Stereo Depth Estimation

CS576 Homework #1

Version 2

Dependency Matlab Toolbox

- Optimization Toolbox
- Computer Vision System Toolbox

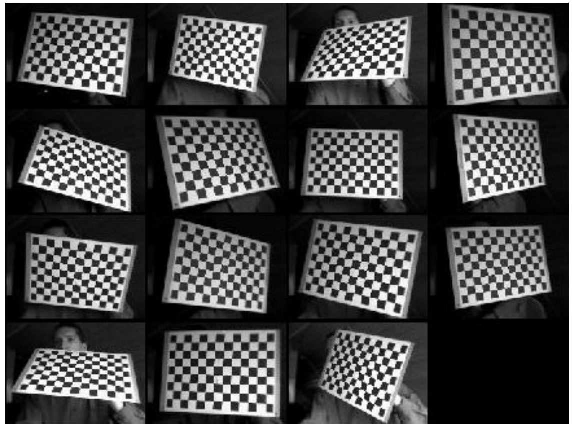
ZHANG'S METHOD (CAMERA CALIBRATION)

Zhang's method

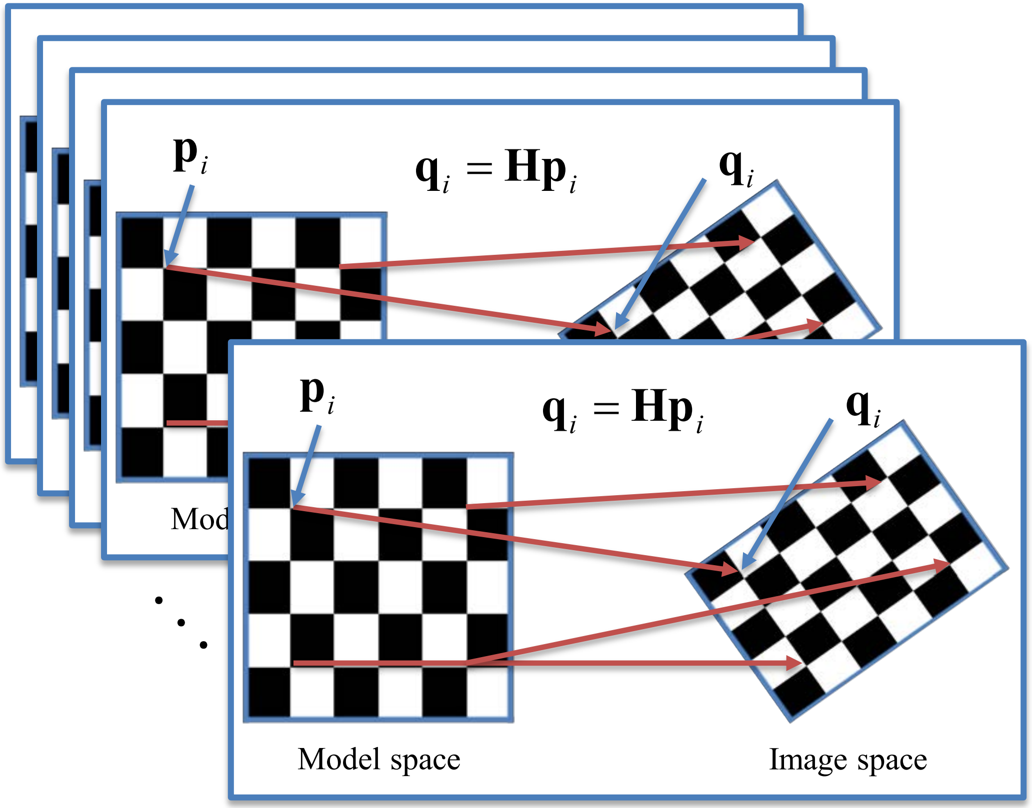
- Z. Zhang, "**A flexible new technique for camera calibration**," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 11, pp. 1330-1334, Nov. 2000.
  doi: 10.1109/34.888718

- In this pptx file, I left a reference of the paper in the lower left corner.

