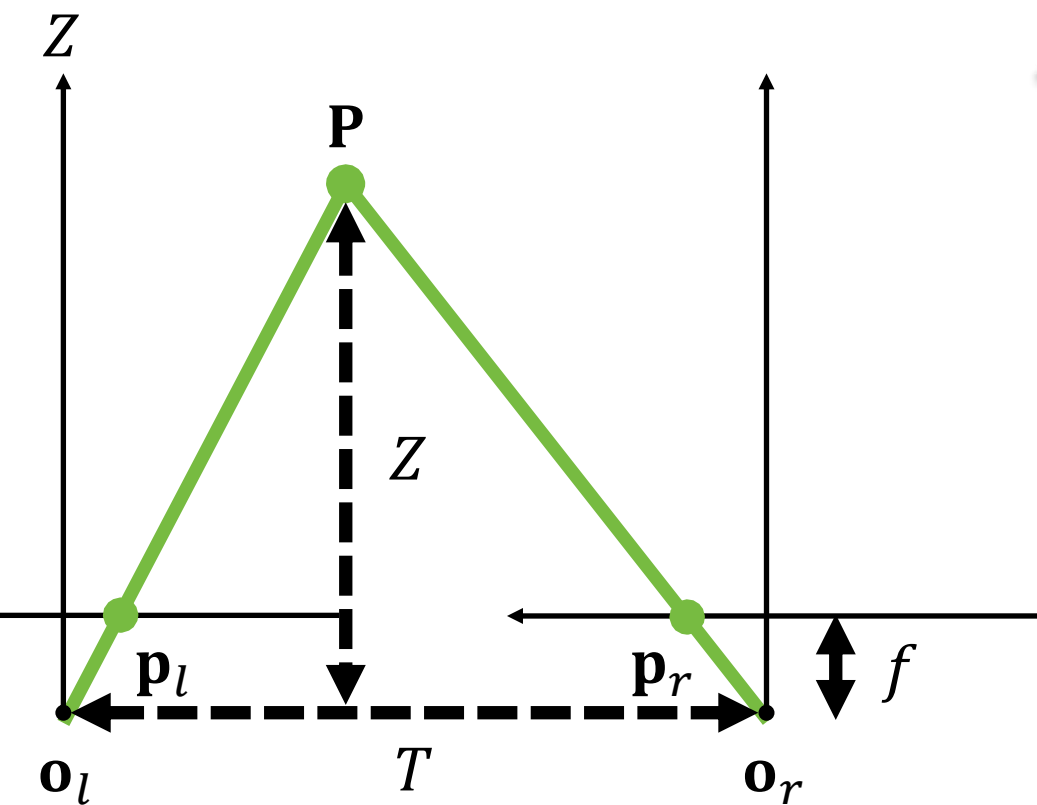
$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

三角测量推导



$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

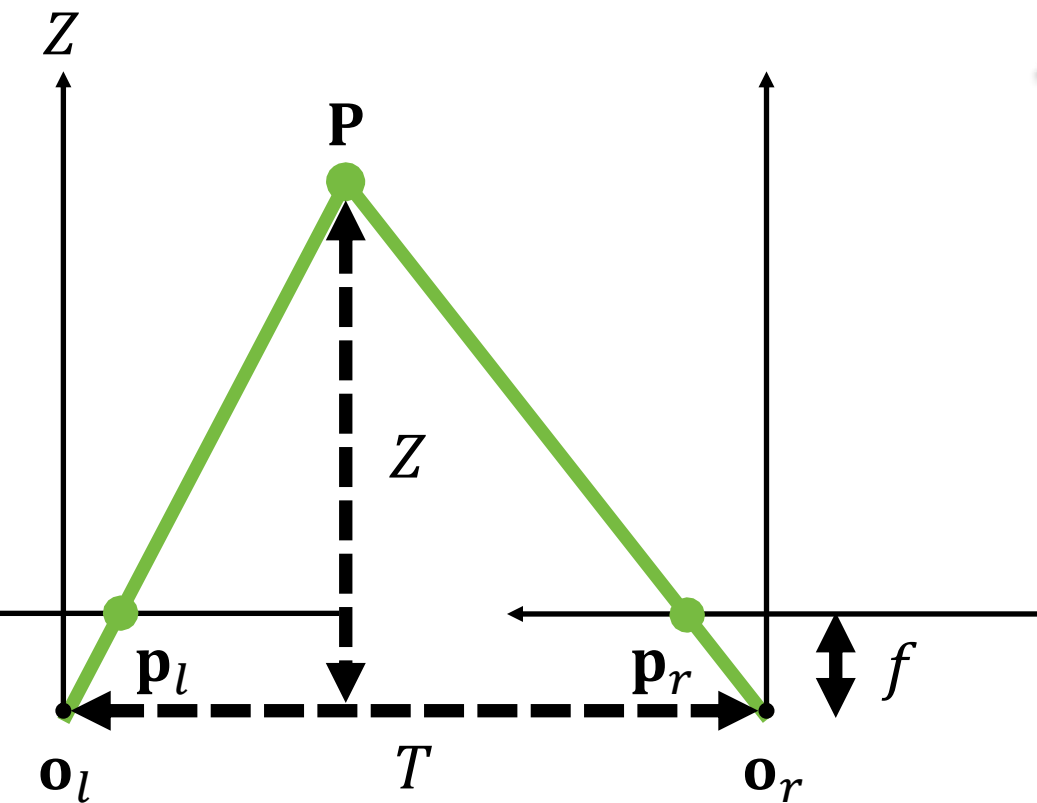
三角测量推导



$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

令 $d = x_l - x_r$ 为视差

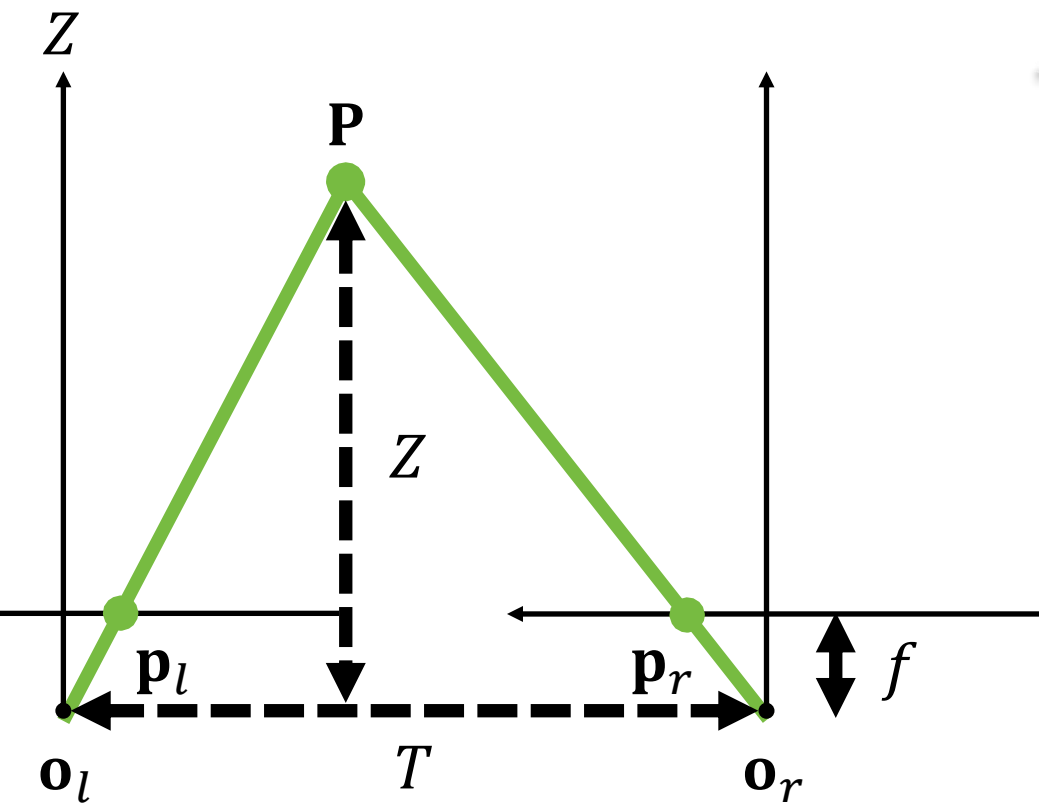
三角测量推导



$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

令 $d = x_l - x_r$ 为视差

三角测量推导

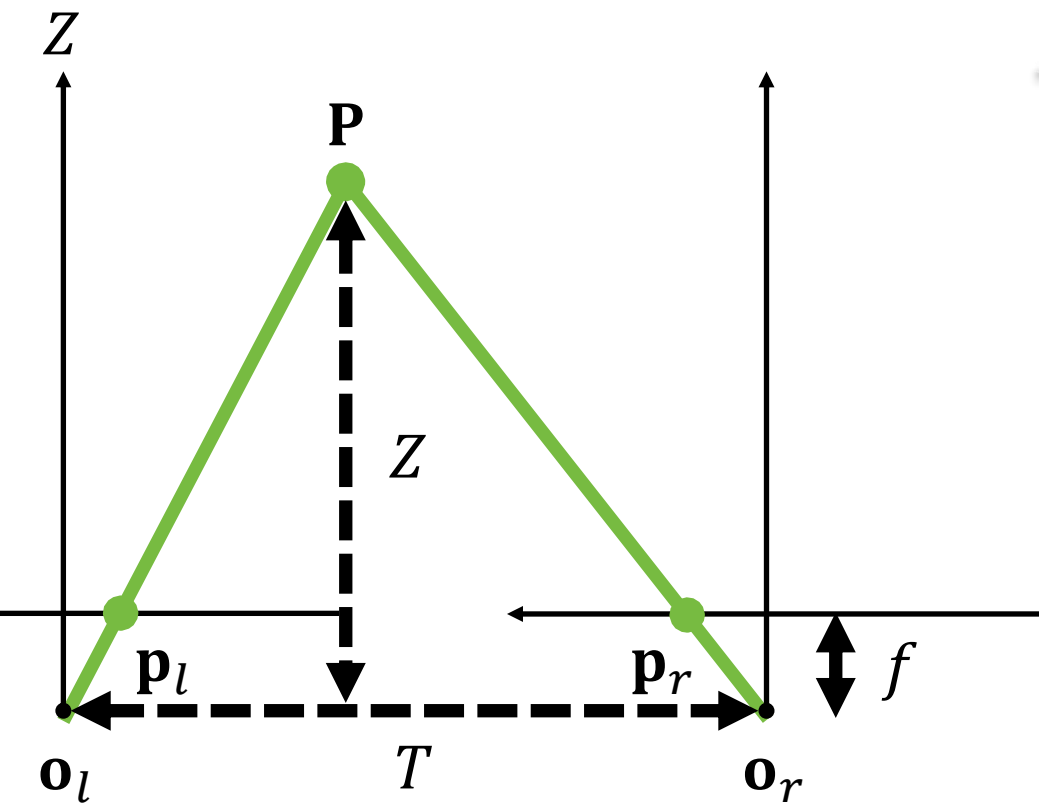


$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

令 $d = x_l - x_r$ 为视差

$$\frac{T + d}{Z - f} = \frac{T}{Z}$$

三角测量推导



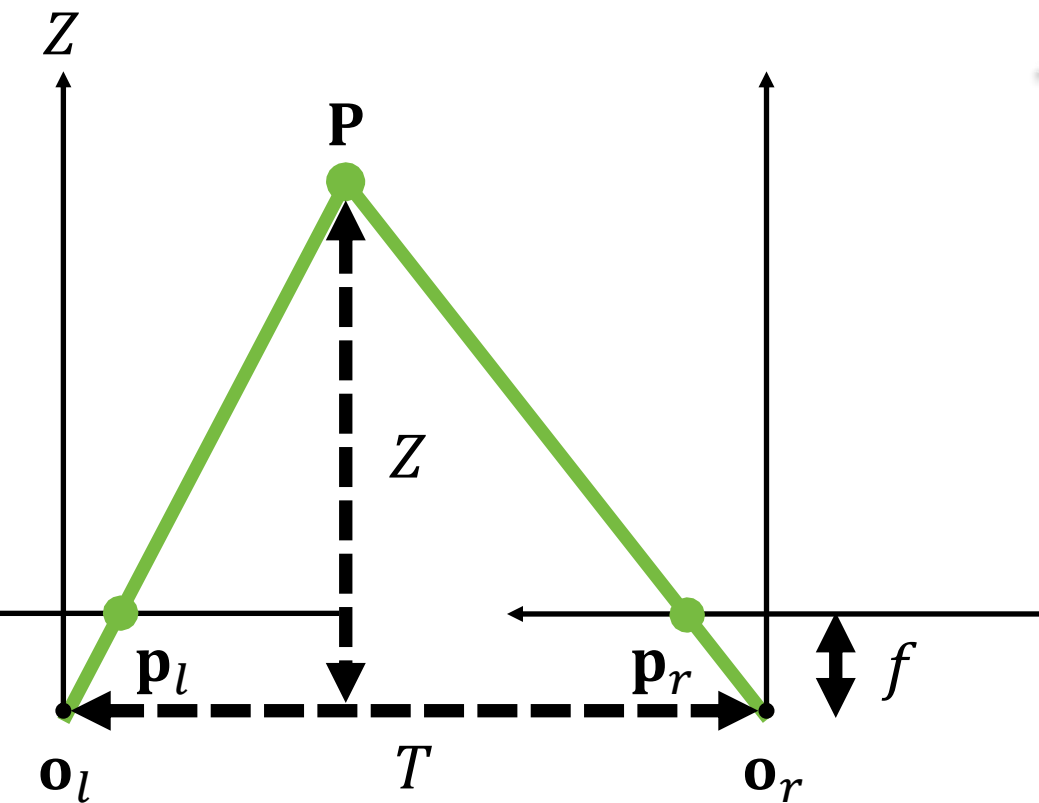
$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

令 $d = x_l - x_r$ 为视差

$$\frac{T + d}{Z - f} = \frac{T}{Z}$$

整理

三角测量推导



$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

令 $d = x_l - x_r$ 为视差

$$\frac{T + d}{Z - f} = \frac{T}{Z}$$

整理

$$\text{视差方程: } Z = f \frac{T}{d}$$

视差方程： $Z = f \frac{T}{d}$

备注：

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备注：

假设立体相机是完全平行的

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假设立体相机是完全平行的

假设对应点完全匹配

视差方程： $Z = f \frac{T}{d}$

备注：

假设立体相机是完全平行的

假设对应点完全匹配

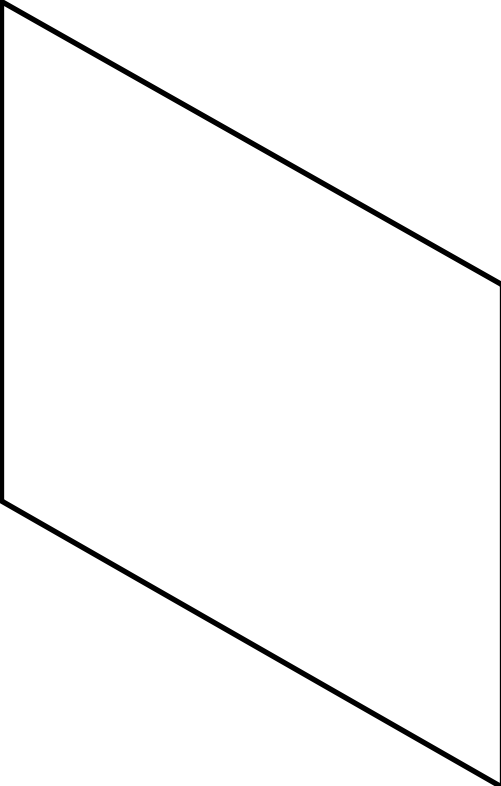
深度与视差成反比

假设我们有一个完全标定的立体视觉装置

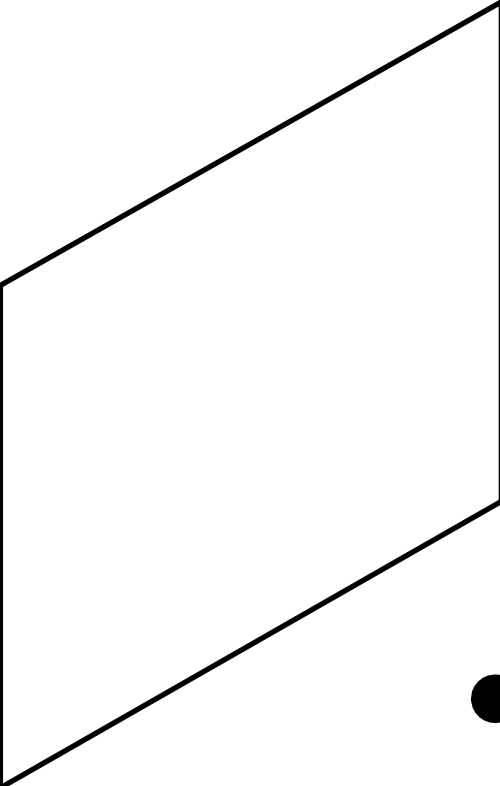
假设我们有一个完全标定的立体视觉装置

假设我们有一个完全标定的立体视觉装置

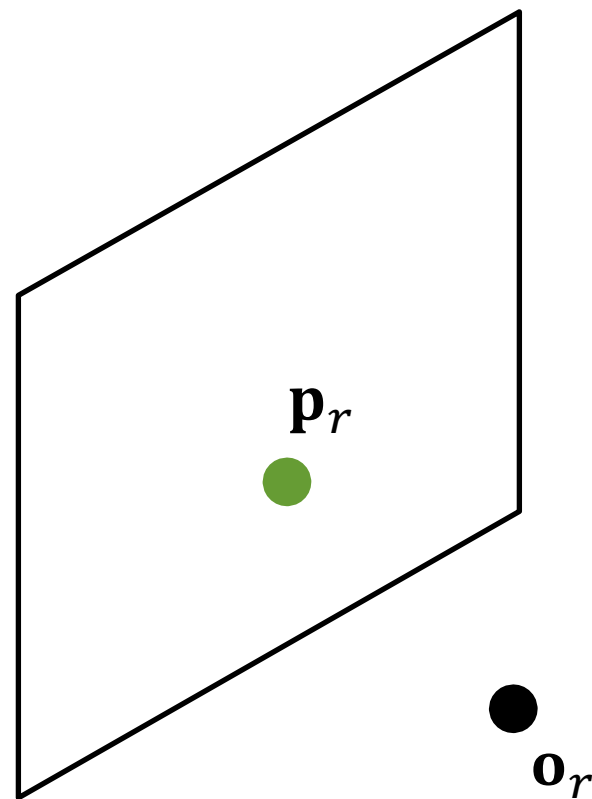
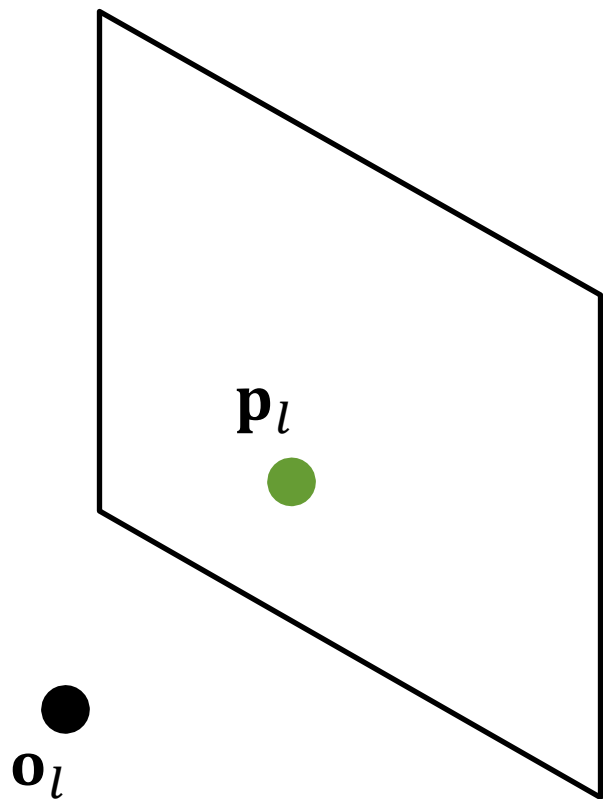
摄像机的内参和外参是已知的

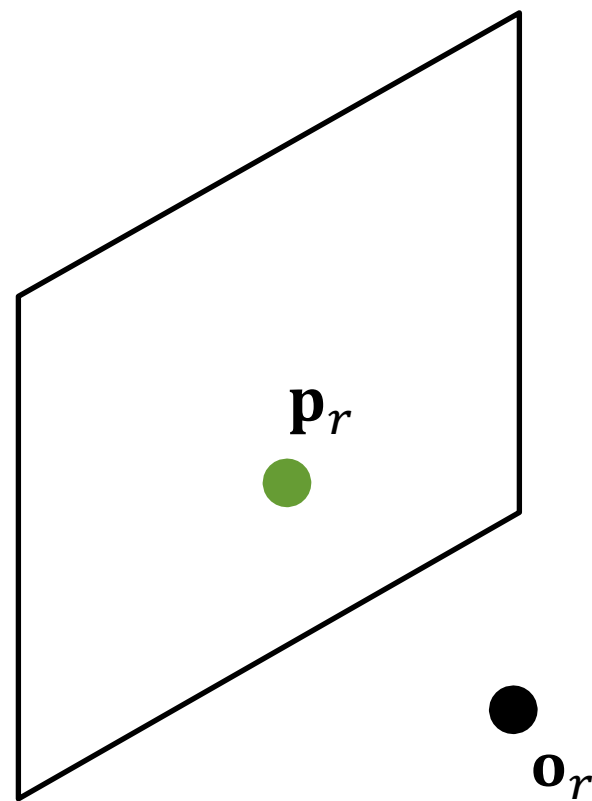
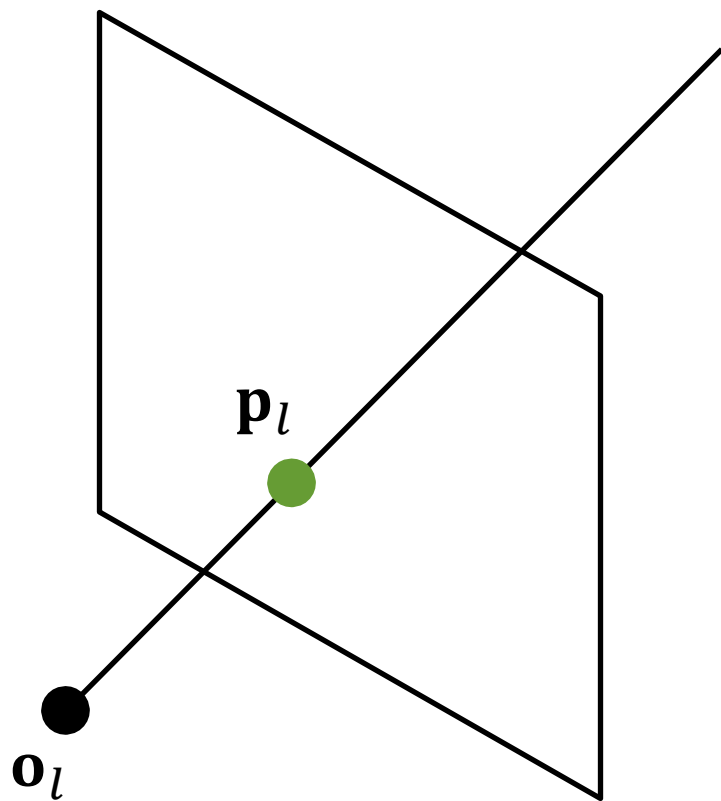