Outline



2D checkerboard pattern images



Model space – image homographies per images

$$\mathbf{K} = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

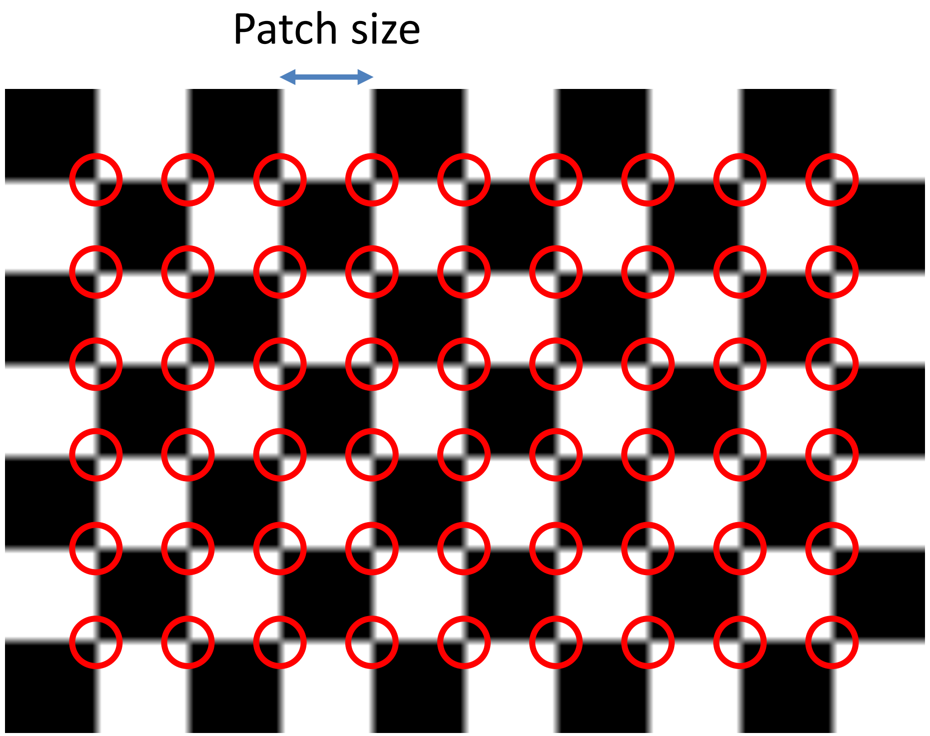
Camera intrinsic parameters

Checkerboard Specification

Size of checkerboard: 6 x 9

Total number of corners: 54

Patch size: 30mm



Homography calculation

- All points on the checkerboard lie in one plane
- Without loss of generality, the *Z* component for each point is 0 in world coordinates

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \mathbf{K}\begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{r}_3 & \mathbf{t} \end{bmatrix}\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \mathbf{K}\begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \cancel{\mathbf{r}_3} & \mathbf{t} \end{bmatrix}\begin{bmatrix} X \\ Y \\ 0 \\ 1 \end{bmatrix}$$

$$= \mathbf{K}\begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix}\begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

for some scalar s

Section 2.2 in [Zhang 2000]

Homography calculation

- A homography $\mathbf{H}$ can represent the relation between model points $\tilde{\mathbf{p}}$ and image points $\tilde{\mathbf{q}}$

$$s\tilde{\mathbf{q}} = \mathbf{H}\tilde{\mathbf{p}} \quad \text{with} \quad \mathbf{H} = \mathbf{K}\begin{bmatrix}\mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t}\end{bmatrix}$$

$$\text{where} \quad \tilde{\mathbf{q}} = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \quad \tilde{\mathbf{p}} = \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

Homography calculation

- The homography is the result of a nonlinear optimization

$$\min_{\mathbf{H}} \sum_{j=1}^{m} \left\| \mathbf{q}_j - \hat{\mathbf{q}}_j \right\|^2$$

where

$$\mathbf{q}_j = \begin{bmatrix} u_j \\ v_j \end{bmatrix} \qquad \hat{\mathbf{q}}_j = \frac{1}{h_{31}X_j + h_{32}Y_j + h_{33}} \begin{bmatrix} h_{11}X_j + h_{12}Y_j + h_{13} \\ h_{21}X_j + h_{22}Y_j + h_{23} \end{bmatrix}$$

(image coordinate for the *j*th point)

$$\mathbf{H} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}$$

Section 3.2 in [Zhang 2000]

Homography calculation

- The cost function $\sum_j \left\| \mathbf{q}_j - \hat{\mathbf{q}}_j \right\|^2$ becomes zero in an ideal case.

$$\mathbf{q}_j - \hat{\mathbf{q}}_j = \begin{bmatrix} u_0 - \dfrac{h_{11}X_j + h_{12}Y_j + h_{13}}{h_{31}X_j + h_{32}Y_j + h_{33}} \\ v_0 - \dfrac{h_{21}X_j + h_{22}Y_j + h_{23}}{h_{31}X_j + h_{32}Y_j + h_{33}} \end{bmatrix} = 0$$

Equivalently,

$$\begin{bmatrix} u_0\left(h_{31}X_j + h_{32}Y_j + h_{33}\right) - \left(h_{11}X_j + h_{12}Y_j + h_{13}\right) \\ v_0\left(h_{31}X_j + h_{32}Y_j + h_{33}\right) - \left(h_{21}X_j + h_{22}Y_j + h_{23}\right) \end{bmatrix} = 0$$

Section 3.2 and Appendix A in [Zhang 2000]

Homography calculation

- We can get a closed-form solution to optimize the second cost function and use it as an initial guess for the nonlinear optimization with the first cost function.

$$\min_{\mathbf{H}} \sum_j \left\| \mathbf{q}_j - \hat{\mathbf{q}}_j \right\|^2$$

← Cost function with a physical meaning
(distance error at the image space)
But difficult to optimize for its nonlinearity

$$\min_{\mathbf{H}} \sum_j \left\| \begin{bmatrix} u_0 \left(h_{31} X_j + h_{32} Y_j + h_{33} \right) - \left(h_{11} X_j + h_{12} Y_j + h_{13} \right) \\ v_0 \left(h_{31} X_j + h_{32} Y_j + h_{33} \right) - \left(h_{21} X_j + h_{22} Y_j + h_{23} \right) \end{bmatrix} \right\|^2$$

← Cost function which is not physically meaningful
But have a closed-form solution

VISUAL COMPUTING Lab

Homography calculation

- The initial guess of the nonlinear optimization can be obtained from a least square approximation

$$\min_{\mathbf{H}} \sum_j \left\| \begin{bmatrix} u_0\left(h_{31}X_j + h_{32}Y_j + h_{33}\right) - \left(h_{11}X_j + h_{12}Y_j + h_{13}\right) \\ v_0\left(h_{31}X_j + h_{32}Y_j + h_{33}\right) - \left(h_{21}X_j + h_{22}Y_j + h_{23}\right) \end{bmatrix} \right\|^2$$

- Express this cost function for $\mathbf{H}$

$$\begin{bmatrix} u_0\left(h_{31}X_j + h_{32}Y_j + h_{33}\right) - \left(h_{11}X_j + h_{12}Y_j + h_{13}\right) \\ v_0\left(h_{31}X_j + h_{32}Y_j + h_{33}\right) - \left(h_{21}X_j + h_{22}Y_j + h_{23}\right) \end{bmatrix} = \begin{bmatrix} -X_j & -Y_j & -1 & 0 & 0 & 0 & u_jX_j & u_jY_j & u_j \\ 0 & 0 & 0 & -X_j & -Y_j & -1 & v_jX_j & v_jY_j & v_j \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \\ h_{33} \end{bmatrix}$$

Homography calculation

- The initial guess of the nonlinear optimization can be obtained from a least square approximation

$$\min_{\mathbf{H}} \sum_j \left\| \begin{bmatrix} u_0\left(h_{31}X_j + h_{32}Y_j + h_{33}\right) - \left(h_{11}X_j + h_{12}Y_j + h_{13}\right) \\ v_0\left(h_{31}X_j + h_{32}Y_j + h_{33}\right) - \left(h_{21}X_j + h_{22}Y_j + h_{23}\right) \end{bmatrix} \right\|^2 = \min_{\mathbf{H}} \sum_j \left\| \mathbf{L}_j \mathbf{x} \right\|^2$$

- Express this cost function for **H**

$$\mathbf{L}_j \mathbf{x} = \begin{bmatrix} -X_j & -Y_j & -1 & 0 & 0 & 0 & u_j X_j & u_j Y_j & u_j \\ 0 & 0 & 0 & -X_j & -Y_j & -1 & v_j X_j & v_j Y_j & v_j \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \\ h_{33} \end{bmatrix}$$

Homography calculation

- The initial guess of the nonlinear optimization can be obtained from a least square approximation

$$\min_{\mathbf{x}} \|\mathbf{L}\mathbf{x}\|^2 \qquad \text{Subject to} \qquad \|\mathbf{x}\|^2 = 1$$

$$\text{where} \qquad \mathbf{L} = \begin{bmatrix} \mathbf{L}_1 \\ \mathbf{L}_2 \\ \vdots \\ \mathbf{L}_m \end{bmatrix}$$

Homography calculation

- The initial guess of the nonlinear optimization can be obtained from a least square approximation

$$\min_{\mathbf{x}} \|\mathbf{L}\mathbf{x}\|^2$$

Subject to $\|\mathbf{x}\|^2 = 1$

$\rightarrow$

$$\min_{\mathbf{x}} \mathbf{x}^T\mathbf{L}^T\mathbf{L}\mathbf{x}$$

Subject to $\|\mathbf{x}\|^2 = 1$

$\rightarrow$

The solution is
the eigenvector of L^TL associated with the smallest eigenvalue
(the right singular vector of L associated with the smallest singular value)