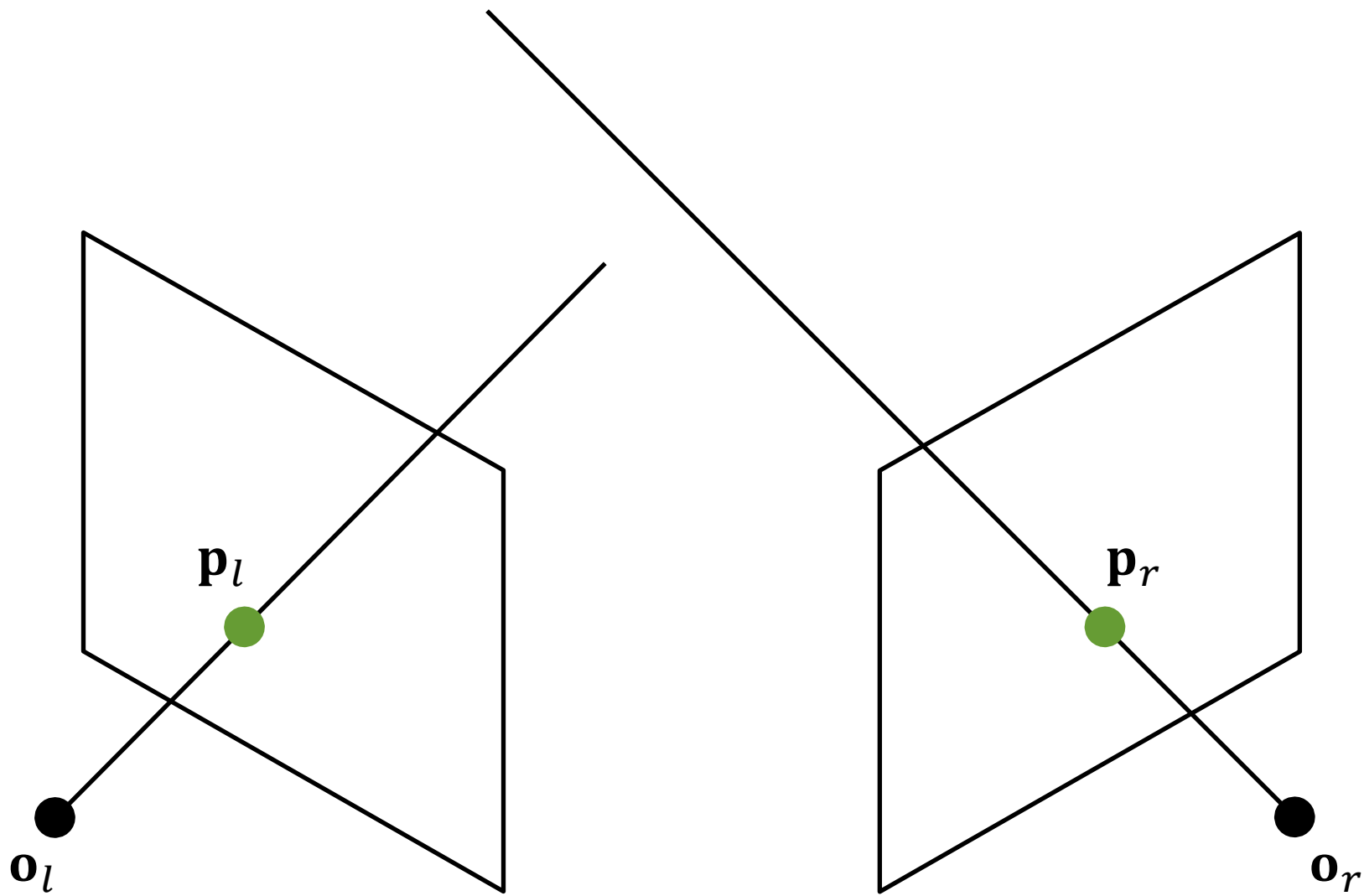
$\bullet$
 $\mathbf{o}_l$



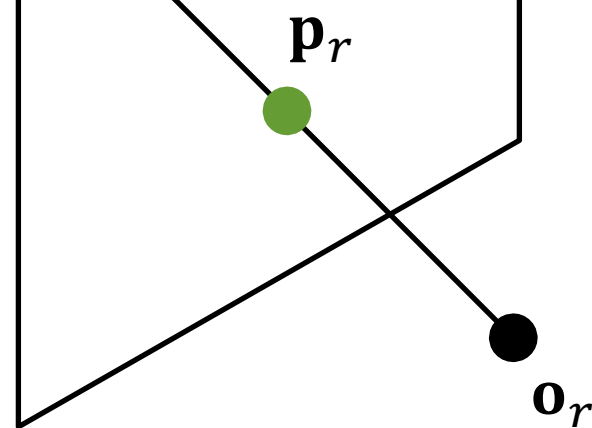
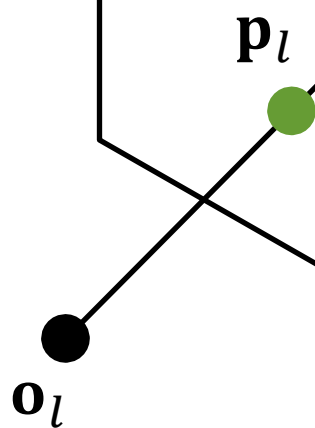
$\bullet$
 $\mathbf{o}_r$



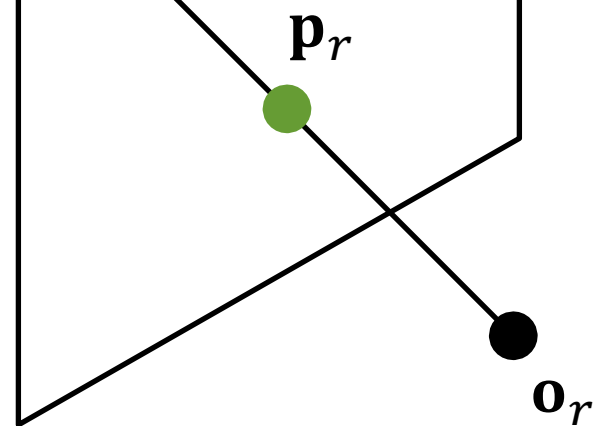
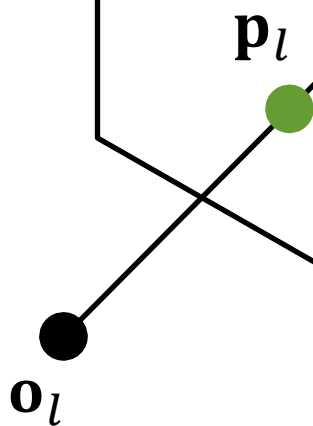