It become initial guess of the optimization of slide 7

Intrinsic parameters

- When we know the homography **H** then we can extract the intrinsic **K** from it.
- Intrinsic parameters have constraints from orthogonality of the rotation matrix

$$\mathbf{H} = \mathbf{K}\begin{bmatrix}\mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t}\end{bmatrix} \qquad \mathbf{r}_1{}^T\mathbf{r}_1 = \mathbf{r}_2{}^T\mathbf{r}_2 \qquad \mathbf{r}_1{}^T\mathbf{r}_2 = 0 \qquad \mathbf{H} = \begin{bmatrix}\mathbf{h}_1 & \mathbf{h}_2 & \mathbf{h}_3\end{bmatrix}$$

$$\mathbf{r}_1 = \mathbf{K}^{-1}\mathbf{h}_1$$

$$\mathbf{r}_2 = \mathbf{K}^{-1}\mathbf{h}_2$$

$$\mathbf{h}_1{}^T\mathbf{K}^{-T}\mathbf{K}^{-1}\mathbf{h}_2 = 0$$

$$\mathbf{h}_1{}^T\mathbf{K}^{-T}\mathbf{K}^{-1}\mathbf{h}_1 = \mathbf{h}_2{}^T\mathbf{K}^{-T}\mathbf{K}^{-1}\mathbf{h}_2$$

Section 3.1 in [Zhang 2000]

Intrinsic parameter

- From constraints and homographies, the linear equations with respect to intrinsic parameters are obtained

$$\mathbf{B} = \mathbf{K}^{-T}\mathbf{K}^{-1} = \begin{bmatrix} B_{11} & B_{12} & B_{13} \\ B_{12} & B_{22} & B_{23} \\ B_{13} & B_{23} & B_{33} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\alpha^2} & -\frac{\gamma}{\alpha^2\beta} & \frac{v_0\gamma - u_0\beta}{\alpha^2\beta} \\ -\frac{\gamma}{\alpha^2\beta} & -\frac{\gamma}{\alpha^2\beta} + \frac{1}{\beta^2} & -\frac{\gamma(v_0\gamma - u_0\beta)}{\alpha^2\beta^2} - \frac{v_0}{\beta^2} \\ \frac{v_0\gamma - u_0\beta}{\alpha^2\beta} & -\frac{\gamma(v_0\gamma - u_0\beta)}{\alpha^2\beta^2} - \frac{v_0}{\beta^2} & \frac{(v_0\gamma - u_0\beta)^2}{\alpha^2\beta^2} + \frac{v_0{}^2}{\beta^2} + 1 \end{bmatrix}$$

$$\mathbf{K} = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

Camera intrinsic parameters

Section 3.1 and Appendix B in [Zhang 2000]

Intrinsic parameter

- From constraints and homographies, the linear equations with respect to intrinsic parameters are obtained

$$\mathbf{B} = \mathbf{K}^{-T}\mathbf{K}^{-1} = \begin{bmatrix} B_{11} & B_{12} & B_{13} \\ B_{12} & B_{22} & B_{23} \\ B_{13} & B_{23} & B_{33} \end{bmatrix}$$

- Since $\mathbf{B}$ is a symmetric matrix, we only should obtain a vector:

$$\mathbf{b} = \begin{bmatrix} B_{11} & B_{12} & B_{13} & B_{22} & B_{23} & B_{33} \end{bmatrix}^T$$

Section 3.1 in [Zhang 2000]

Intrinsic parameter

- From constraints and homographies, the linear equations with respect to intrinsic parameters are obtained
- We have formulae in formed as $\mathbf{h}_k^T\mathbf{B}\mathbf{h}_l$ for $k, l = 1$ or 2. It can be expressed as the inner product of a vector and the vector $\mathbf{b}$.

$$\mathbf{h}_k{}^T\mathbf{B}\mathbf{h}_l = \mathbf{v}_{kl}{}^T\mathbf{b} \quad \text{with} \quad \begin{aligned}\mathbf{v}_{kl} = [&h_{1k}h_{1l},\ h_{1k}h_{2l} + h_{2k}h_{1l},\ h_{1k}h_{3l} + h_{3k}h_{1l},\\ &h_{2k}h_{2l},\ h_{2k}h_{3l} + h_{3k}h_{2l},\ h_{3k}h_{3l}]^T\end{aligned}$$

where $\mathbf{b} = \begin{bmatrix} B_{11} & B_{12} & B_{13} & B_{22} & B_{23} & B_{33} \end{bmatrix}^T \quad \mathbf{H} = \begin{bmatrix} \mathbf{h}_1 & \mathbf{h}_2 & \mathbf{h}_3 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}$

Intrinsic parameter

- From constraints and homographies, the linear equations with respect to intrinsic parameters are obtained as:

$$\mathbf{h}_1{}^T \mathbf{K}^{-T} \mathbf{K}^{-1} \mathbf{h}_2 = 0$$

$$\mathbf{h}_1{}^T \mathbf{K}^{-T} \mathbf{K}^{-1} \mathbf{h}_1 = \mathbf{h}_2{}^T \mathbf{K}^{-T} \mathbf{K}^{-1} \mathbf{h}_2$$

$$\longrightarrow \begin{bmatrix} \mathbf{v}_{12}{}^T \\ \left(\mathbf{v}_{11} - \mathbf{v}_{22}\right)^T \end{bmatrix} \mathbf{b} = 0$$