由于噪声导致匹配光线可能不相交



计算两条射线之间最短线段的中点



P_{midpoint}

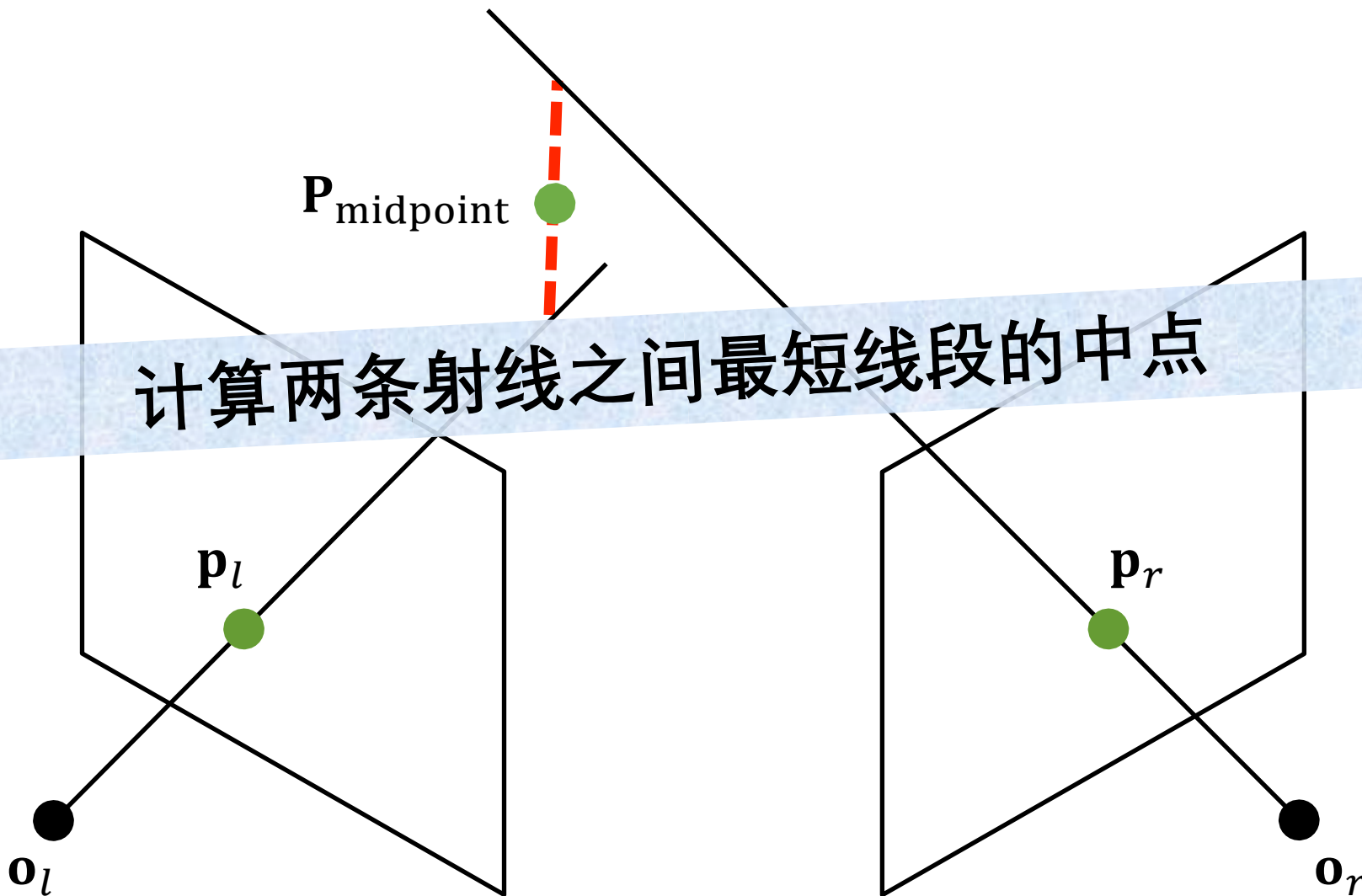
计算两条射线之间最短线段的中点

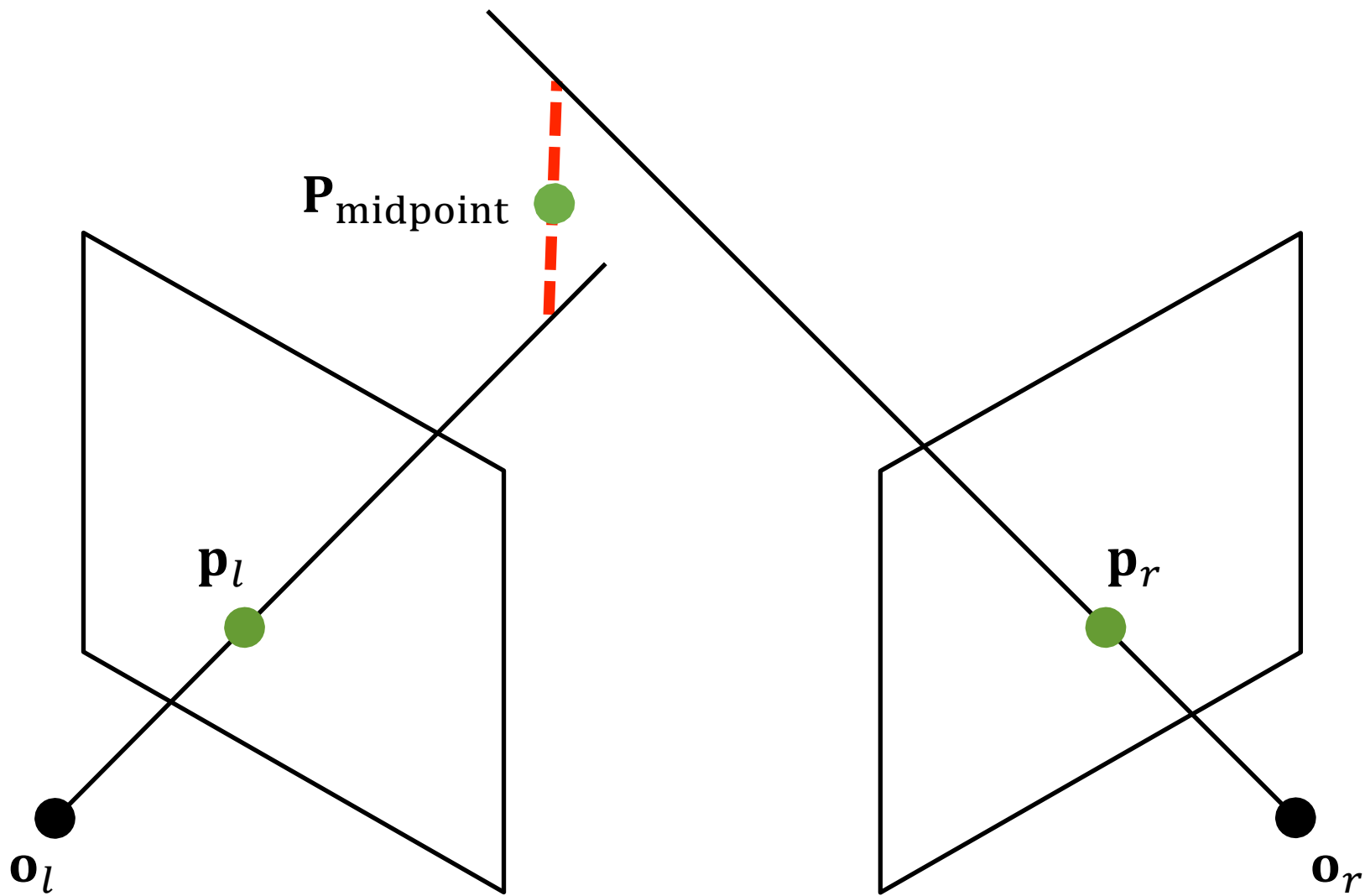
p_l

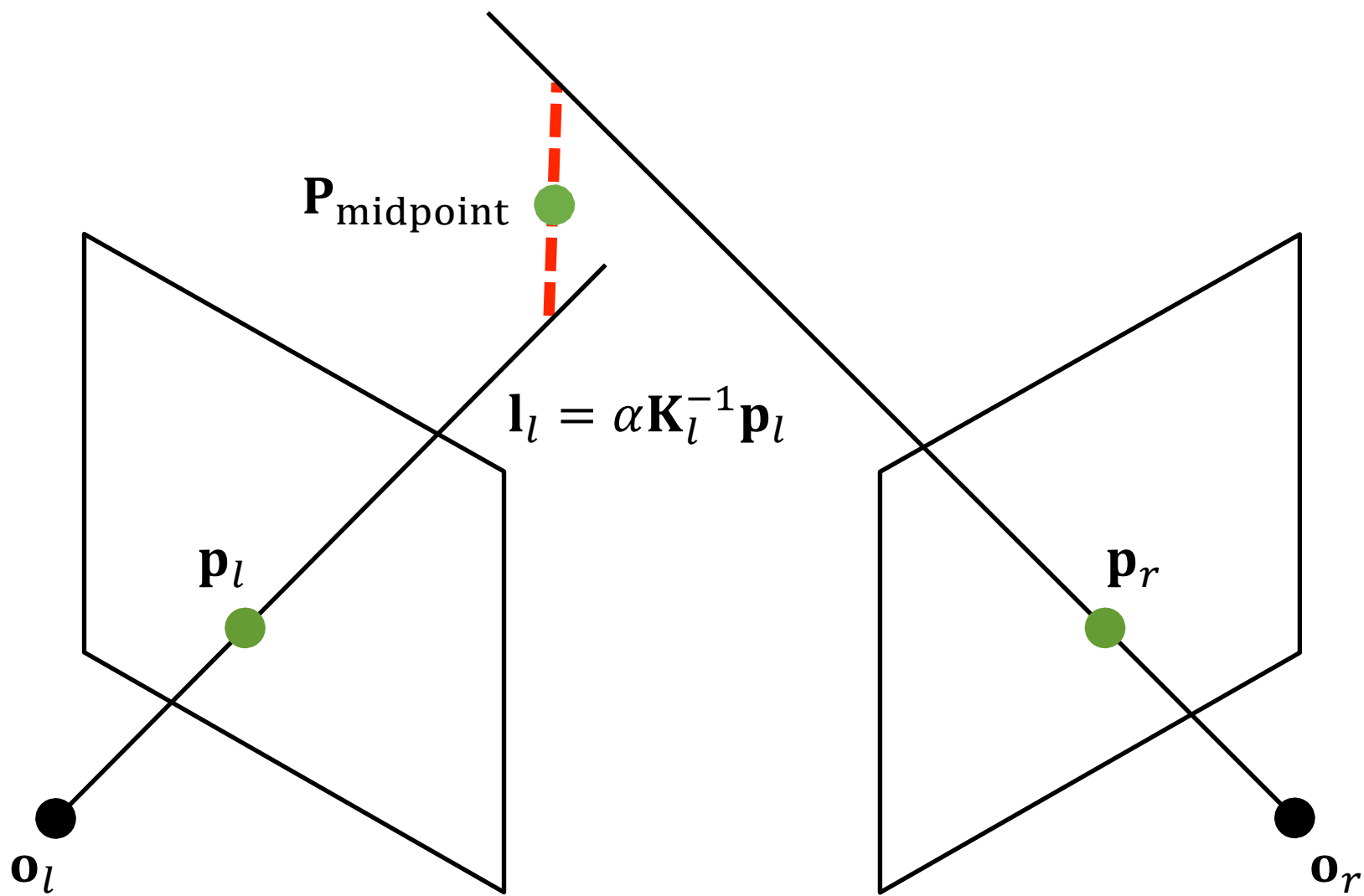
p_r

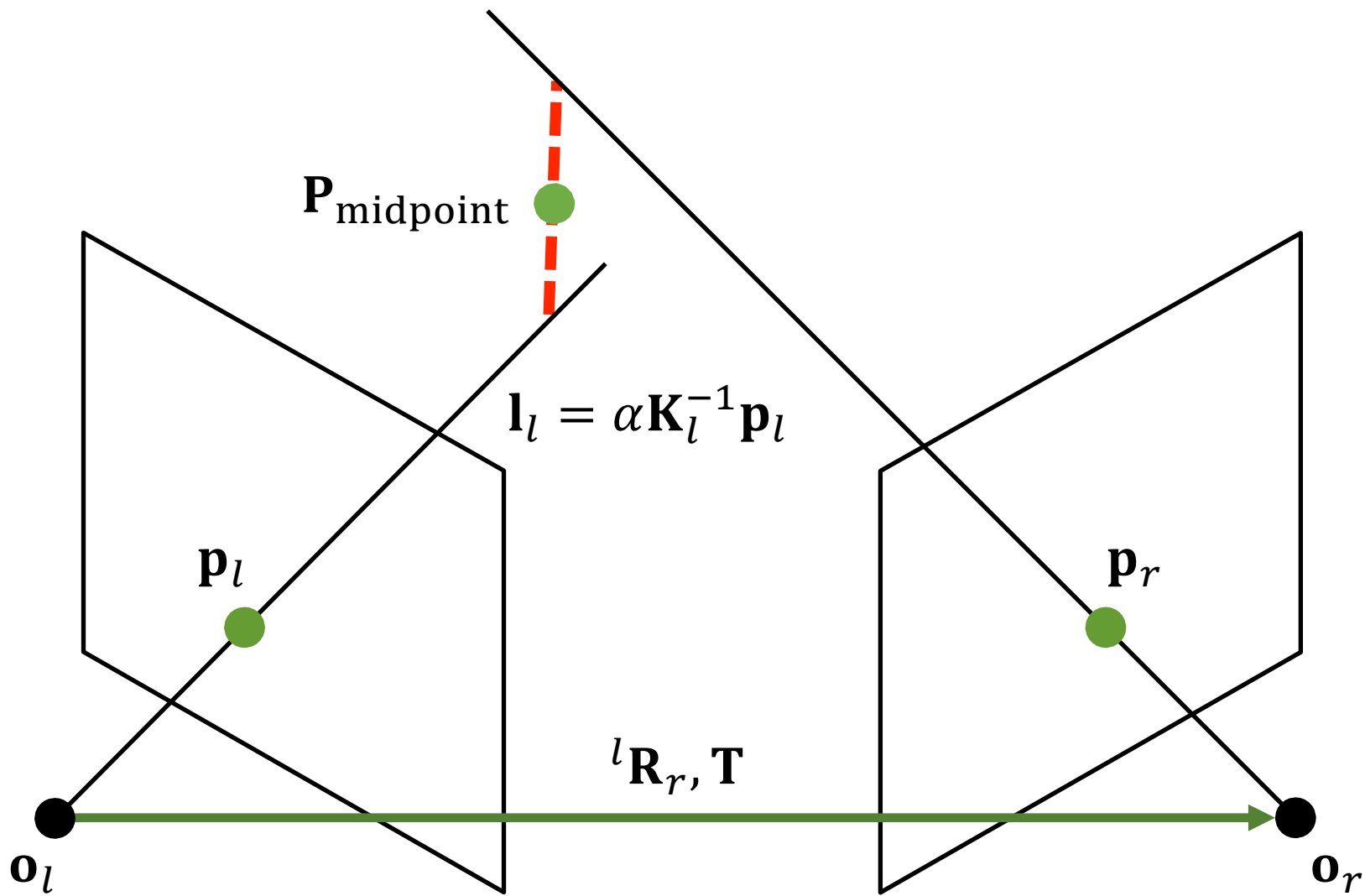
o_l

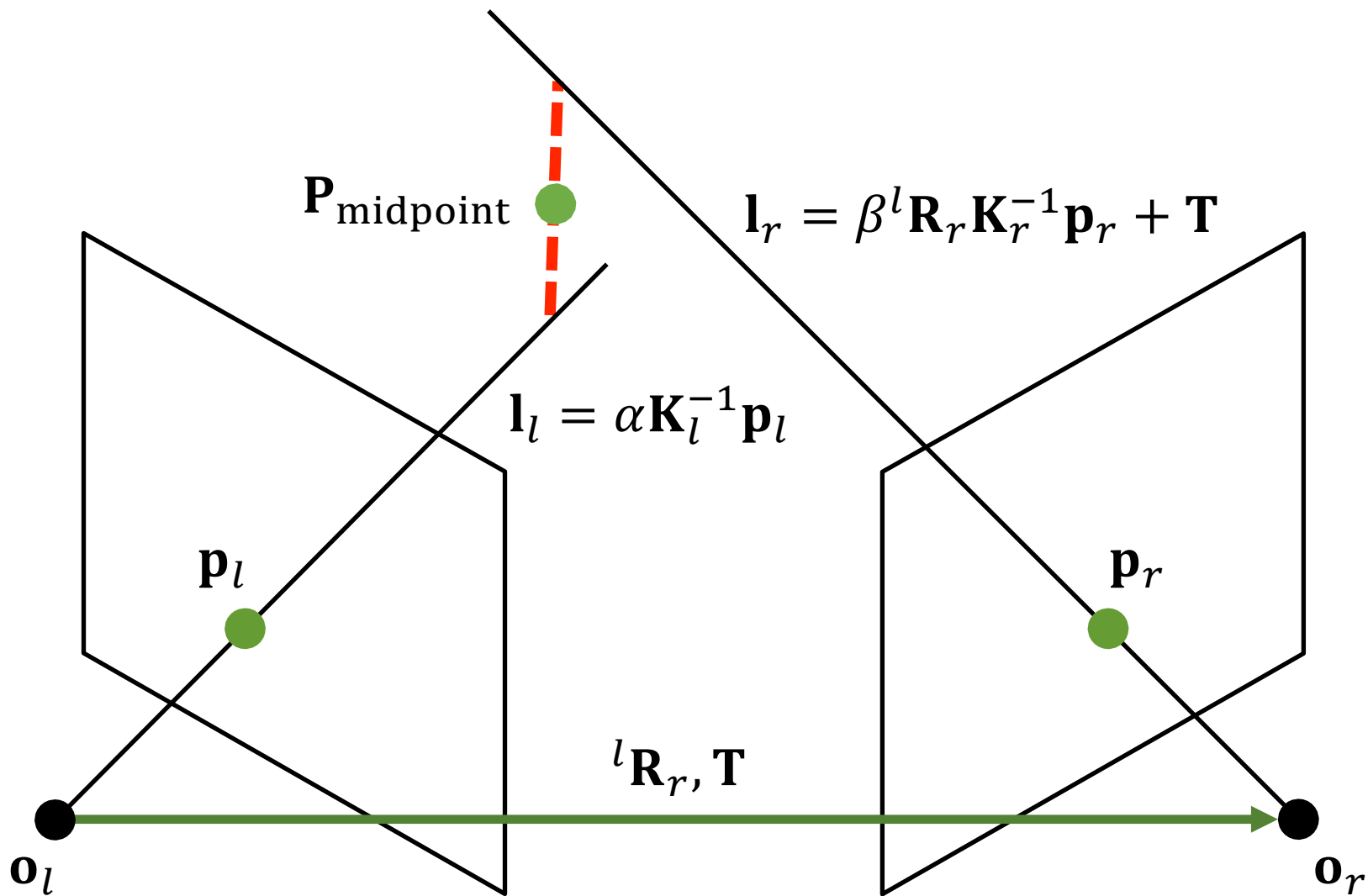
o_r

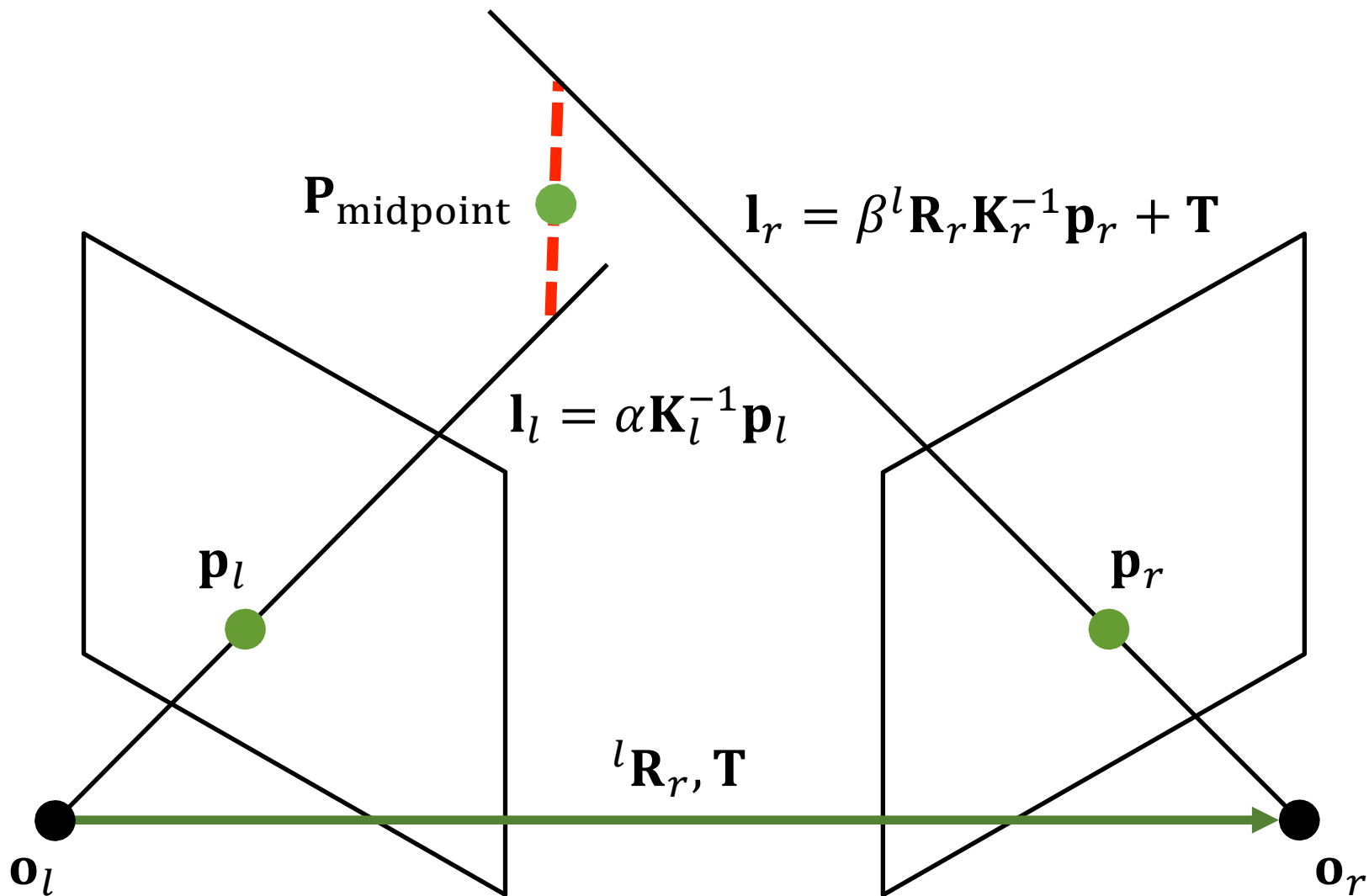












$$\arg \min_{\alpha, \beta} \left\| \alpha \mathbf{K}_l^{-1} \mathbf{p}_l - \left(\beta {}^l\mathbf{R}_r \mathbf{K}_r^{-1} \mathbf{p}_r + \mathbf{T} \right) \right\|$$

立体匹配

基于块的方法

左视图



右视图



左视图



右视图



假设两台相机是平行的

左视图



右视图



对于左视图中的每个点，
找到右视图中“最佳”匹配块

左视图



右视图



对于左视图中的每个点，
找到右视图中“最佳”匹配块

左视图



右视图



对于左视图中的每个点，
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左视图



右视图



对于左视图中的每个点，
找到右视图中“最佳”匹配块

左视图



右视图



左视图



右视图



匹配代价
(SAD)



视差

左视图



右视图



匹配代价
(SAD)

绝对误差和

视差

左视图



右视图



匹配代价
(SAD)



视差

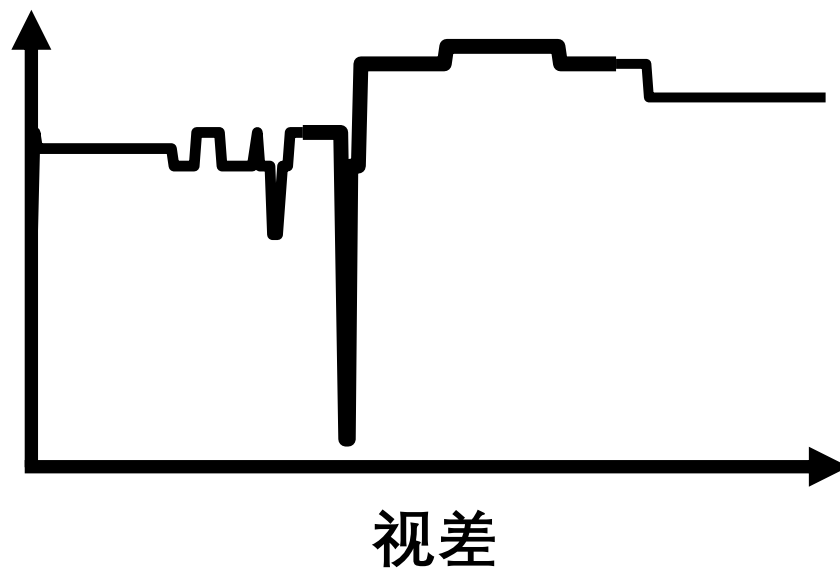
左视图



右视图



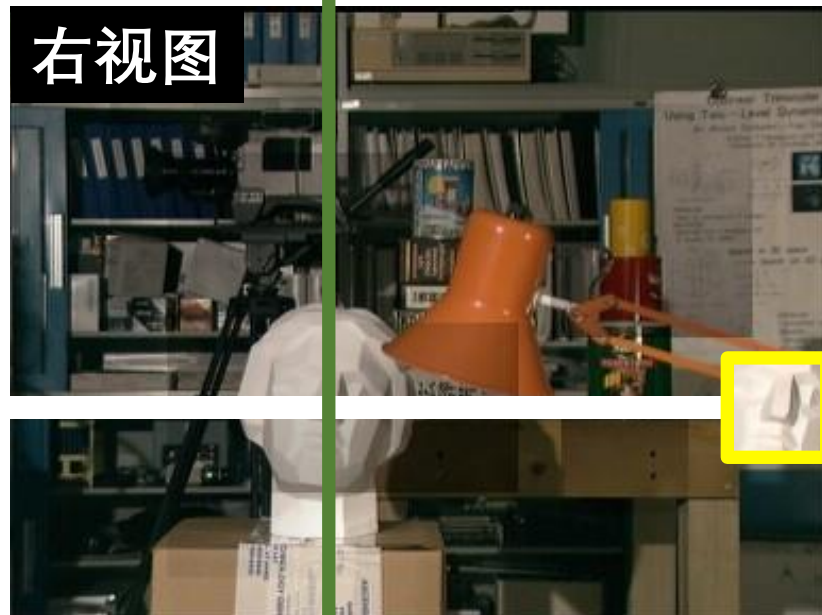
匹配代价
(SAD)



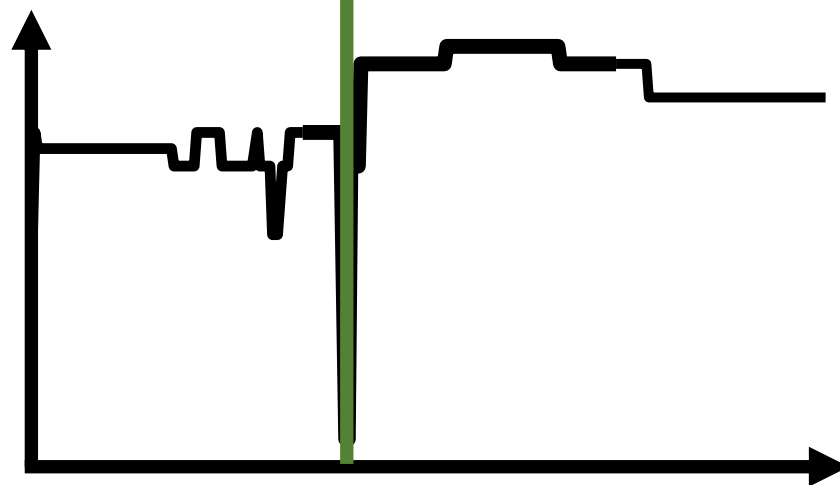
左视图



右视图

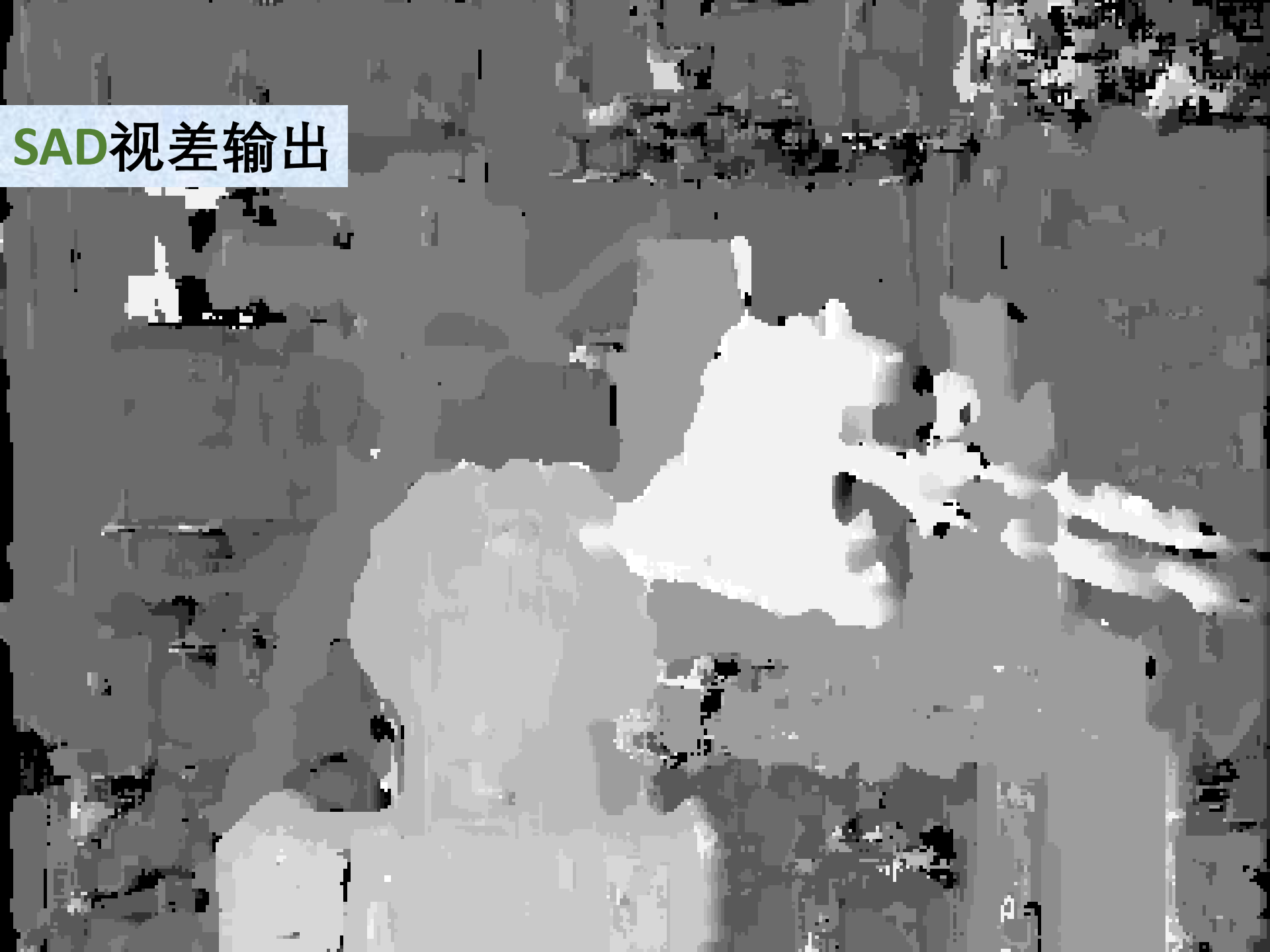


匹配代价
(SAD)



视差

SAD视差输出



图割视差输出



PatchmatchNet: Learned Multi-View Patchmatch Stereo

Fangjinhua Wang¹ Silvano Galliani² Christoph Vogel² Pablo Speciale² Marc Pollefeys^{1,2}

¹Department of Computer Science, ETH Zurich

²Microsoft Mixed Reality & AI Zurich Lab

Abstract

We present *PatchmatchNet*, a novel and learnable cascade formulation of Patchmatch for high-resolution multi-view stereo. With high computation speed and low memory requirement, *PatchmatchNet* can process higher resolution imagery and is more suited to run on resource limited devices than competitors that employ 3D cost volume regularization. For the first time we introduce an iterative multi-scale Patchmatch in an end-to-end trainable architecture and improve the Patchmatch core algorithm with a novel and learned adaptive propagation and evaluation scheme for each iteration. Extensive experiments show a very competitive performance and generalization for our method on DTU, Tanks & Temples and ETH3D, but at a significantly higher efficiency than all existing top-performing models: at least two and a half times faster than state-of-the-art methods with twice less memory usage. Code is available at <https://github.com/FangjinhuaWang/PatchmatchNet>.

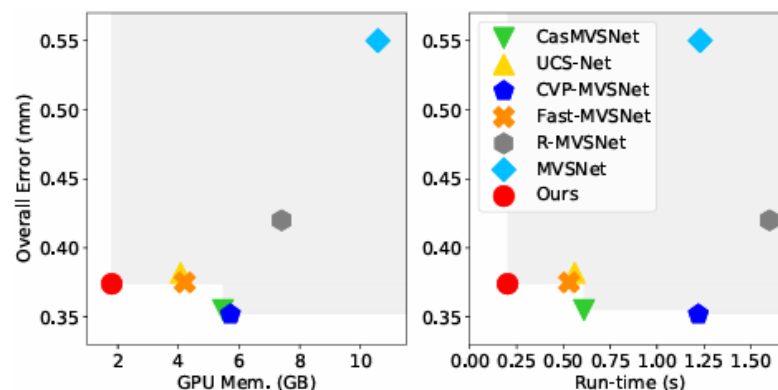


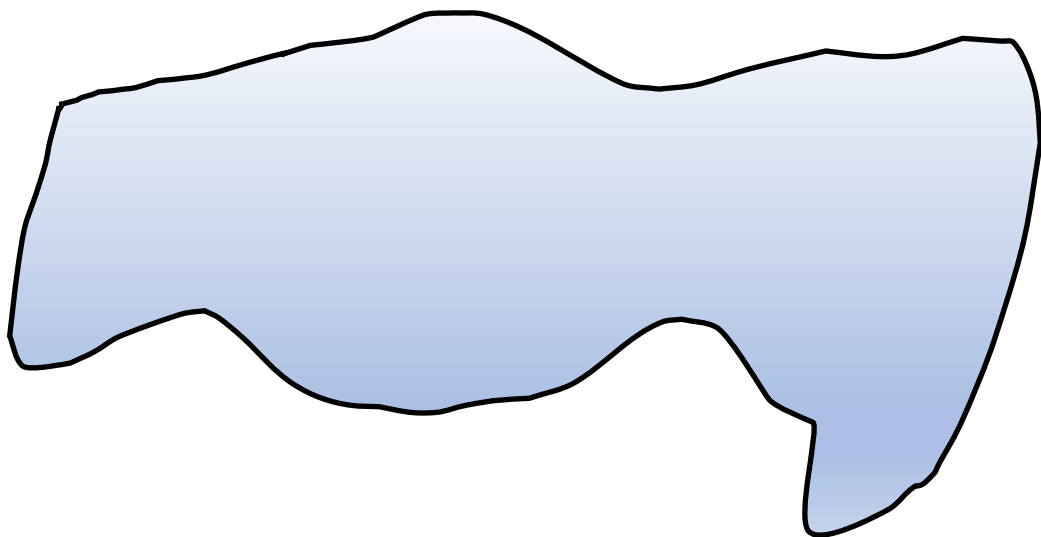
Figure 1: Comparison with state-of-the-art learning-based multi-view stereo methods [7, 17, 41, 42, 43, 44] on DTU [1]. Relationship between error, GPU memory and run-time with image size 1152×864 .

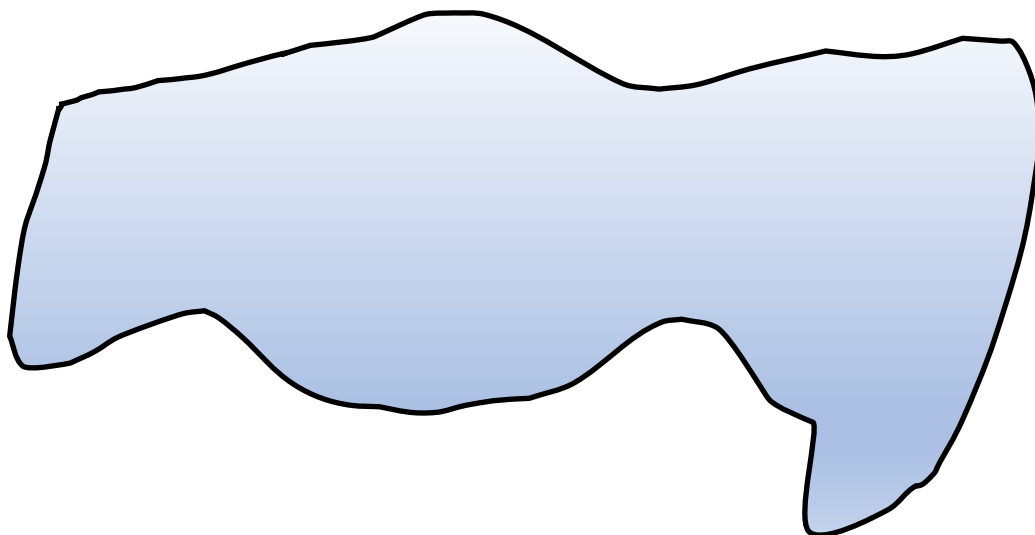
learning-based MVS methods [6, 28, 39, 42] construct a 3D cost volume, regularize it with a 3D CNN and regress the depth. As 3D CNNs are usually time and memory consuming, some methods [39, 42] down-sample the input during feature extraction and compute both, the cost volume and the depth map at low-resolution. Yet, according to Fig. 1, the depth maps at low-resolution can harm accuracy.