Intrinsic parameter

- From constraints and homographies, the linear equations with respect to intrinsic parameters are obtained as:

$$\mathbf{h}_1^T \mathbf{K}^{-T} \mathbf{K}^{-1} \mathbf{h}_2 = 0$$

$$\mathbf{h}_1^T \mathbf{K}^{-T} \mathbf{K}^{-1} \mathbf{h}_1 = \mathbf{h}_2^T \mathbf{K}^{-T} \mathbf{K}^{-1} \mathbf{h}_2$$

$$\longrightarrow$$

$$\mathbf{V}\mathbf{b} = \begin{bmatrix} \mathbf{v}_{12}^T \\ \left(\mathbf{v}_{11} - \mathbf{v}_{22}\right)^T \end{bmatrix} \mathbf{b} = 0$$

$$\mathbf{V}_i \mathbf{b} = 0$$

(It can be obtained for each image i)

Intrinsic parameter

- From constraints and homographies, the linear equations with respect to intrinsic parameters are obtained

$$\min_{\mathbf{b}} \|\mathbf{V}\mathbf{b}\|^2 \quad \text{Subject to} \quad \|\mathbf{b}\|^2 = 1$$

$$\text{where} \quad \mathbf{V} = \begin{bmatrix} \mathbf{V}_1 \\ \mathbf{V}_2 \\ \vdots \\ \mathbf{V}_n \end{bmatrix}$$

(n is the number of images)

Intrinsic parameter

- From constraints and homographies, the linear equations with respect to intrinsic parameters are obtained

$$\min_{\mathbf{b}} \left\| \mathbf{V}\mathbf{b} \right\|^2 \qquad \text{Subject to} \qquad \left\| \mathbf{b} \right\|^2 = 1$$

where $$\mathbf{V} = \begin{bmatrix} \mathbf{V}_1 \\ \mathbf{V}_2 \\ \vdots \\ \mathbf{V}_n \end{bmatrix}$$

The solution is
the eigenvector of $\mathbf{V}^T\mathbf{V}$ assosiated with
the smallest eigenvalue
(the right singular vector of $\mathbf{V}$ assosiated
with the smallest singular value)

The same optimization problem as Slide 13

Intrinsic parameter

- We can obtain intrinsic parameters α, β, γ, u_0, and v_0 from vector $\mathbf{b}$

$$v_0 = \left(B_{12}B_{13} - B_{11}B_{23}\right) / \left(B_{11}B_{22} - B_{12}{}^2\right)$$

$$\lambda = B_{33} - \left[B_{13}{}^2 + v_0\left(B_{12}B_{13} - B_{11}B_{23}\right)\right] / B_{11}$$

$$\alpha = \sqrt{\lambda / B_{11}}$$

$$\beta = \sqrt{\lambda B_{11} / \left(B_{11}B_{22} - B_{12}{}^2\right)}$$

$$\gamma = -B_{12}\alpha^2\beta / \lambda$$

$$u_0 = \gamma v_0 / \beta - B_{13}\alpha^2 / \lambda$$

Just equivalent formulae to Slide 15

Section 3.1 and Appendix B in [Zhang 2000]

Extrinsic parameter

- We can obtain extrinsic parameters $\mathbf{r}_1$, $\mathbf{r}_2$, $\mathbf{r}_3$, and $\mathbf{t}$ from the homography $\mathbf{H}$ and the intrinsic parameters
- However, as the scale parameter λ is computed from all views, λ is not always correct for each individual view.
- We have to update λ as λ' for each view.

$$\lambda' = \frac{1/\left\|\mathbf{K}^{-1}\mathbf{h}_1\right\| + 1/\left\|\mathbf{K}^{-1}\mathbf{h}_2\right\|}{2}$$

- Then calculate extrinsic parameters for each individual view.

$$\mathbf{r}_1 = \lambda'\mathbf{K}^{-1}\mathbf{h}_1 \qquad \mathbf{r}_2 = \lambda'\mathbf{K}^{-1}\mathbf{h}_2 \qquad \mathbf{r}_3 = \mathbf{r}_1 \times \mathbf{r}_2 \qquad \mathbf{t} = \lambda'\mathbf{K}^{-1}\mathbf{h}_3$$

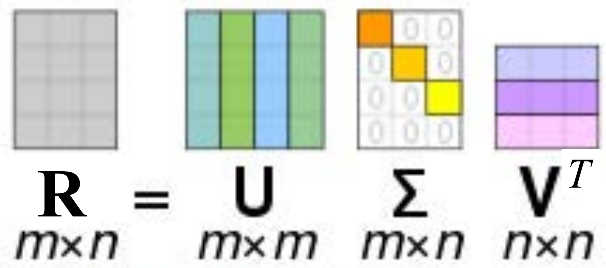
Section 3.1 in [Zhang 2000]

Estimate the best rotation matrix

- The so-computed matrix $\mathbf{R} = [\mathbf{r}_1, \mathbf{r}_2, \mathbf{r}_3]$ does not in general satisfy the properties of a rotation matrix.
- Estimate the best rotation matrix $\mathbf{R}'$ from $\mathbf{R}$.

Singular value decomposition: $\mathbf{R} = \mathbf{U}\Sigma\mathbf{V}^T$

$$\mathbf{R}' := \mathbf{U}\mathbf{V}^T$$



(Here $\mathbf{V}$ is notation only for SVD)

Appendix C in [Zhang 2000]

Closed form solution

- We have obtained closed form solution for intrinsic parameter $\mathbf{K}$, rotation $\mathbf{R}_i'$, translation $\mathbf{t}_i$(for each image i)
- However, this solution is obtained through minimizing an algebraic distance which is not physically meaningful.

Section 3.2 in [Zhang 2000]

Maximum likelihood estimation

- Assume that the image points are corrupted by independent and identically distributed Gaussian noise. The maximum likelihood estimate can be obtained by minimizing:

$$\min_{\mathbf{K},\mathbf{R}_i,\mathbf{t}_i} \sum_i \sum_j \left\| \mathbf{q}_{ij} - \hat{\mathbf{q}}_{ij} \right\|^2$$

where

$$\mathbf{q}_{ij} = \begin{bmatrix} u_{ij} \\ v_{ij} \end{bmatrix}, \text{ image coordinates for the } j\text{th point in the } i\text{th image}$$

$$\begin{bmatrix} \hat{u}_{ij} \\ \hat{v}_{ij} \\ \hat{w}_{ij} \end{bmatrix} = \mathbf{K}\begin{bmatrix} \mathbf{r}_{i,1} & \mathbf{r}_{i,2} & \mathbf{t} \end{bmatrix}\tilde{\mathbf{p}}_j$$

$$\tilde{\mathbf{p}}_j = \begin{bmatrix} X_j \\ Y_j \\ 1 \end{bmatrix}, \text{ model coordinates for the } j\text{th point}$$

$$\hat{\mathbf{q}}_{ij} = \begin{bmatrix} \hat{u}_{ij} / \hat{w}_{ij} \\ \hat{v}_{ij} / \hat{w}_{ij} \end{bmatrix}$$

$\mathbf{r}_{i,1}, \mathbf{r}_{i,2}$: the 1st and 2nd column vector for $\mathbf{R}_i$, respectively

Maximum likelihood estimation

- Assume that the image points are corrupted by independent and identically distributed Gaussian noise. The maximum likelihood estimate can be obtained by minimizing:

$$\min_{\mathbf{K},\mathbf{R}_i,\mathbf{t}_i} \sum_i \sum_j \left\| \mathbf{q}_{ij} - \hat{\mathbf{q}}_{ij} \right\|^2$$

- For constraint that $\mathbf{R}_i$ is a rotation matrix, it is parameterized by a vector of 3 parameters, denoted by $\mathbf{r}_i$, which is parallel to the rotation axis and whose magnitude is equal to the rotation angle.

Maximum likelihood estimation

- Assume that the image points are corrupted by independent and identically distributed Gaussian noise. The maximum likelihood estimate can be obtained by minimizing:

$$\min_{\mathbf{K},\mathbf{R}_i,\mathbf{t}_i} \sum_i \sum_j \left\| \mathbf{q}_{ij} - \hat{\mathbf{q}}_{ij} \right\|^2$$

- $\mathbf{R}_i$ and $\mathbf{r}_i$ are related by the Rodrigues rotation formula. It is implemented as Matlab functions "rotationMatrixToVector" and "rotationVectorToMatrix".
- Beware when using these functions.
  - The rotation matrix should be transposed before calling the function "rotationMatrixToVector".
  - The rotation matrix should be transposed after get return value from "rotationVectorToMatrix".

Maximum likelihood estimation

- Assume that the image points are corrupted by independent and identically distributed Gaussian noise. The maximum likelihood estimate can be obtained by minimizing:

$$\min_{\mathbf{K},\mathbf{R}_i,\mathbf{t}_i} \sum_i \sum_j \left\| \mathbf{q}_{ij} - \hat{\mathbf{q}}_{ij} \right\|^2$$

- The local minimum can be obtained by the Matlab solver “lsqnonlin” with the initial guess obtained in Slide 25.