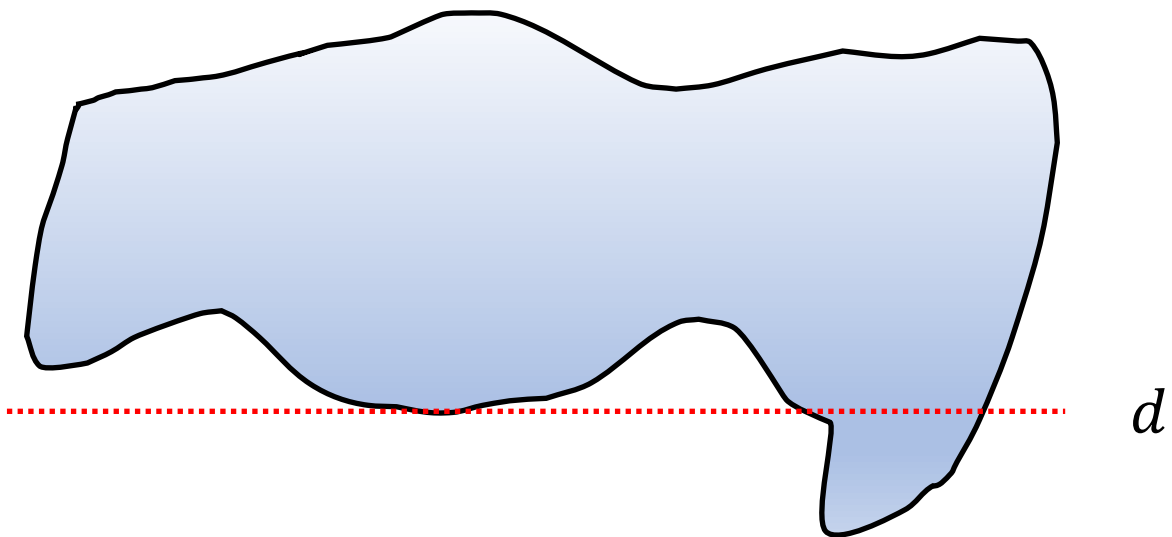
CVPR, 2021

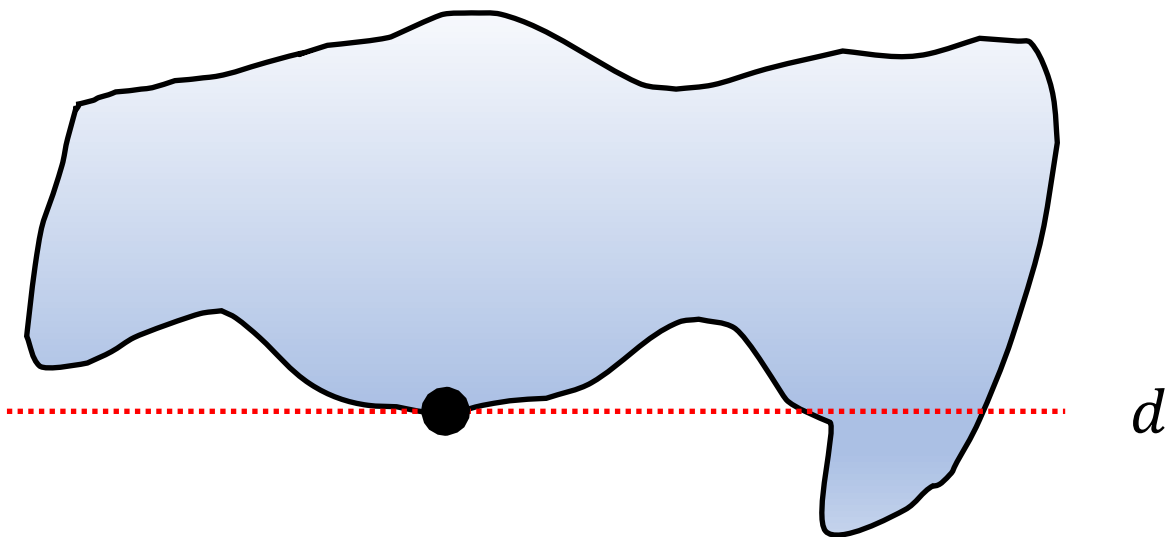
平面扫描

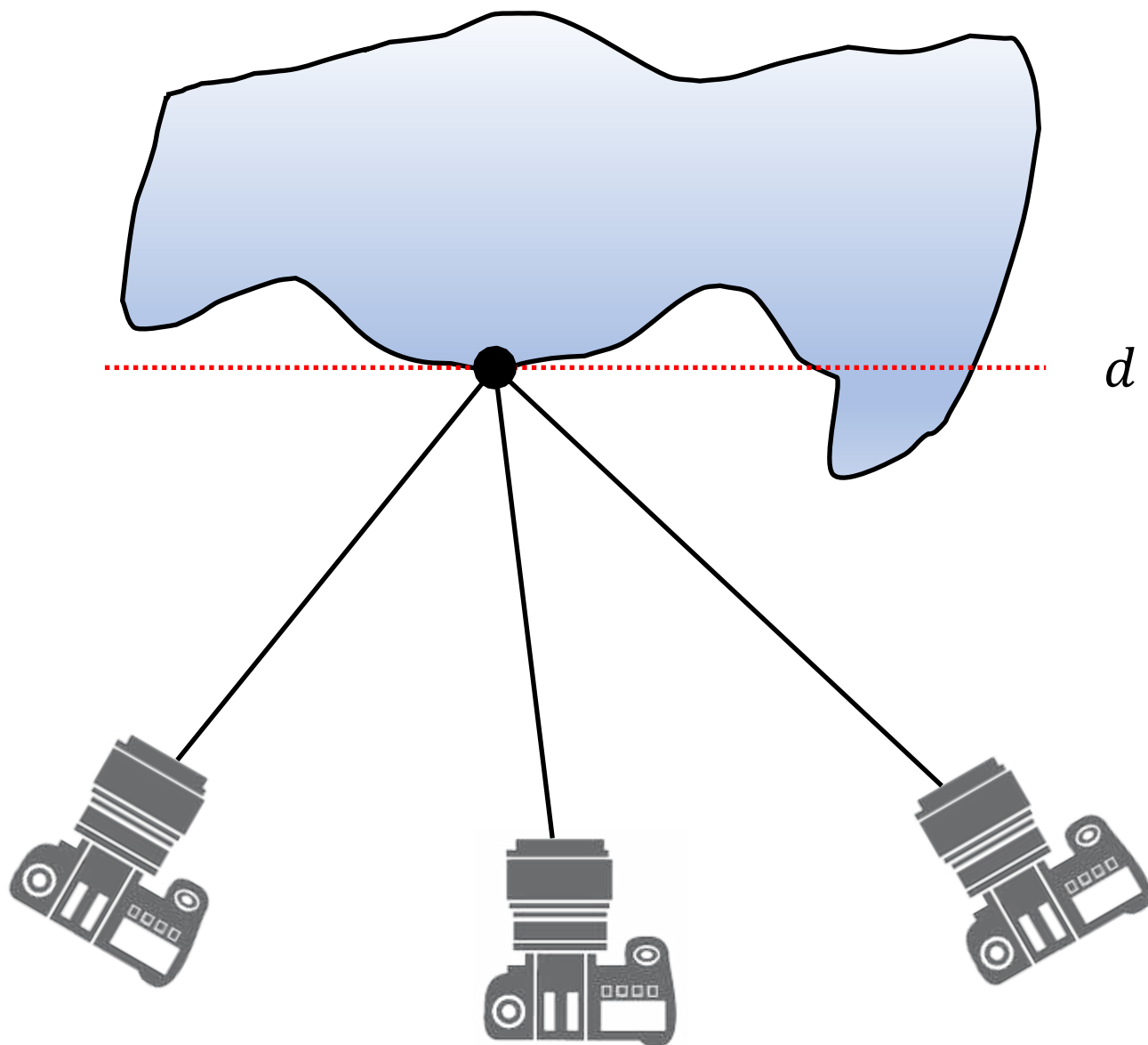
基于单应变换的方法

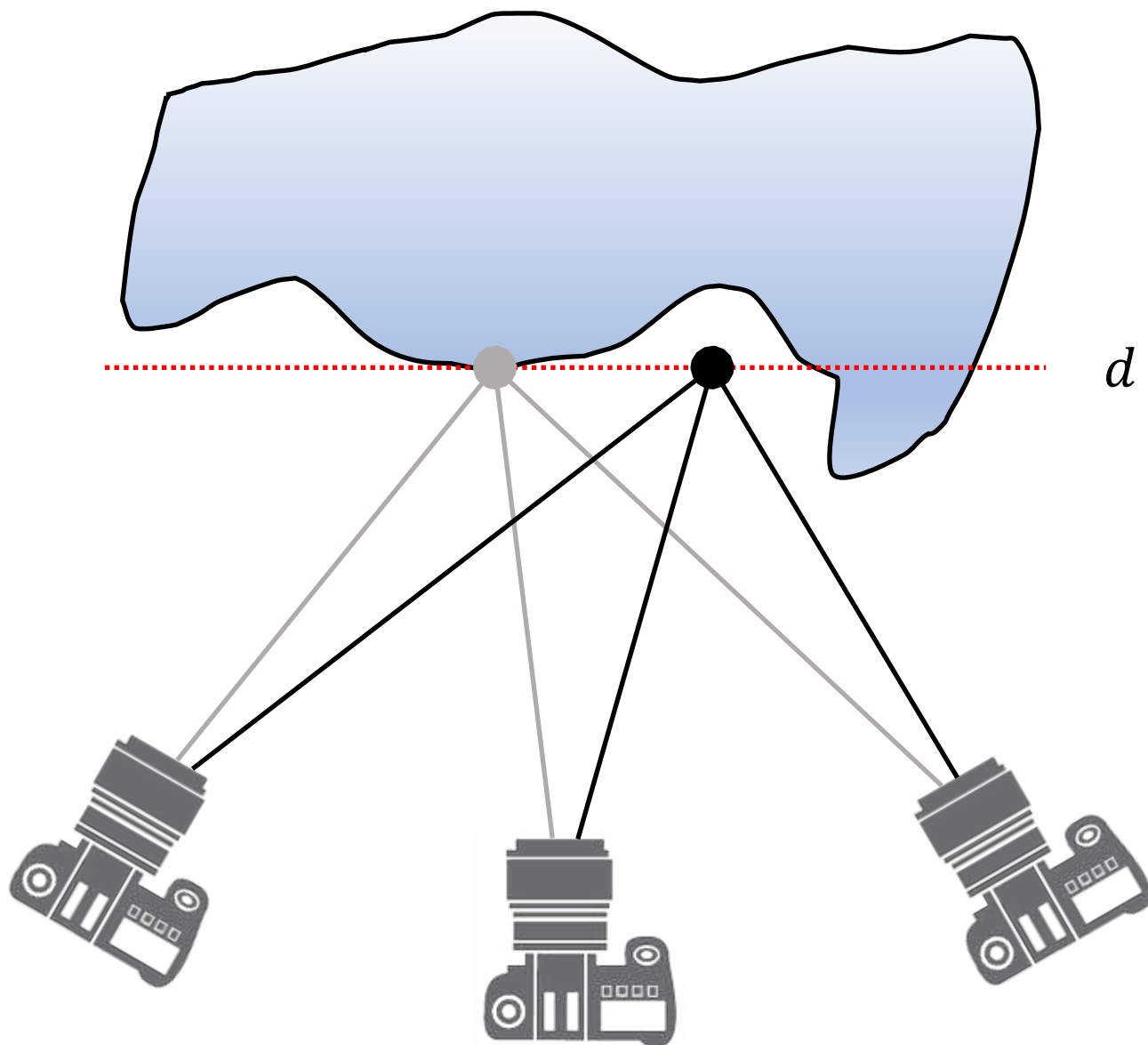


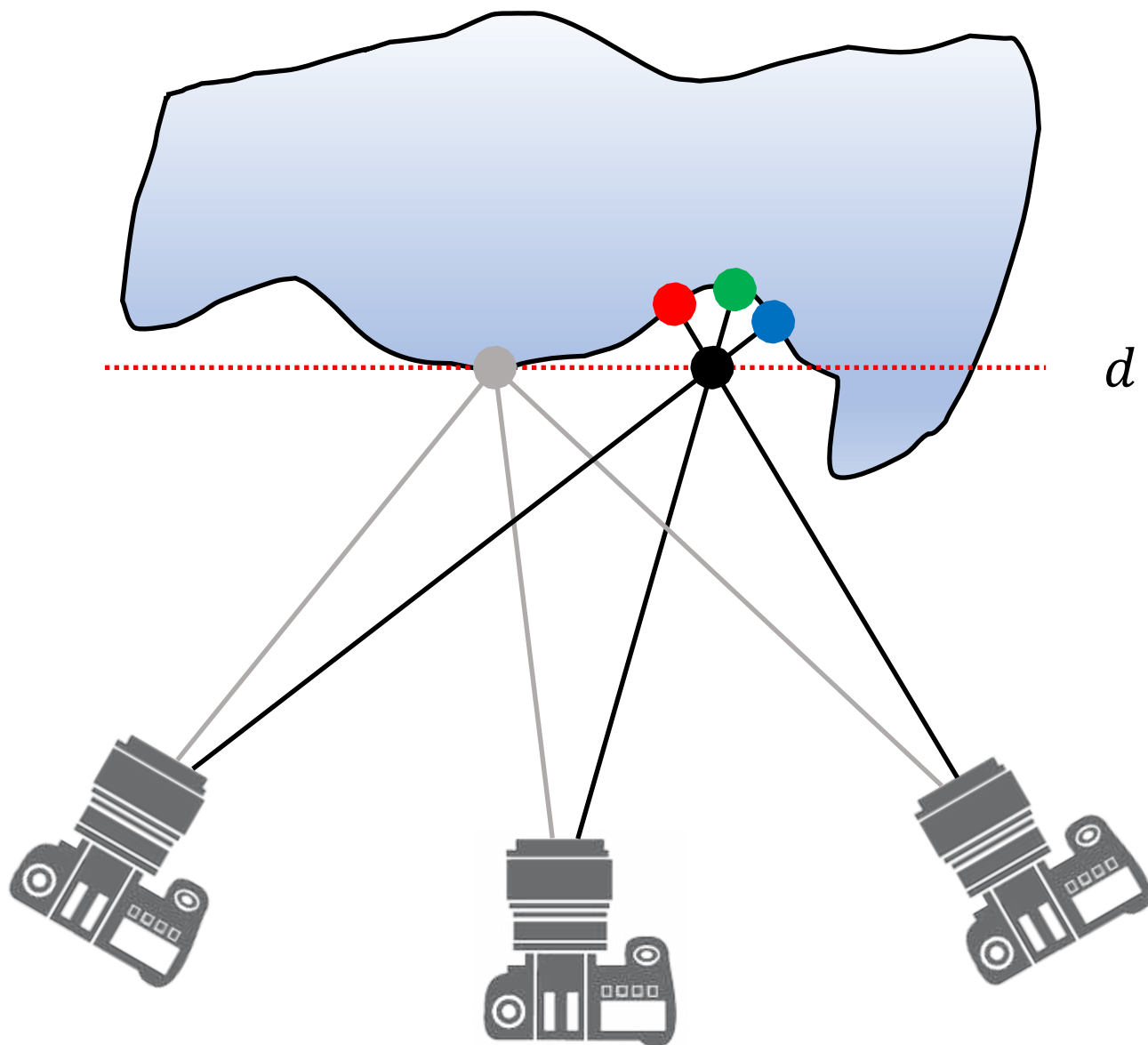


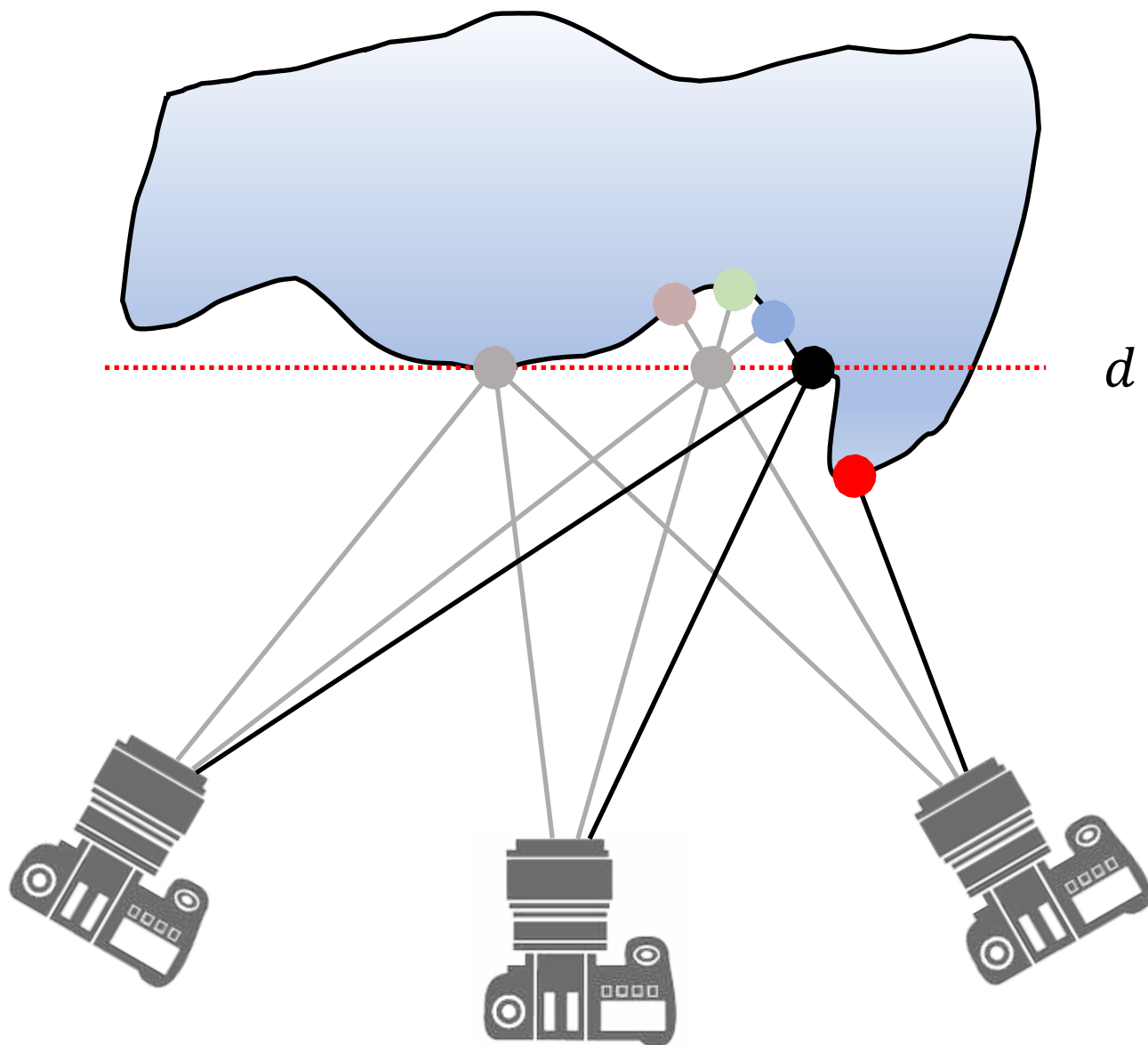


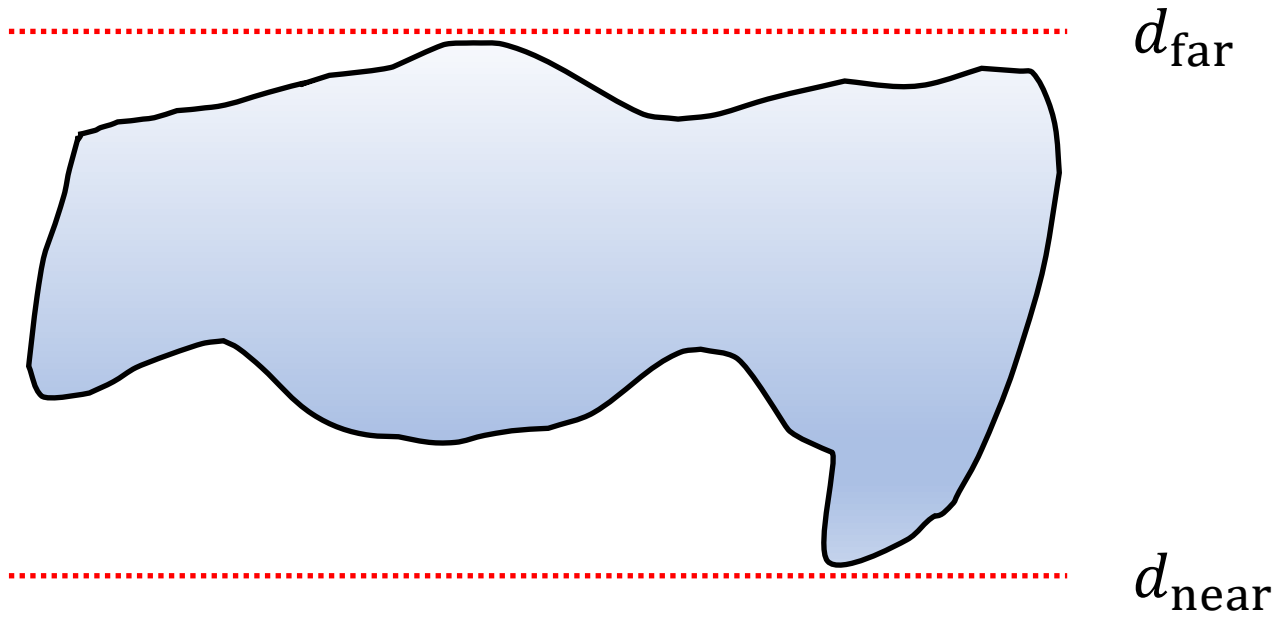




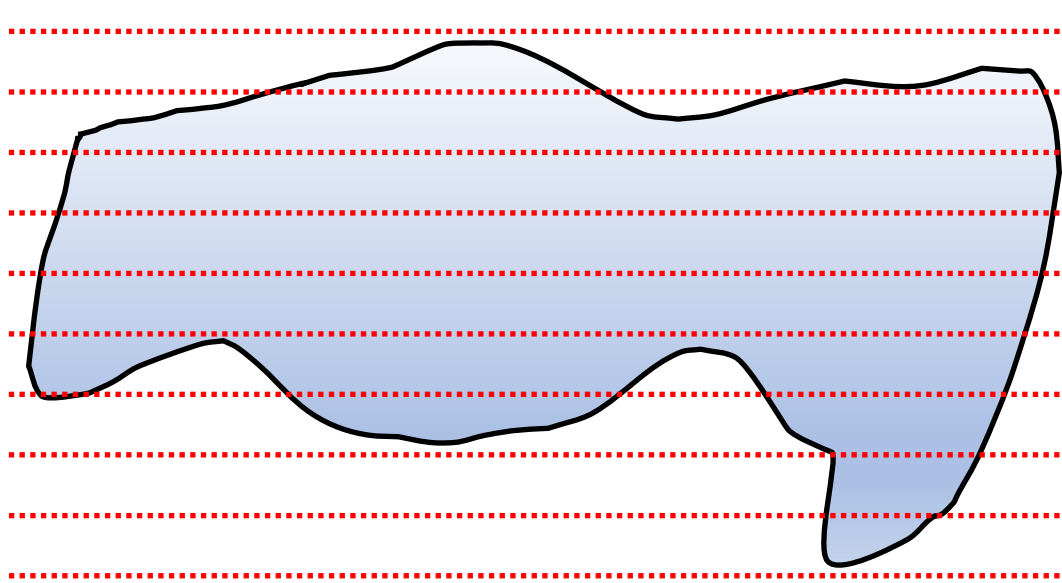








等深度

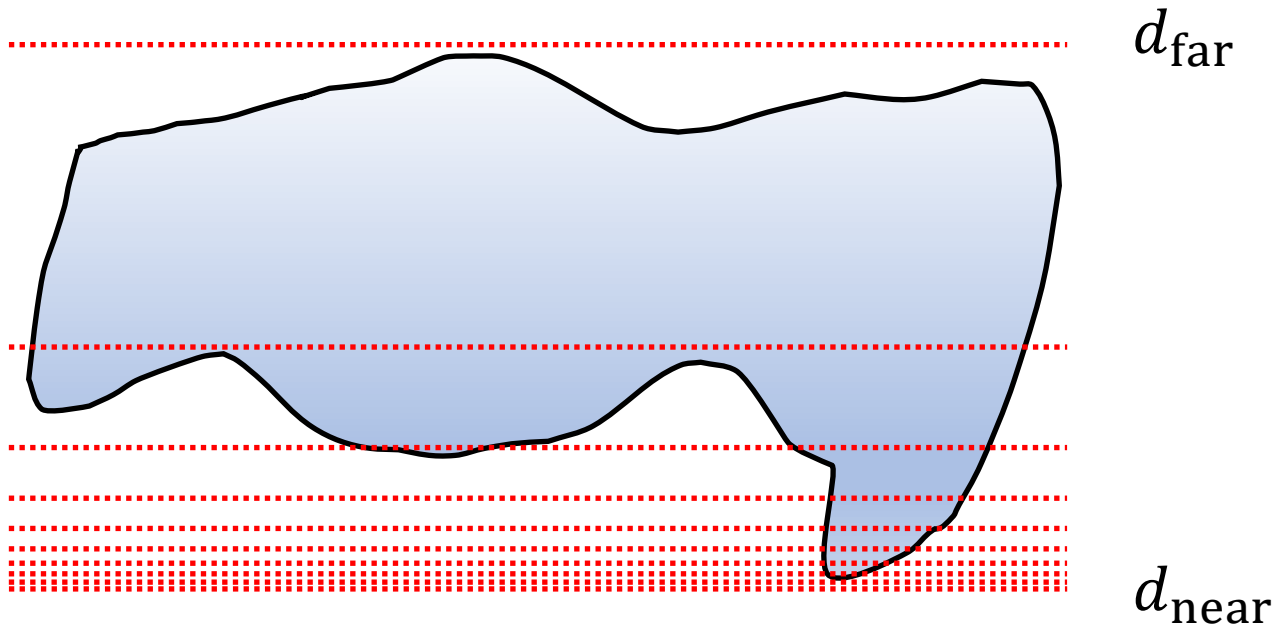


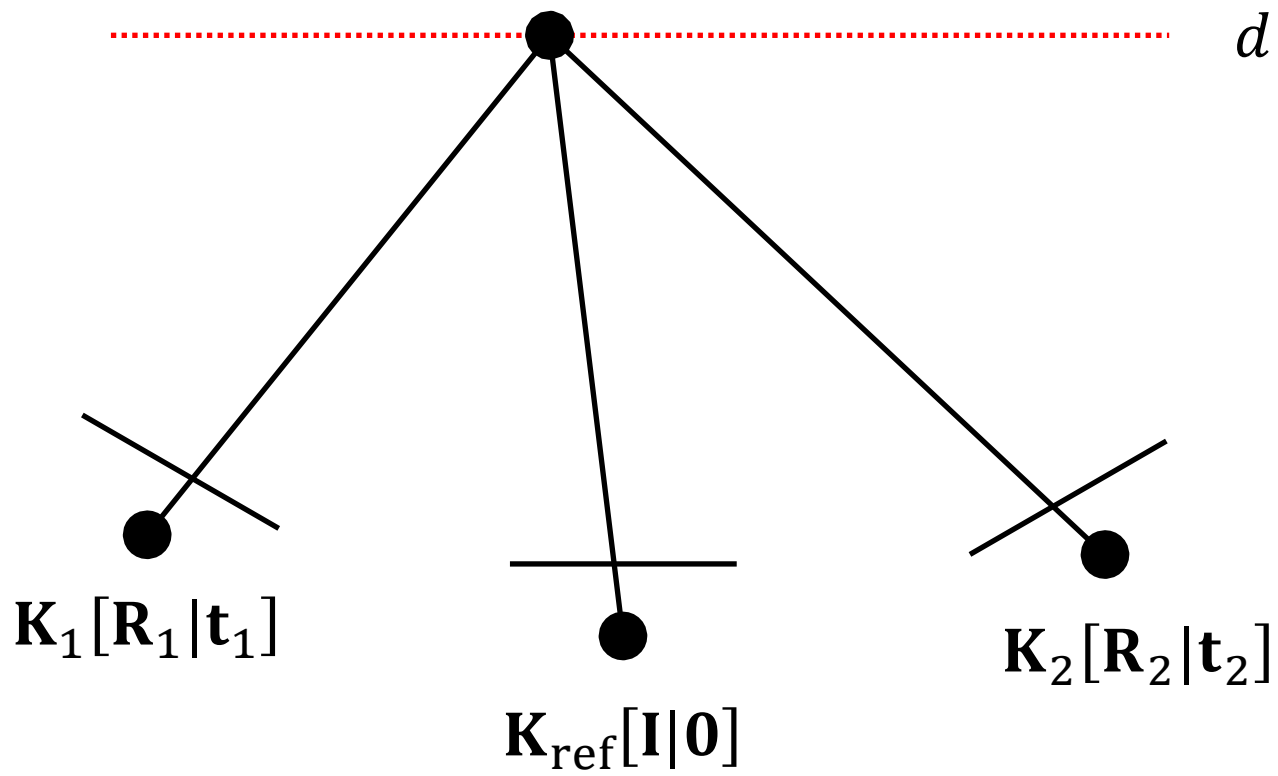
d_{far}

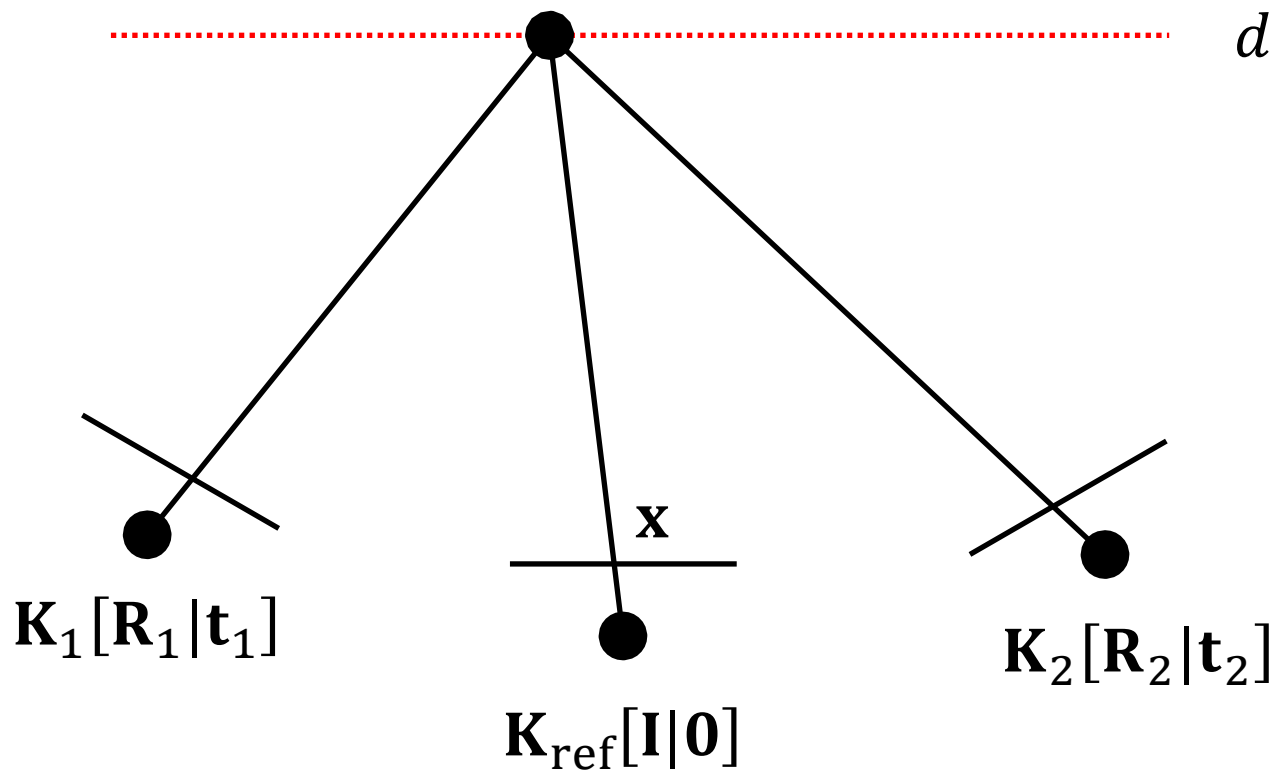
d_{near}

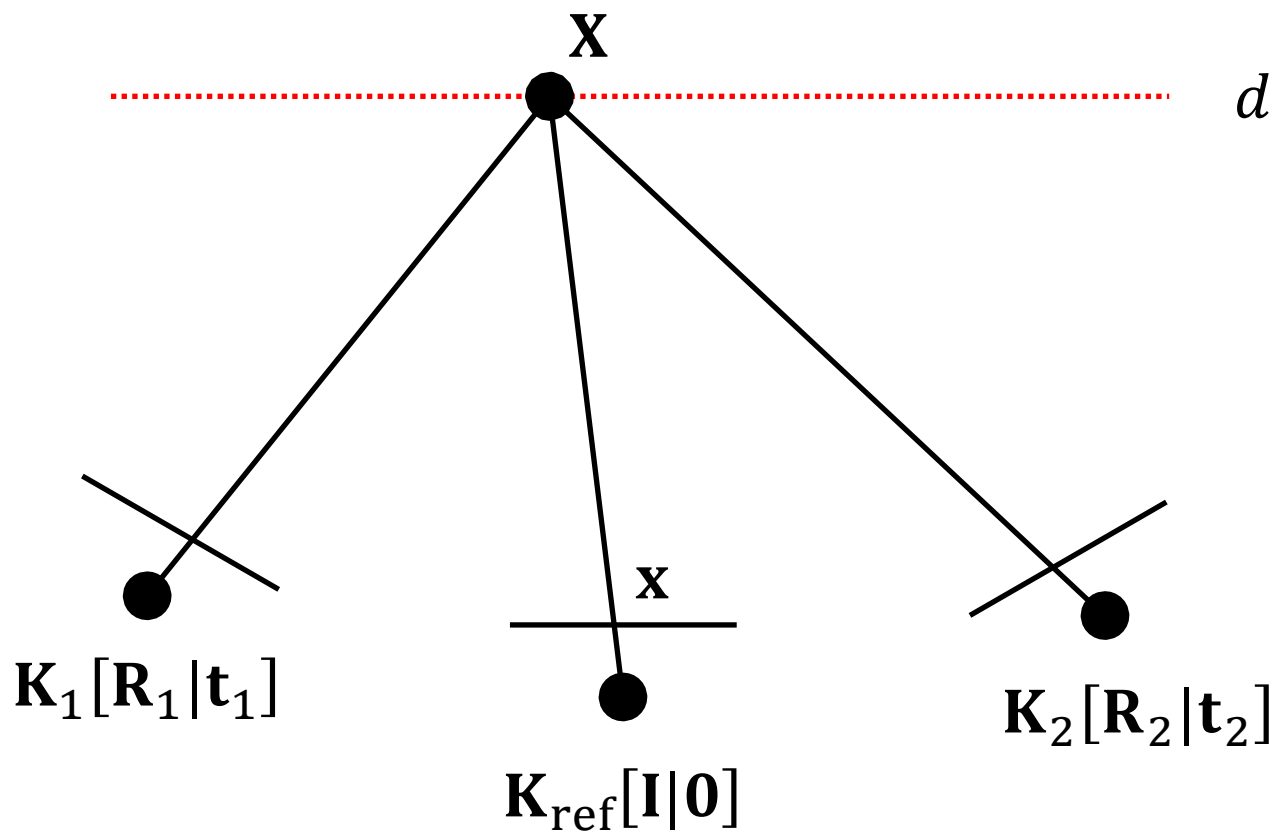


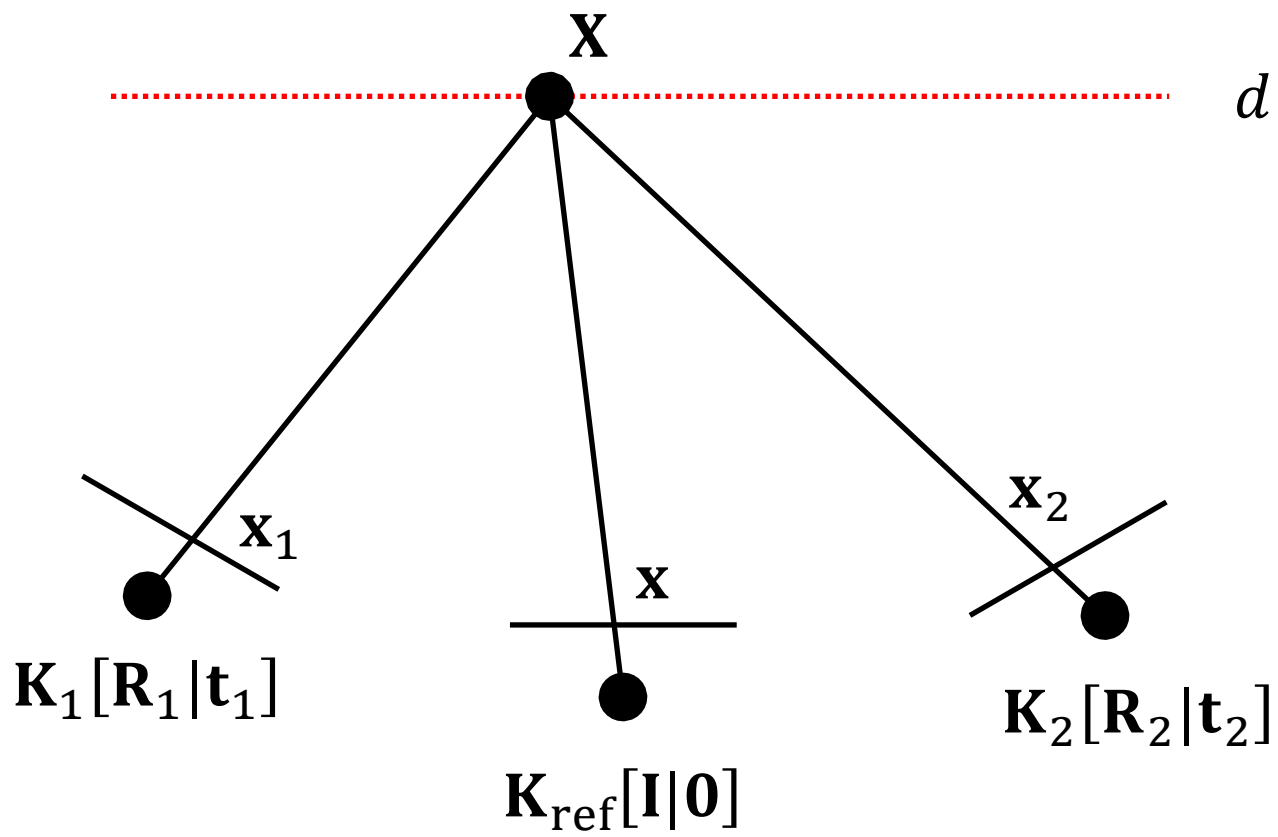
等视差





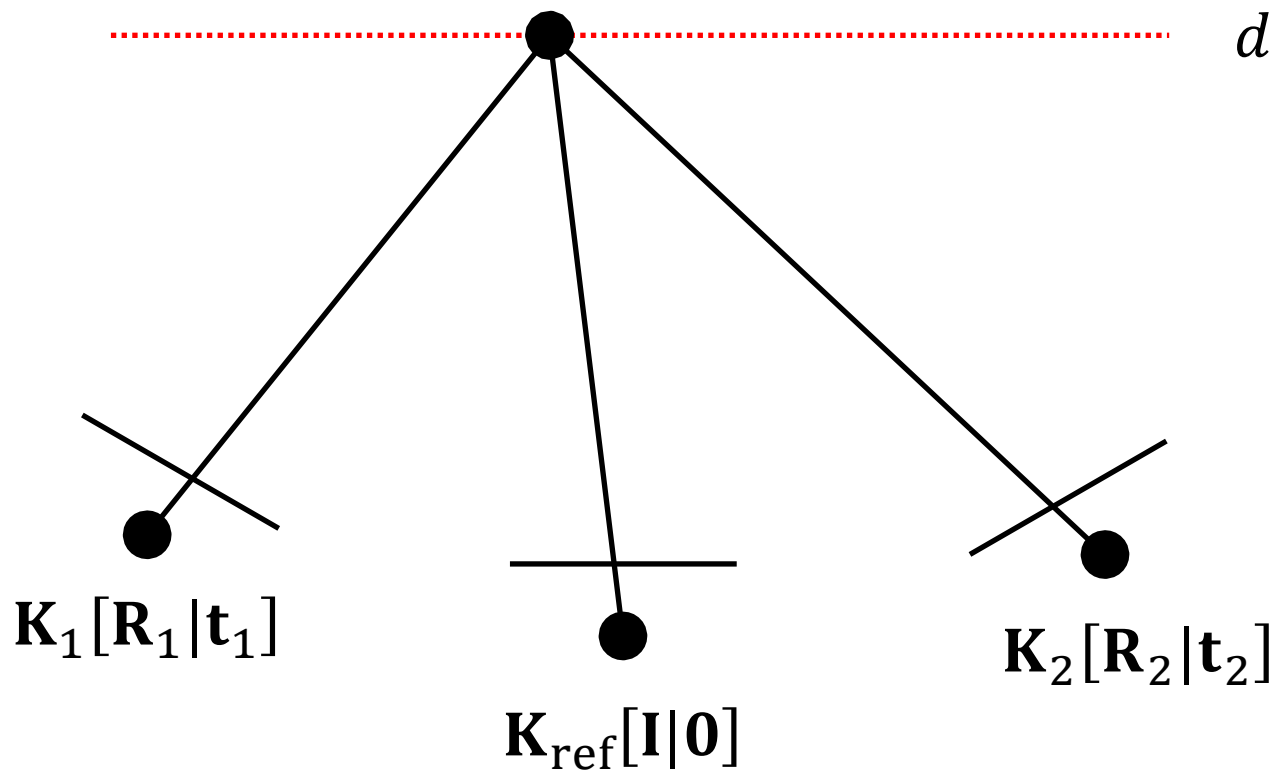




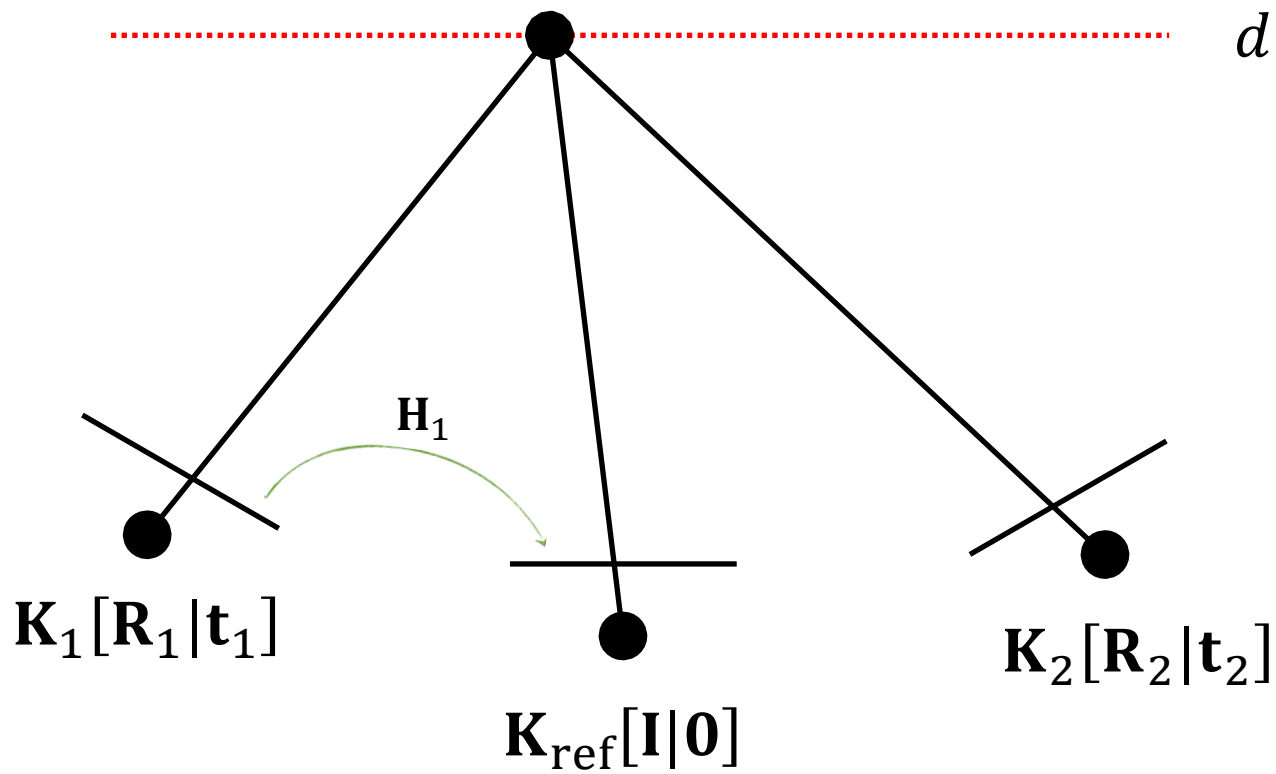


有没有更好的办法？

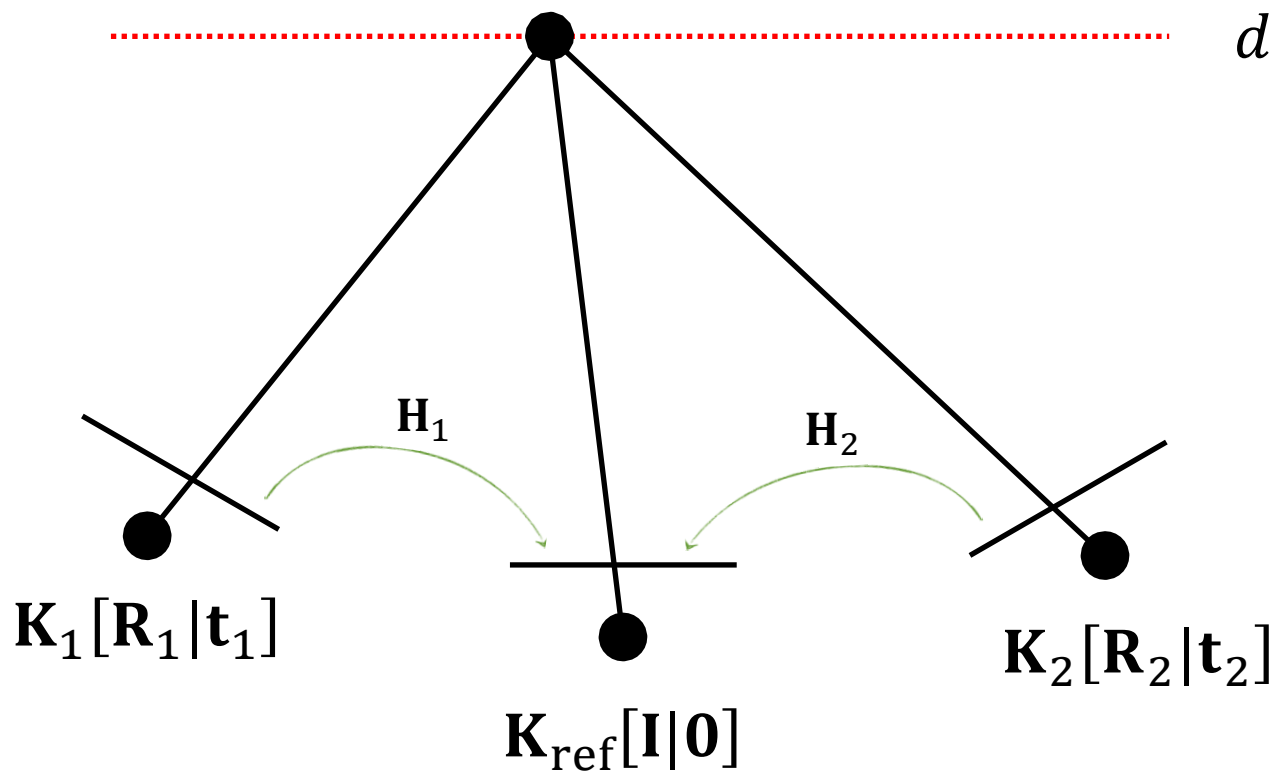
平面扫描



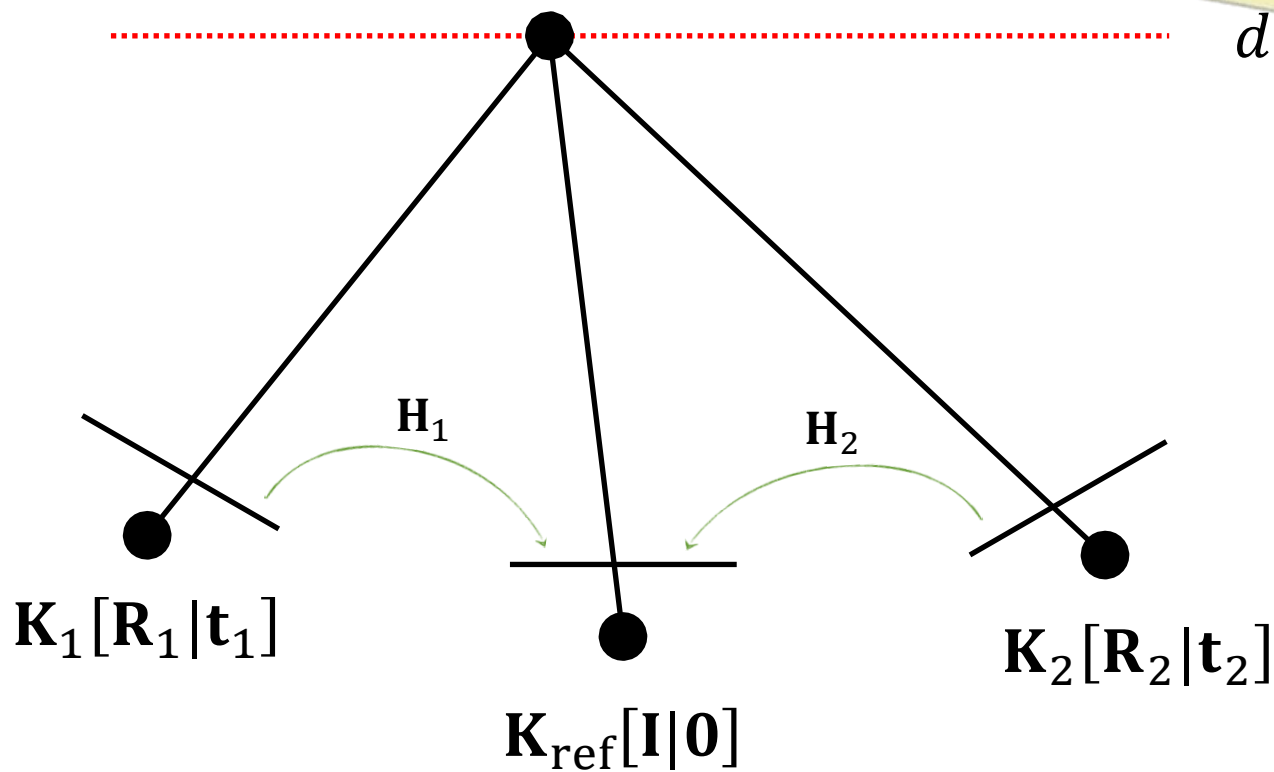
平面扫描



平面扫描

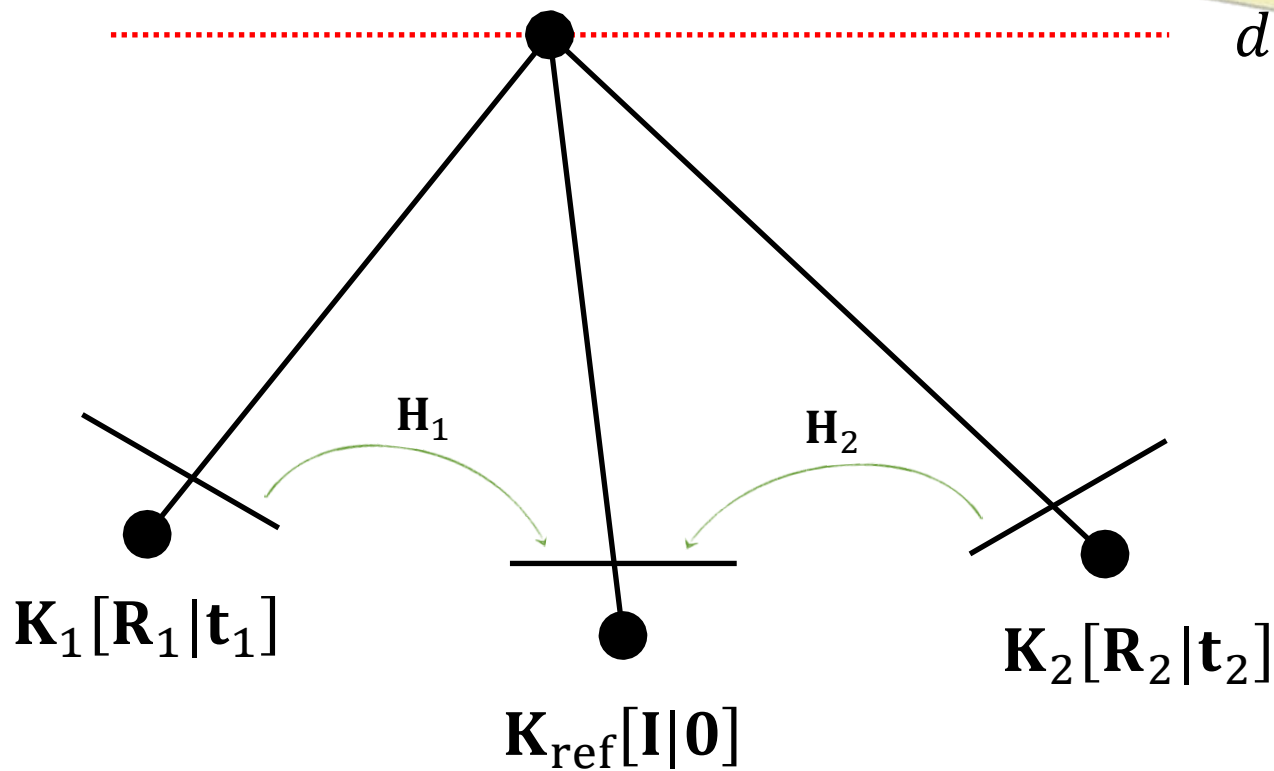


平面扫描



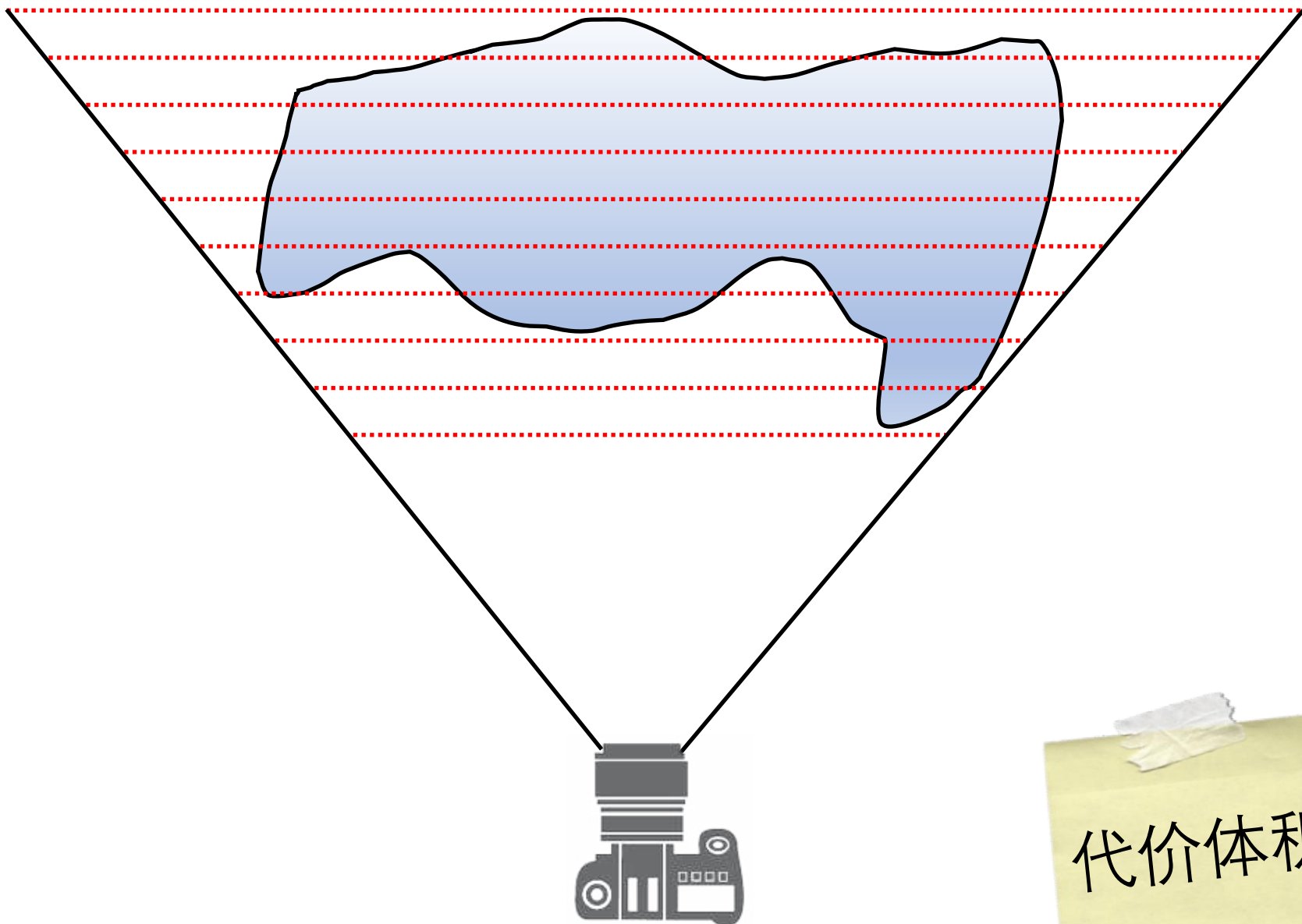
深度 d 平面的单应变换: $\mathbf{H}_k = \mathbf{K}_k \left(\mathbf{R}_k^T + \frac{\mathbf{R}_k^T \mathbf{t}_k \mathbf{n}^T}{d} \right) \mathbf{K}_{\text{ref}}^{-1}$

平面扫描



深度 d 平面的单应变换: $\mathbf{H}_k = \mathbf{K}_k \left(\mathbf{R}_k^T + \frac{\mathbf{R}_k^T \mathbf{t}_k \mathbf{n}^T}{d} \right) \mathbf{K}_{\text{ref}}^{-1}$

代价体积: $C(x, y, d) = \sum_{k=0}^{N-1} \sum_{i,j \in W} |I_{\text{ref}}(x-i, y-j) - \beta_k^{\text{ref}} I_k^d(x_k-i, y_k-j)|$



代价体积

MVSNet: Depth Inference for Unstructured Multi-view Stereo

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Shiwei Li^{1*}[0000-0003-0712-0059], Tian Fang²[0000-0002-5871-3455], and
Long Quan¹[0000-0001-8148-1771]

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Abstract. We present an end-to-end deep learning architecture for depth map inference from multi-view images. In the network, we first extract deep visual image features, and then build the 3D cost volume upon the reference camera frustum via the differentiable homography warping. Next, we apply 3D convolutions to regularize and regress the initial depth map, which is then refined with the reference image to generate the final output. Our framework flexibly adapts arbitrary N-view inputs using a variance-based cost metric that maps multiple features into one cost feature. The proposed MVSNet is demonstrated on the large-scale indoor *DTU* dataset. With simple post-processing, our method not only significantly outperforms previous state-of-the-arts, but also is several times faster in runtime. We also evaluate MVSNet on the complex outdoor *Tanks and Temples* dataset, where our method ranks first before April 18, 2018 without any fine-tuning, showing the strong generalization ability of MVSNet.

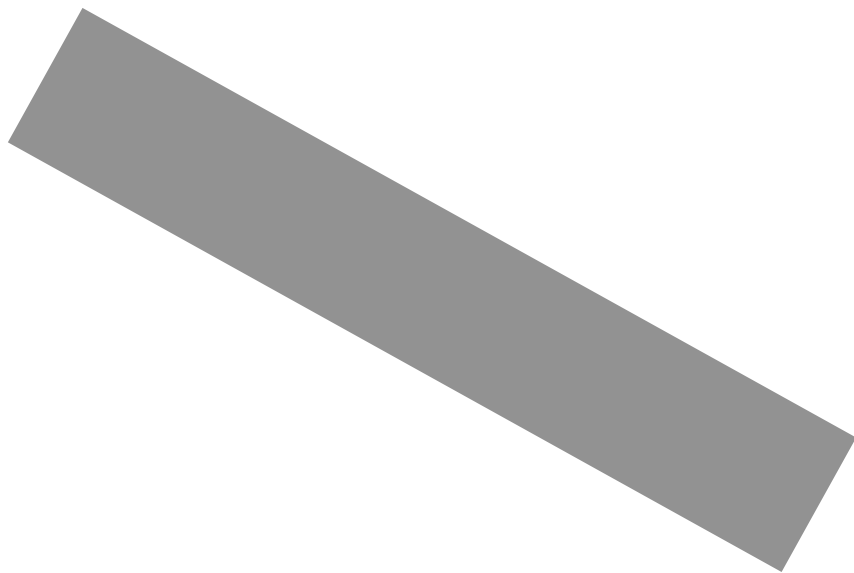
Keywords: Multi-view Stereo, Depth Map, Deep Learning