PLANE SWEEPING ALGORITHM (DEPTH ESTIMATION)

Plane sweeping algorithm

- Input: Two rectified gray images, camera parameters (focal length, baseline)
- Output: Depth map

Left

Right

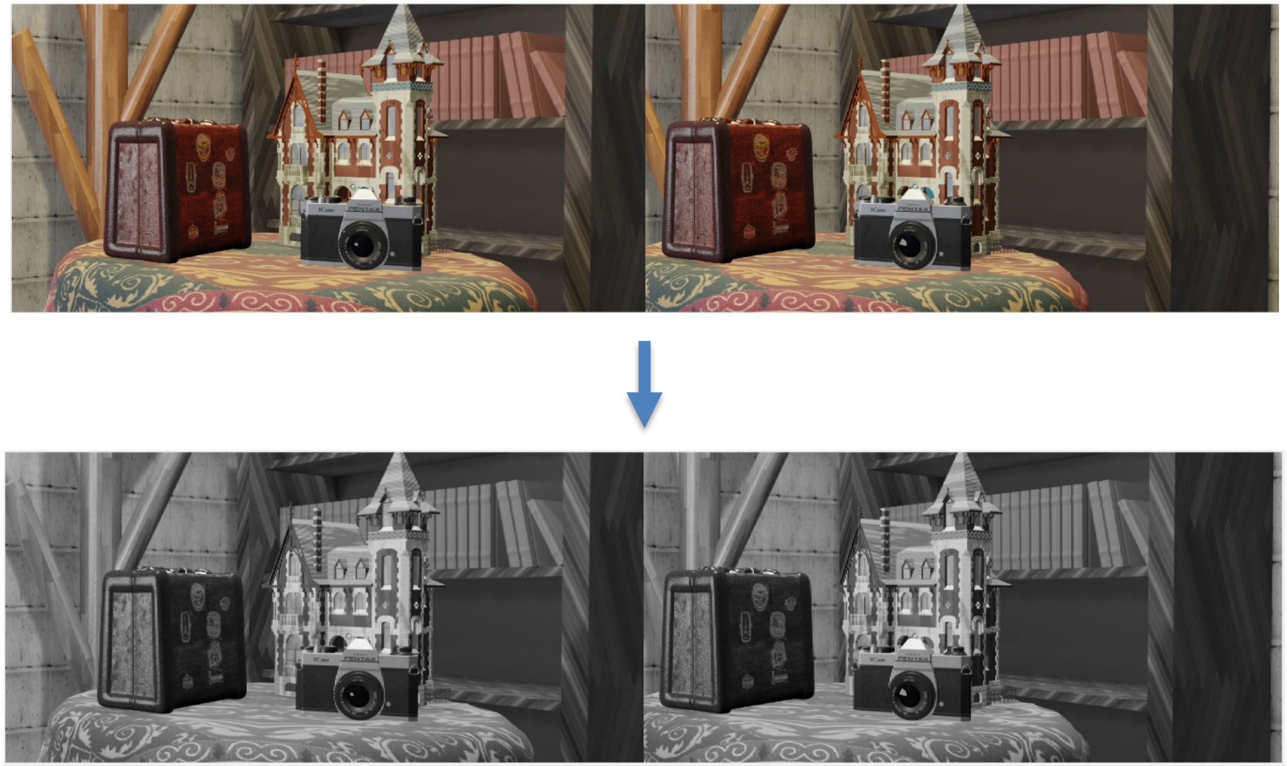
Depth map (Left)

Steps

1. Preprocessing
2. Make a cost volume with a cost function
3. Cost aggregation
4. Obtain a disparity map by selecting minimum cost
5. Convert disparity map into depth map using camera parameters

1. Preprocessing

- For simplicity, convert color images into gray images.