ECCV, 2018

为什么图像对应问题

困难？

投影缩短

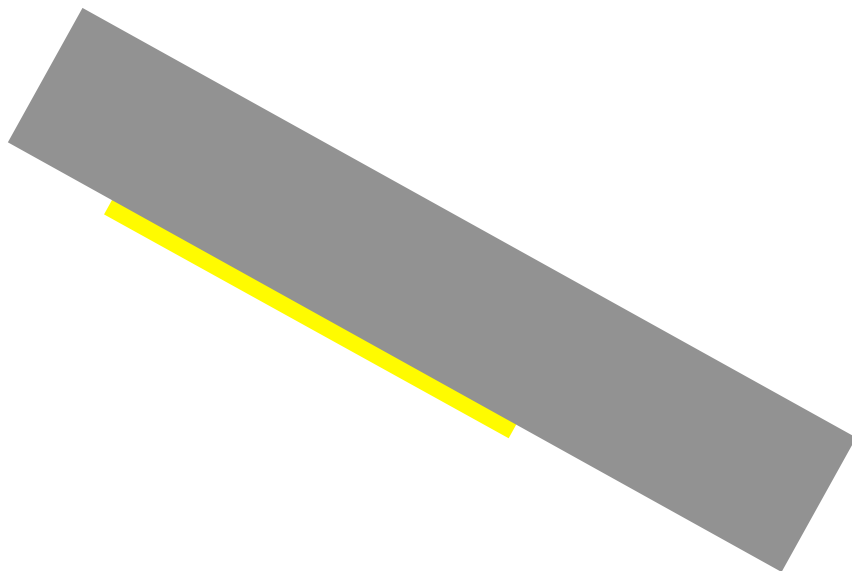


$\dot{O}_l$



$\dot{O}_r$

投影缩短



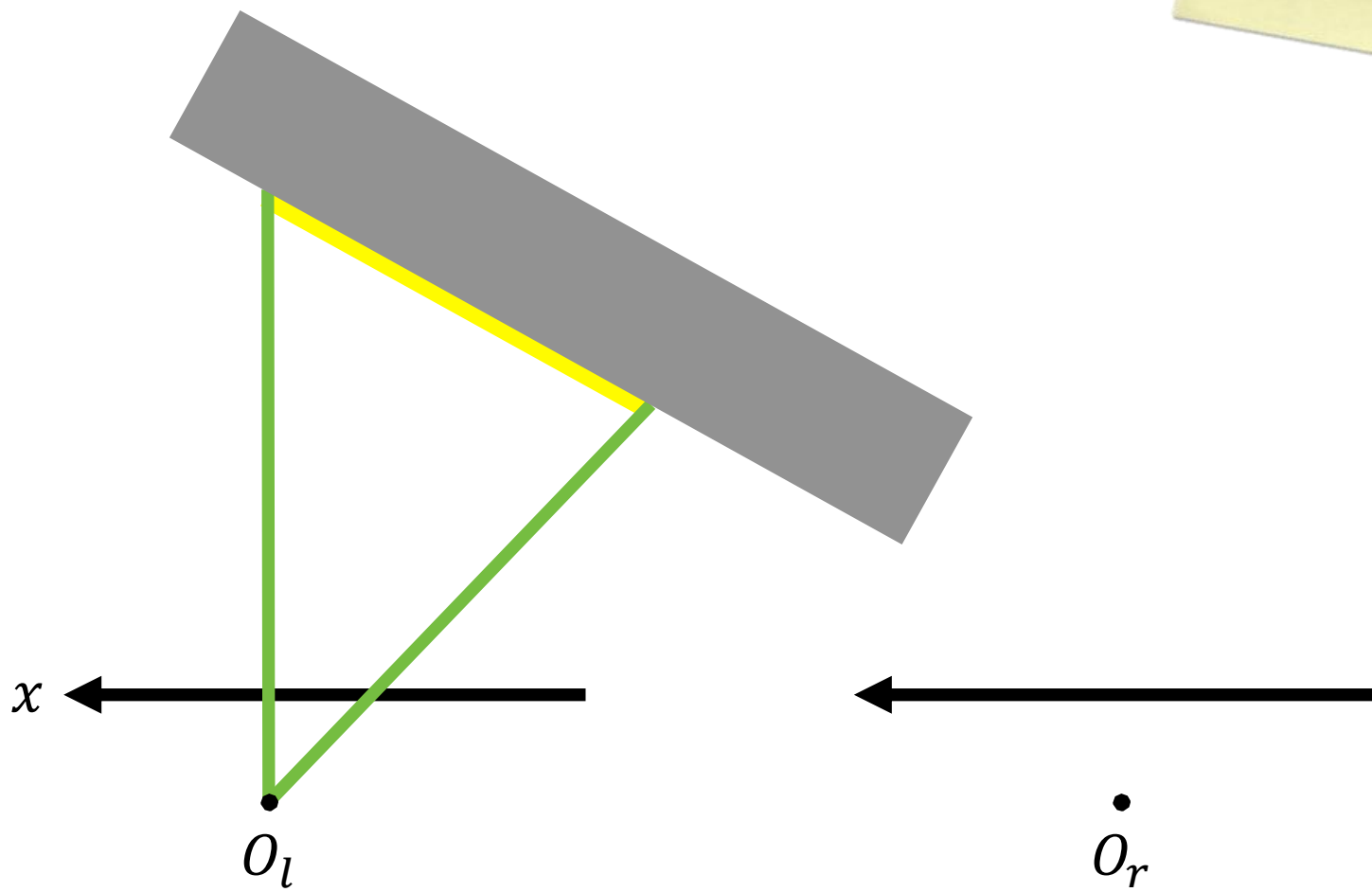
x

$\dot{O}_l$

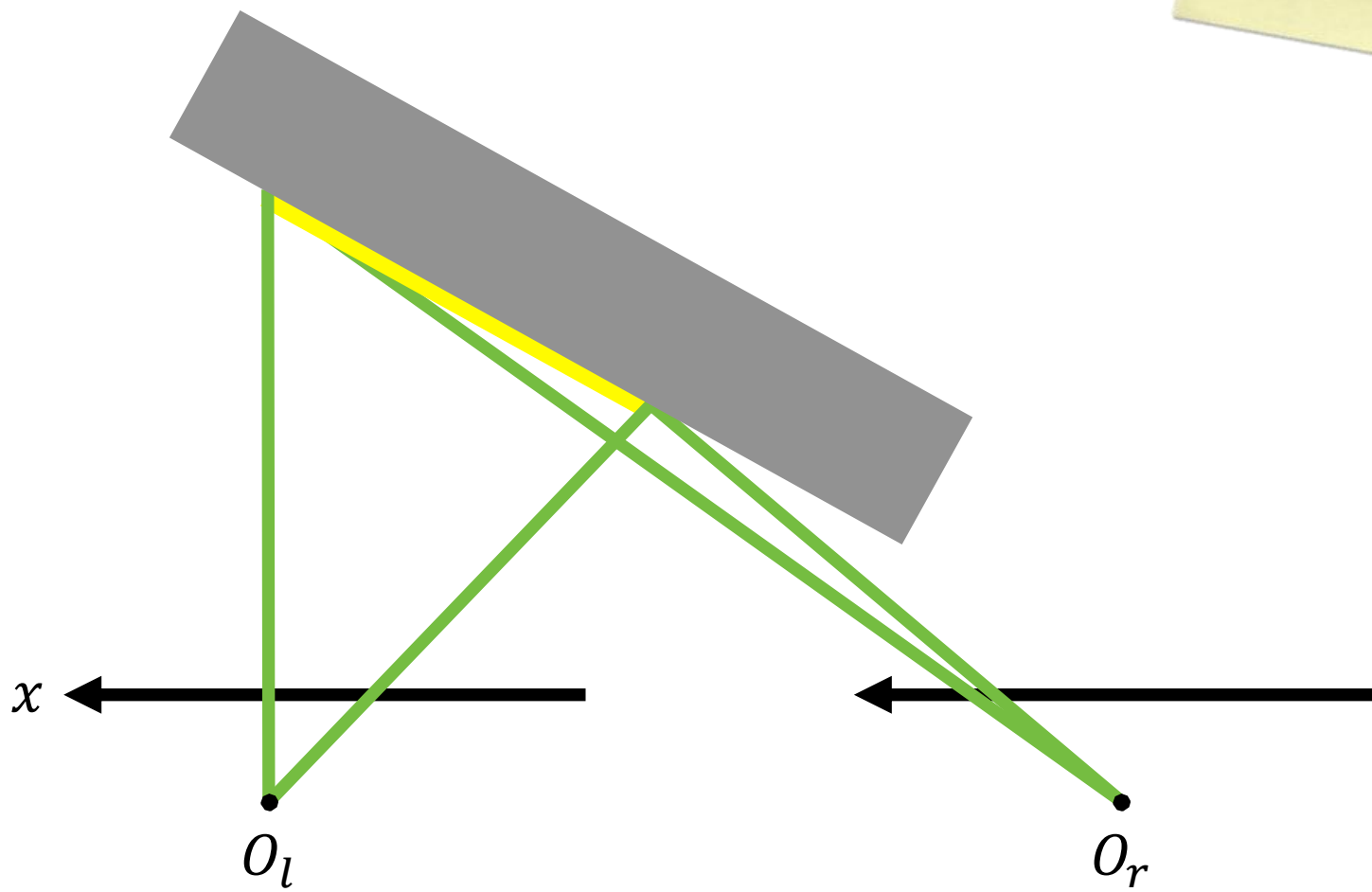


$\dot{O}_r$

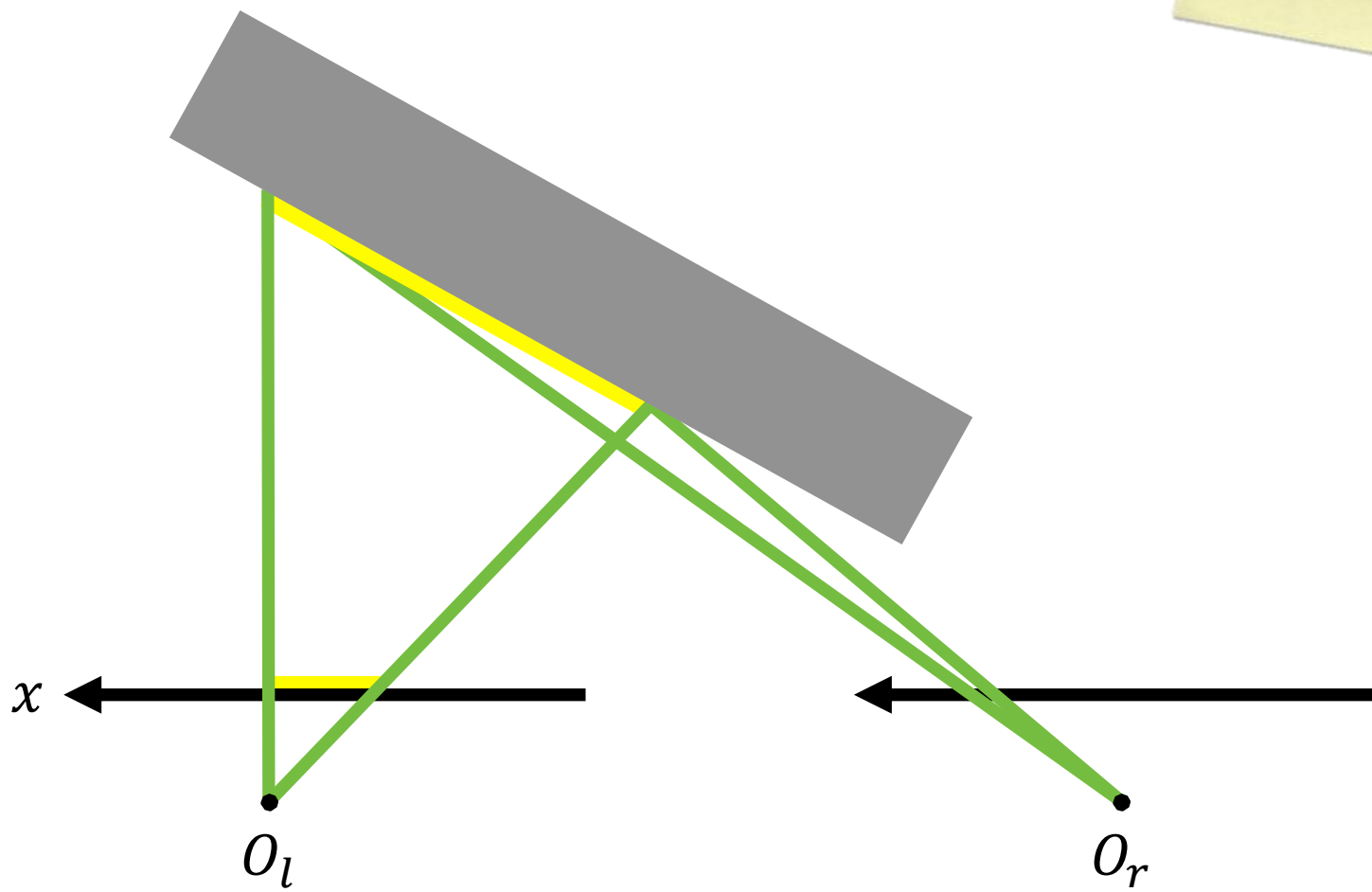
投影缩短



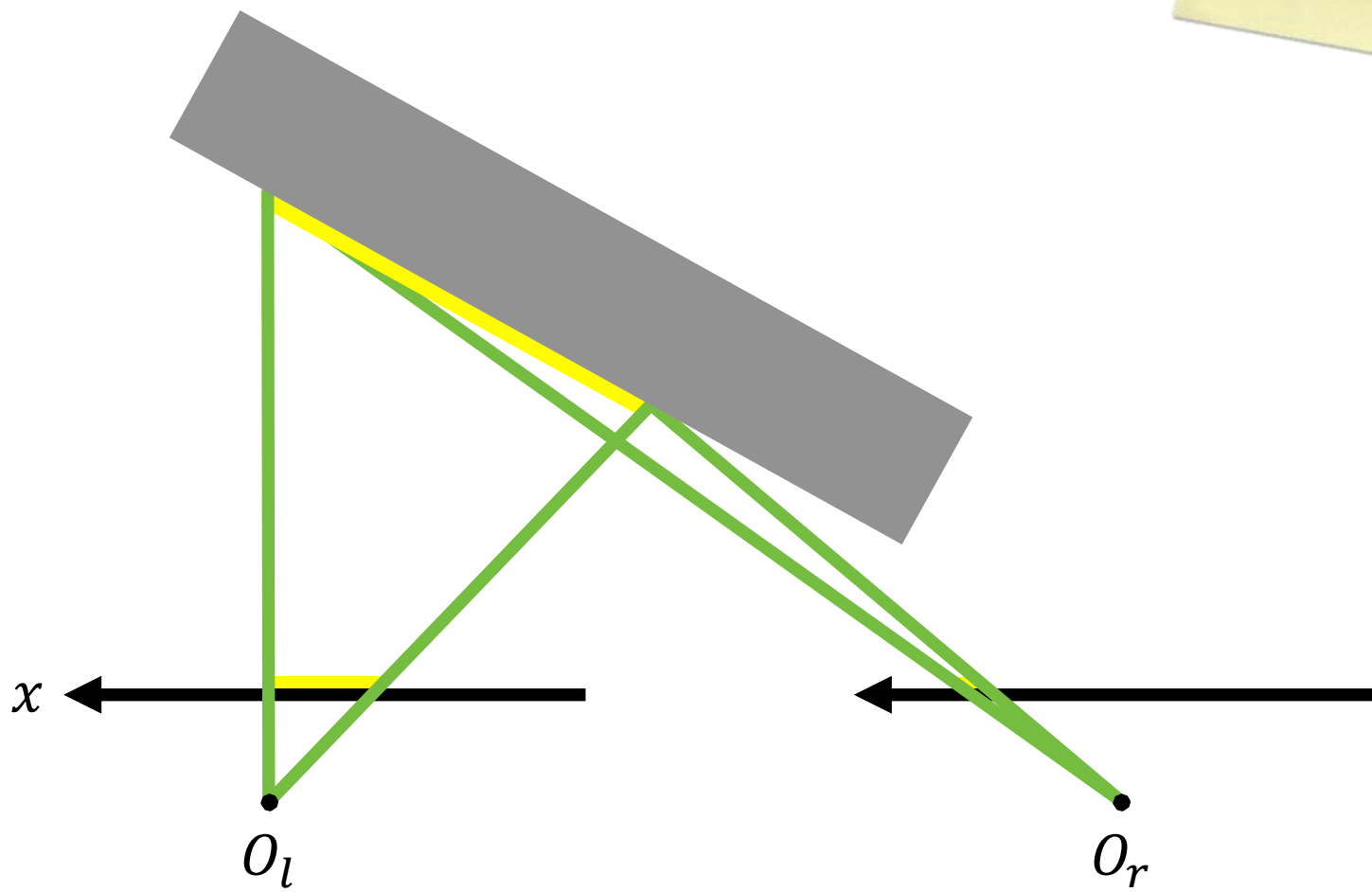
投影缩短



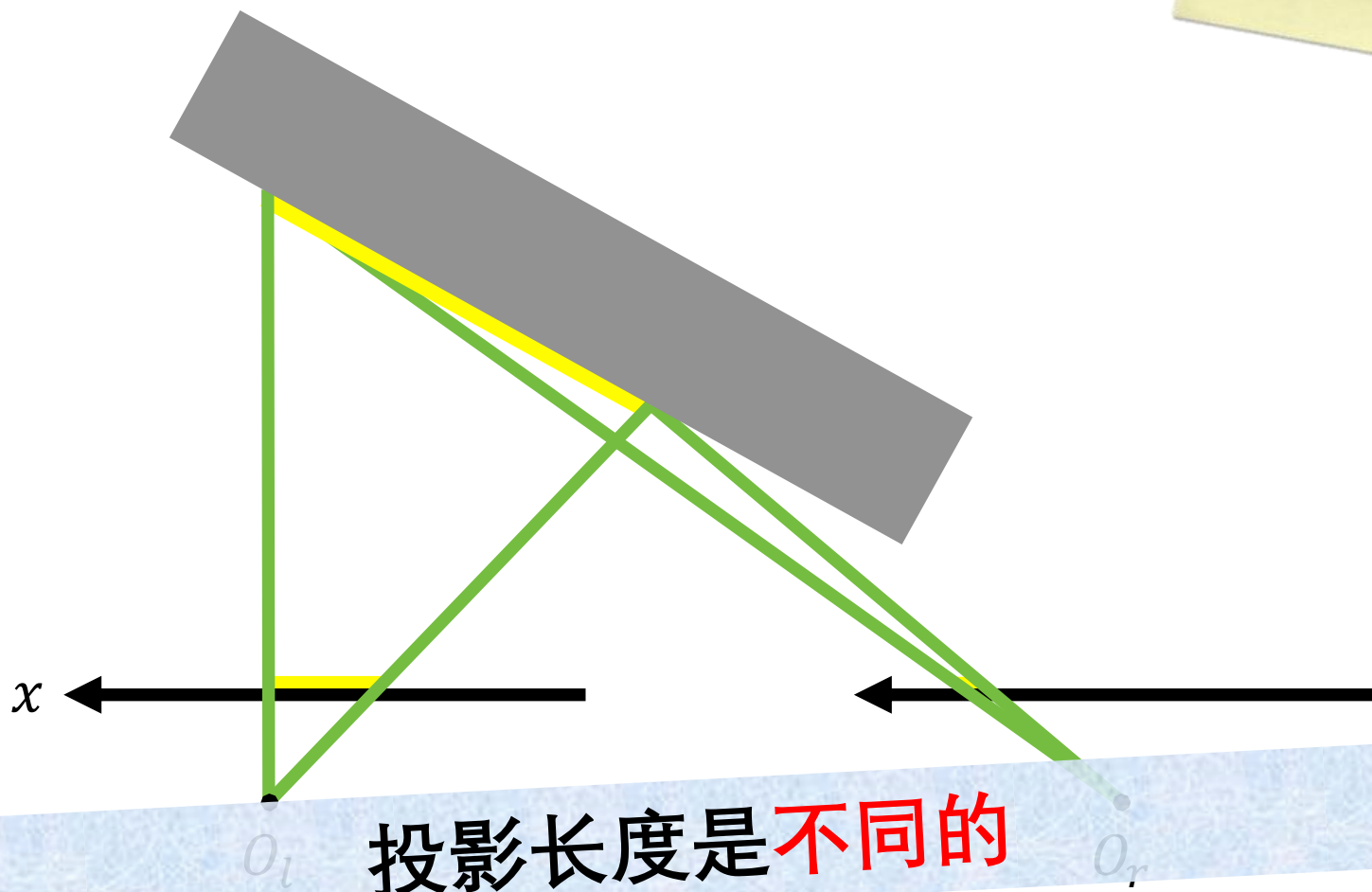
投影缩短



投影缩短



投影缩短



双目
半遮挡



$\dot{o}_l$



$\dot{o}_r$

双目
半遮挡

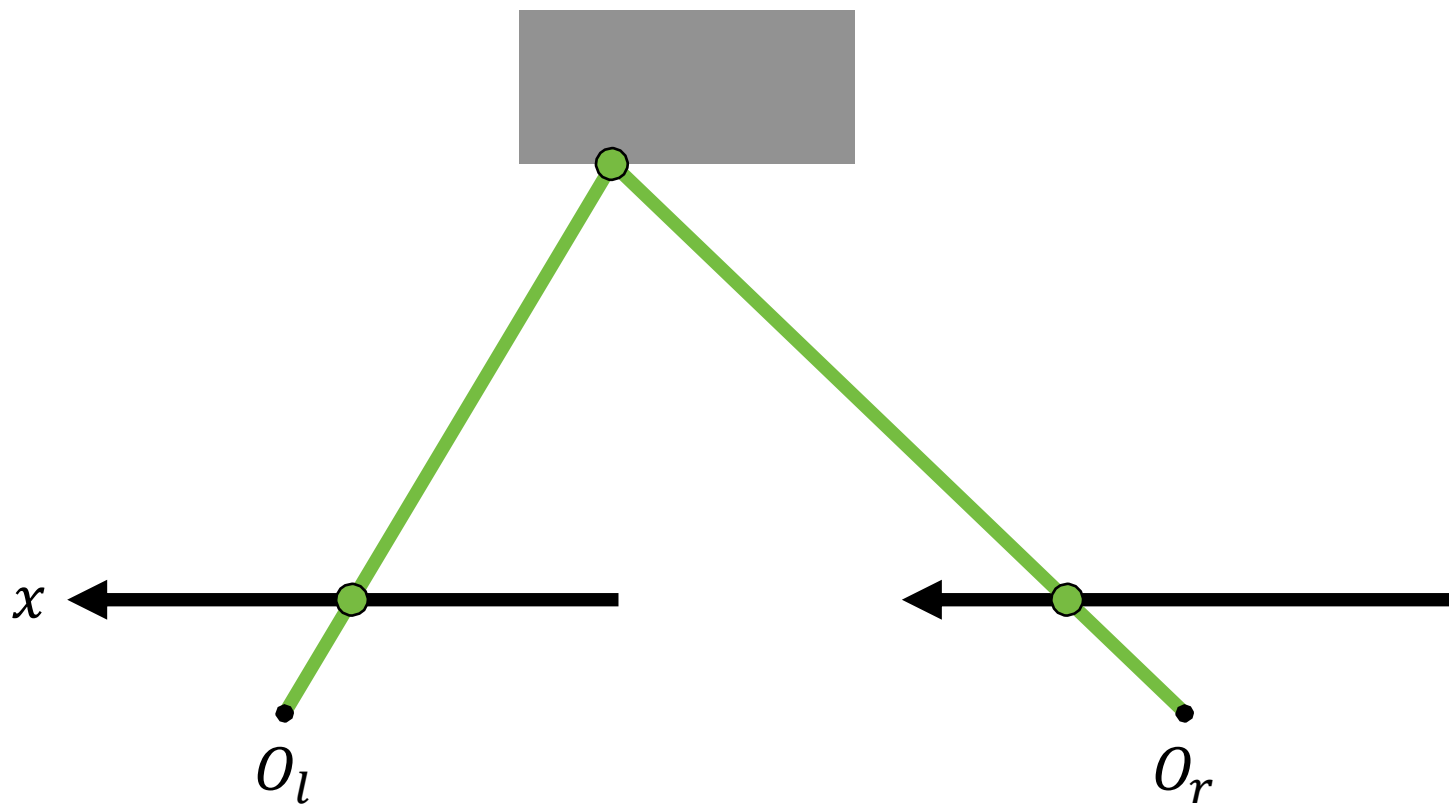


$\dot{O}_l$



$\dot{O}_r$

双目
半遮挡



双目
半遮挡



x

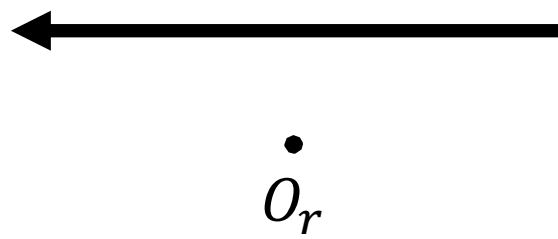
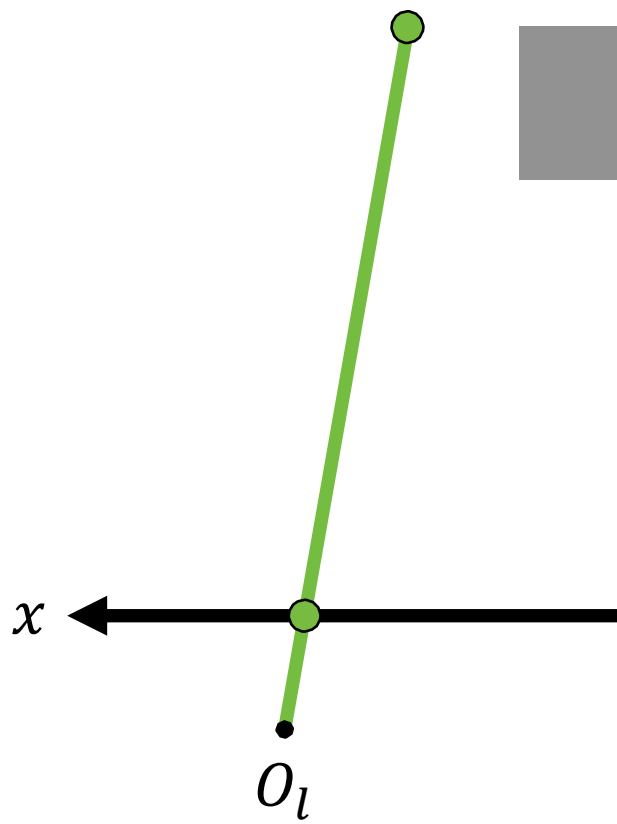


$\dot{O}_l$

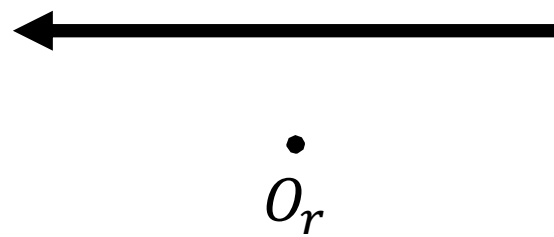
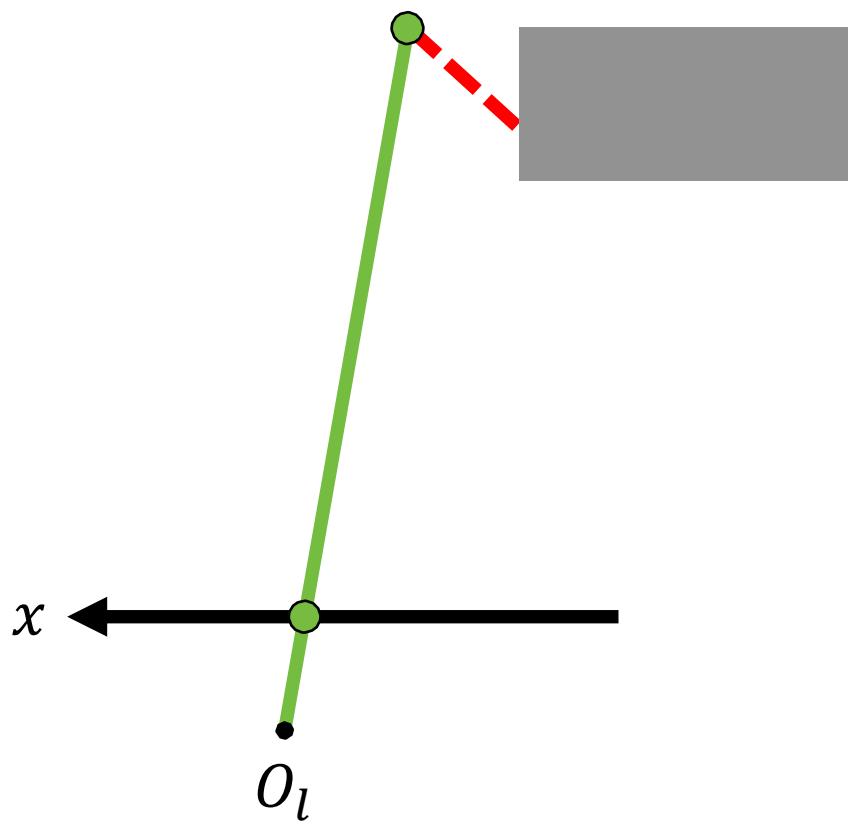


$\dot{O}_r$

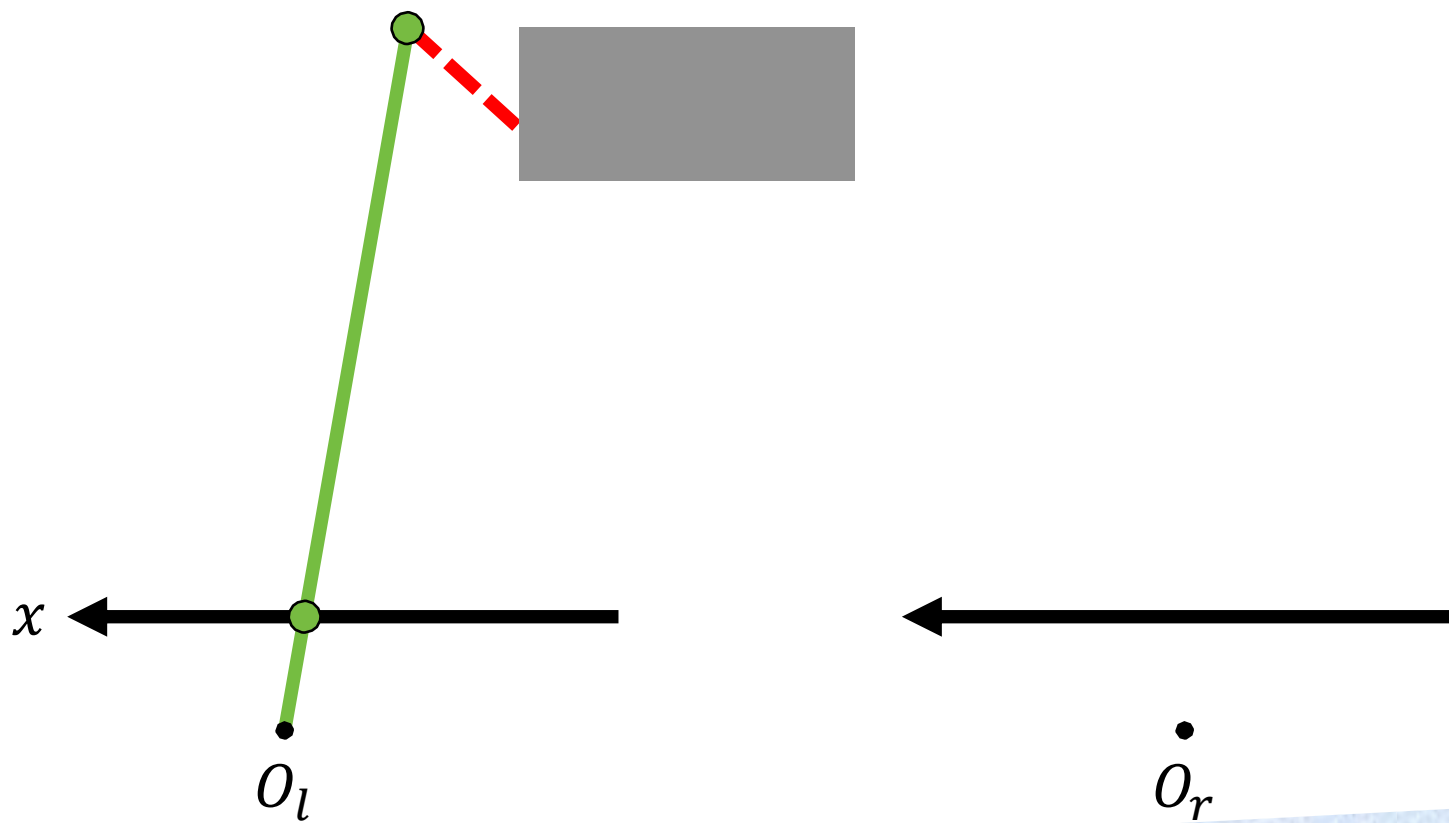
双目
半遮挡



双目
半遮挡



双目
半遮挡



所有点不能同时在两个视图中看到

重复性 结构



重复性 结构



重复性
结构



重复性 结构



重复性
结构

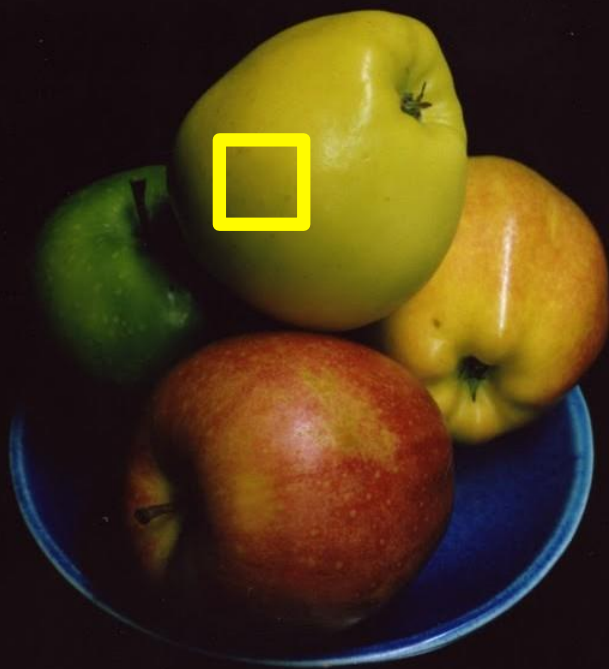


块匹配是有歧义的

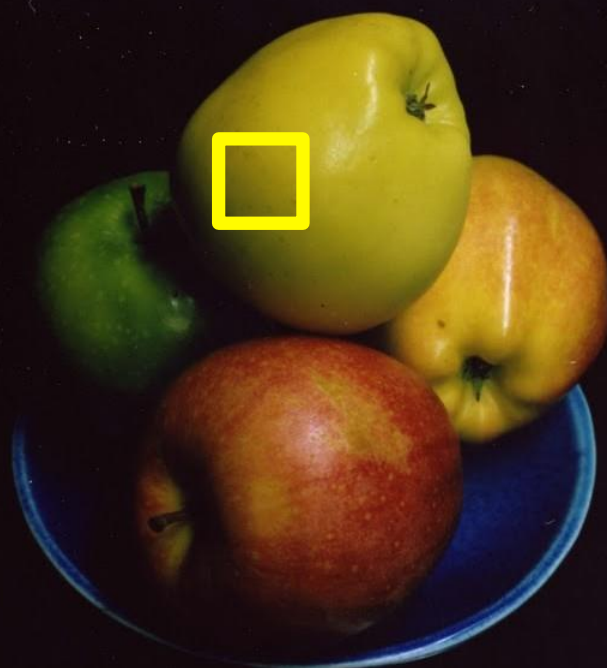
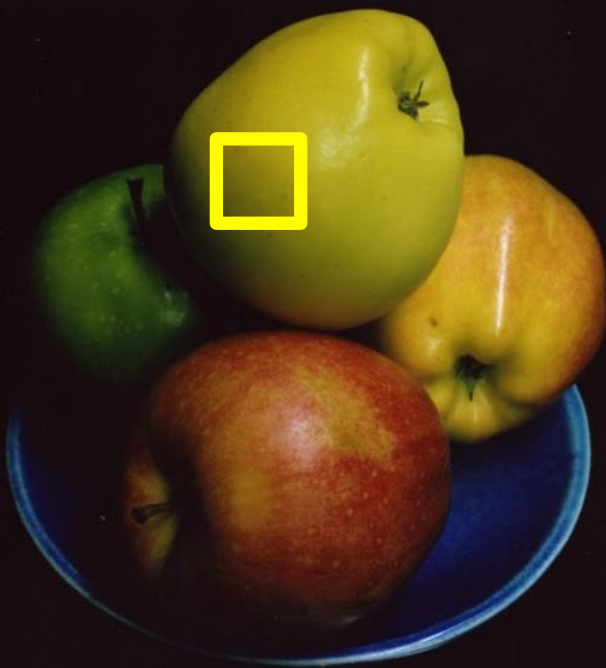
无纹理
表面



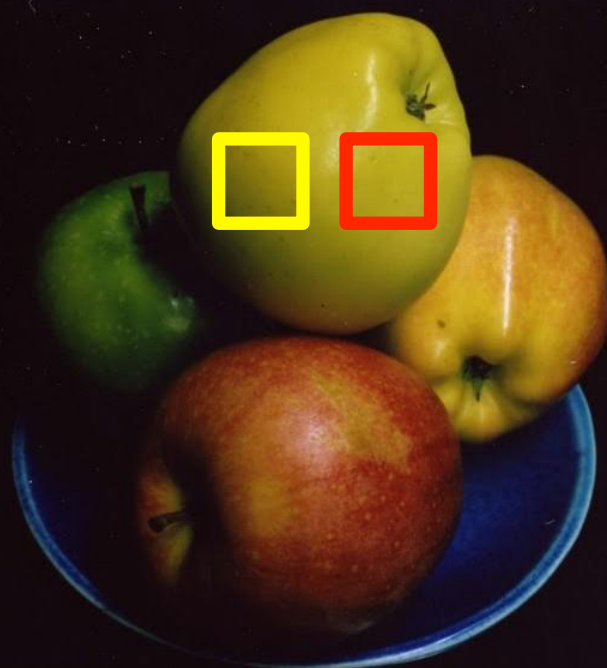
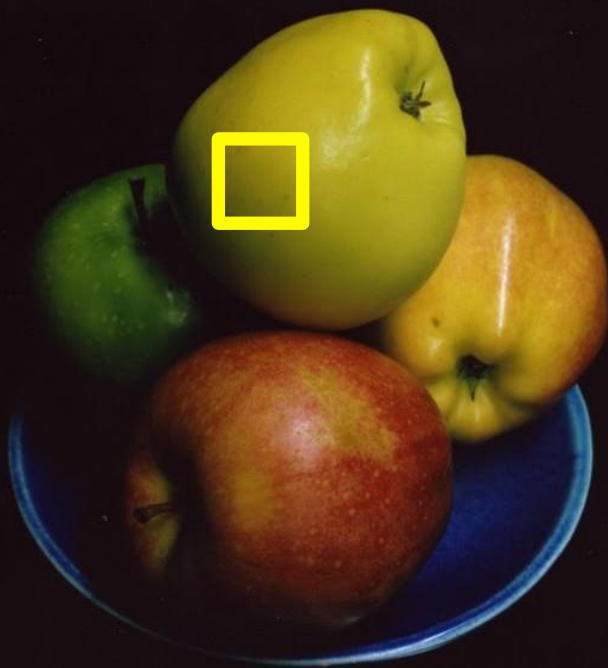
无纹理
表面



无纹理
表面



无纹理
表面



Stereo

Evaluation • Datasets • Code • Submit

[Daniel Scharstein](#) • [Richard Szeliski](#)

Welcome to the Middlebury Stereo Vision Page, formerly located at www.middlebury.edu/stereo. This website accompanies our taxonomy and comparison of two-frame stereo correspondence algorithms [1]. It contains:

- An [on-line evaluation](#) of current algorithms
- Many [stereo datasets](#) with ground-truth disparities
- Our [stereo correspondence software](#)
- An [on-line submission script](#) that allows you to evaluate your stereo algorithm in our framework

How to cite the materials on this website:

We grant permission to use and publish all images and numerical results on this website. If you report performance results, we request that you cite our paper [1]. Instructions on how to cite our datasets are listed on the [datasets page](#). If you want to cite this website, please use the URL "vision.middlebury.edu/stereo/".

References:

- [1] D. Scharstein and R. Szeliski. [A taxonomy and evaluation of dense two-frame stereo correspondence algorithms](#). *International Journal of Computer Vision*, 47(1/2/3):7-42, April-June 2002.
[Microsoft Research Technical Report MSR-TR-2001-81](#), November 2001.

**Other online stereo benchmarks and datasets:**

- [KITTI vision benchmark](#)
- [HCI robust vision challenge](#)

Stereo Matching by Training a Convolutional Neural Network to Compare Image Patches

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Editor: Zhuowen Tu

Abstract

We present a method for extracting depth information from a rectified image pair. Our approach focuses on the first stage of many stereo algorithms: the matching cost computation. We approach the problem by learning a similarity measure on small image patches using a convolutional neural network. Training is carried out in a supervised manner by constructing a binary classification data set with examples of similar and dissimilar pairs of patches. We examine two network architectures for this task: one tuned for speed, the other for accuracy. The output of the convolutional neural network is used to initialize the

Journal of Machine Learning Research, 2016

data sets.

Keywords: stereo, matching cost, similarity learning, supervised learning, convolutional neural networks

1. Introduction

A Large Dataset to Train Convolutional Networks for Disparity, Optical Flow, and Scene Flow Estimation

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²Technical University of Munich

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Daniel Cremers
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Abstract

Recent work has shown that optical flow estimation can be formulated as a supervised learning task and can be successfully solved with convolutional networks. Training of the so-called FlowNet was enabled by a large synthetically generated dataset. The present paper extends the concept of optical flow estimation via convolutional networks to disparity and scene flow estimation. To this end, we propose three synthetic stereo video datasets with sufficient realism, variation, and size to successfully train large networks. Our datasets are the first large-scale datasets to enable training and evaluation of scene flow methods. Besides the datasets,



CVPR, 2016

jointly, we demonstrate the first scene flow estimation from a convolutional network.

dense ground truth for optical flow, disparity and disparity change, as well as other data such as object segmentation.

1. Introduction

with regard to both efficiency and accuracy. One reason for



**M. Sizintsev, et al.
"GPU Accelerated Realtime Stereo for Augmented Reality", 3DPVT, 2010**



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x

$\dot{O}_l$



$\dot{O}_r$



x

光源

$\dot{o}_l$



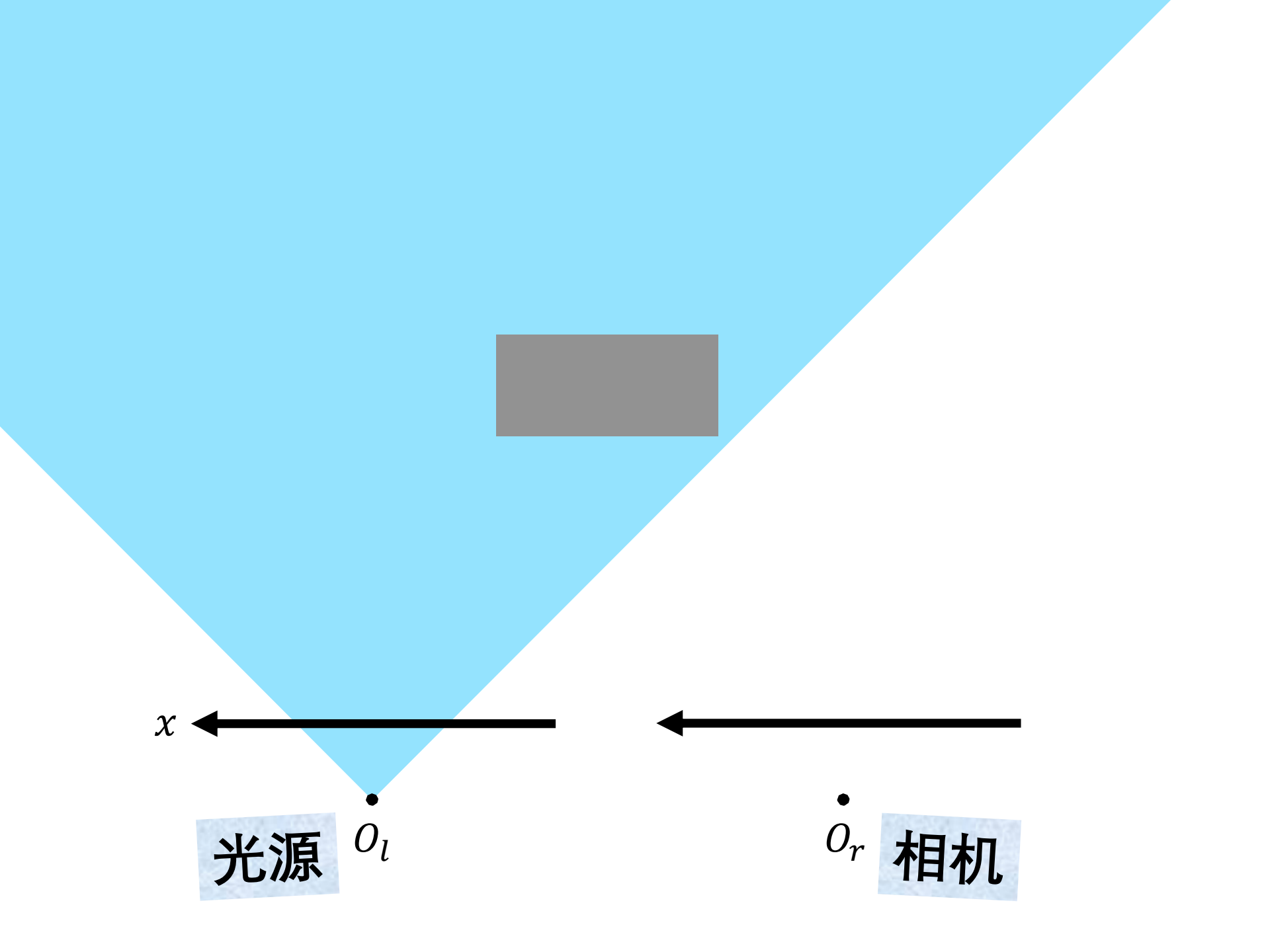
$\dot{o}_r$



光源 $\dot{o}_l$



$\dot{o}_r$ 相机



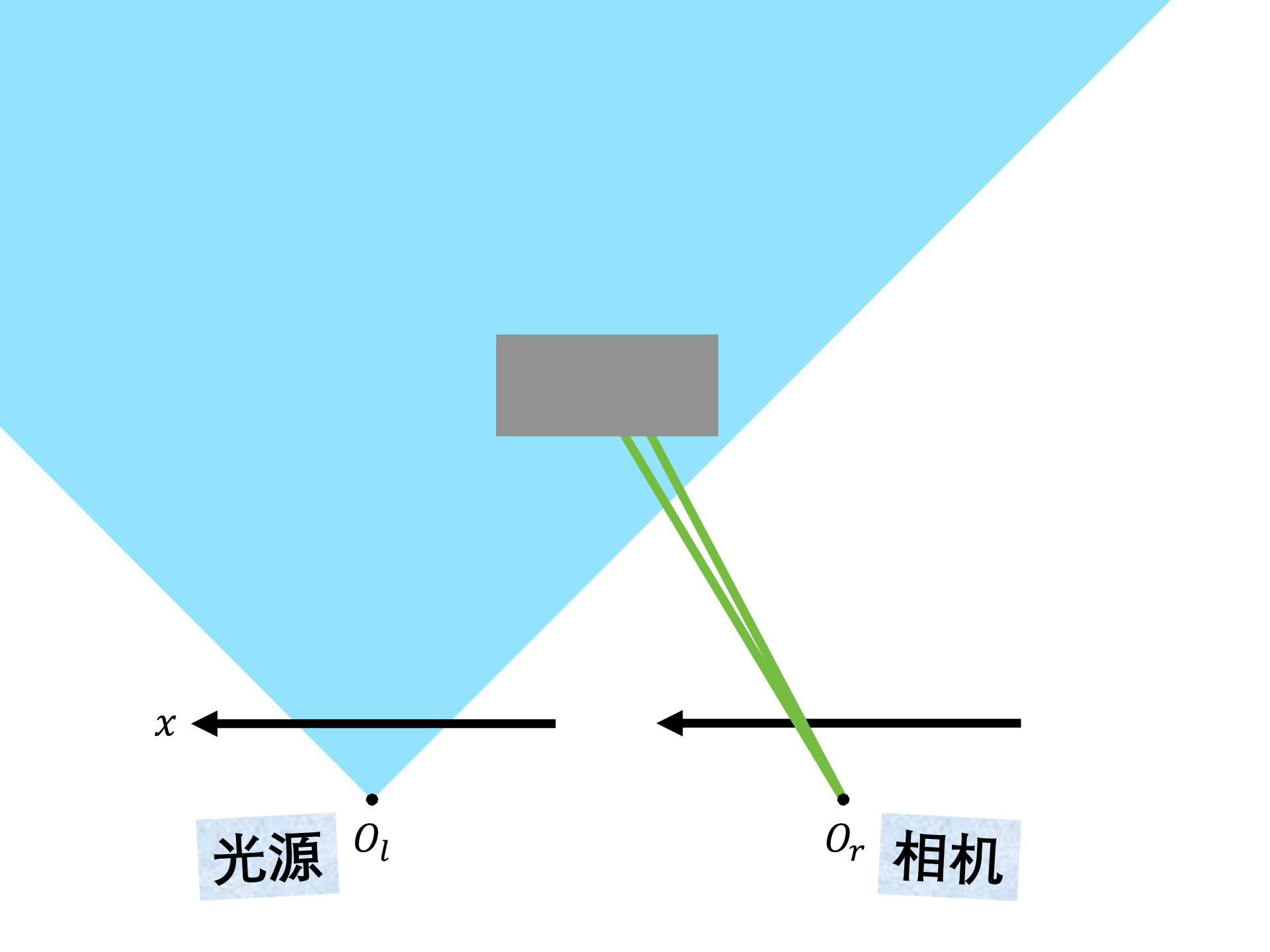
x

光源

O_l

O_r

相机



光源

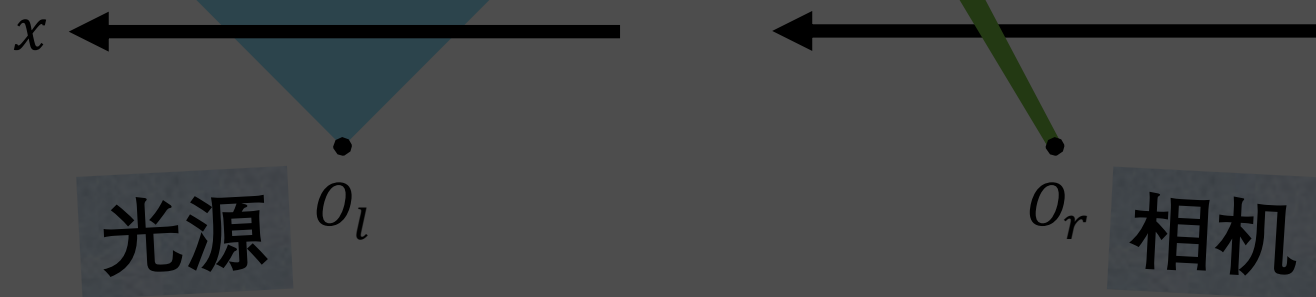
O_l

相机

O_r

x

基于结构光的立体视觉



Kinect的红外视图





iPhone X





红外相机

前置
摄像头



泛光照明器

点投影仪

红外相机

前置
摄像头

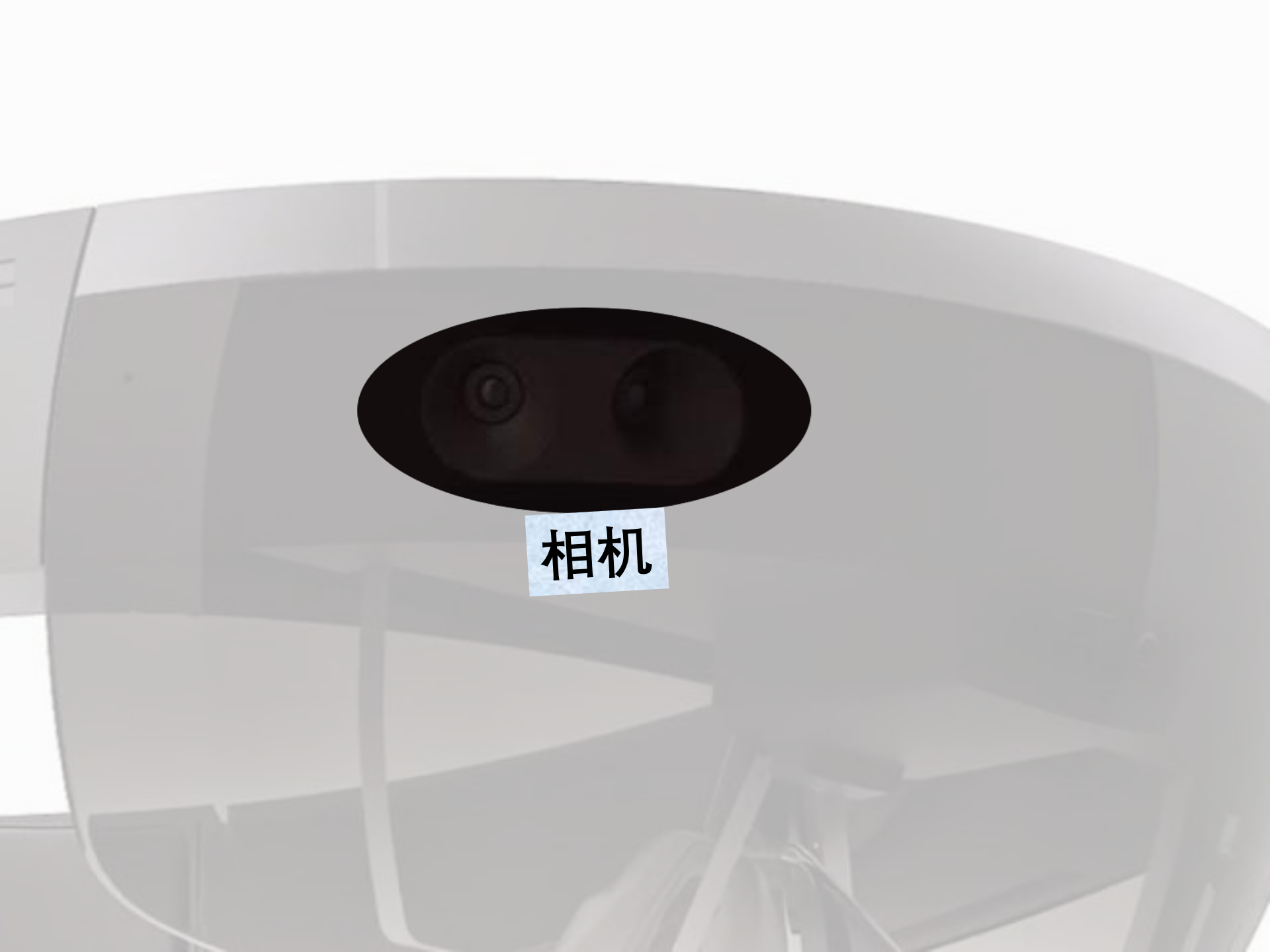






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相机

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