Left　　　　　　Right

2. Make a cost volume with a cost function

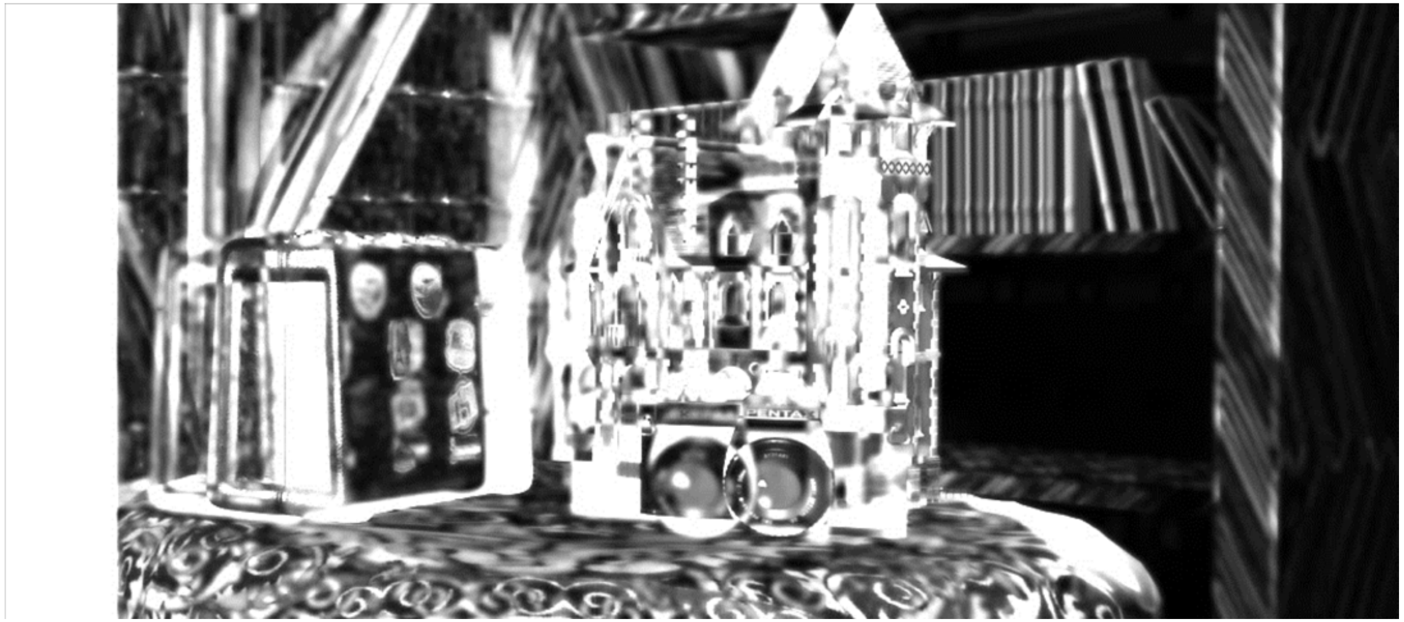
- Decide maxDisparity and minDisparity values.
- Make a 3D cost volume (width x height x (maxDisparity – minDisparity))
- Use NCC cost function.

- Subtract mean $A \leftarrow A - E\left[A\right],\ B \leftarrow B - E\left[B\right]$

- Calculate NCC $NCC = \dfrac{\sum_i \sum_j A(i,j)B(i,j)}{\sqrt{\sum_i \sum_j A(i,j)^2}\sqrt{\sum_i \sum_j B(i,j)^2}}$

3. Cost aggregation

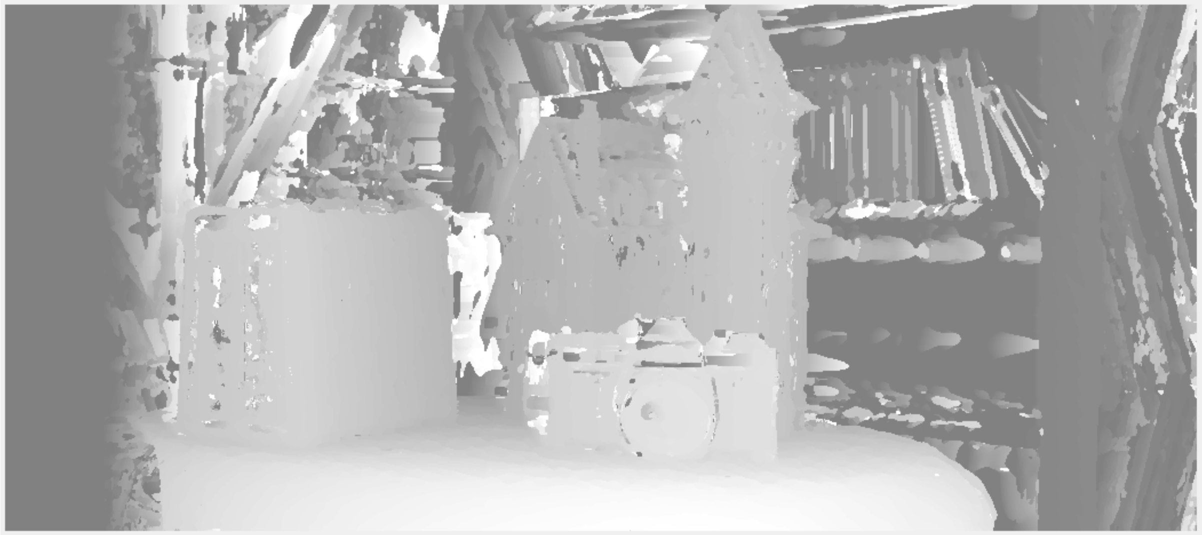
- Aggregate each layer of the cost volume using the box filter and the guided filter.
- Feel free to use 'imfilter' and 'imguidedfilter' functions.



See the video file, named as
Aggregated_cost_volume.mp4

4. Disparity map

- For each pixel, select disparity which have minimum cost.
- The closer pixels have larger disparity values.



Disparity map (Left)

5. Depth map

- Convert disparity map into depth map using the camera parameters.
- The closer pixels have smaller depth values.

$$Z = \frac{fT}{d}$$

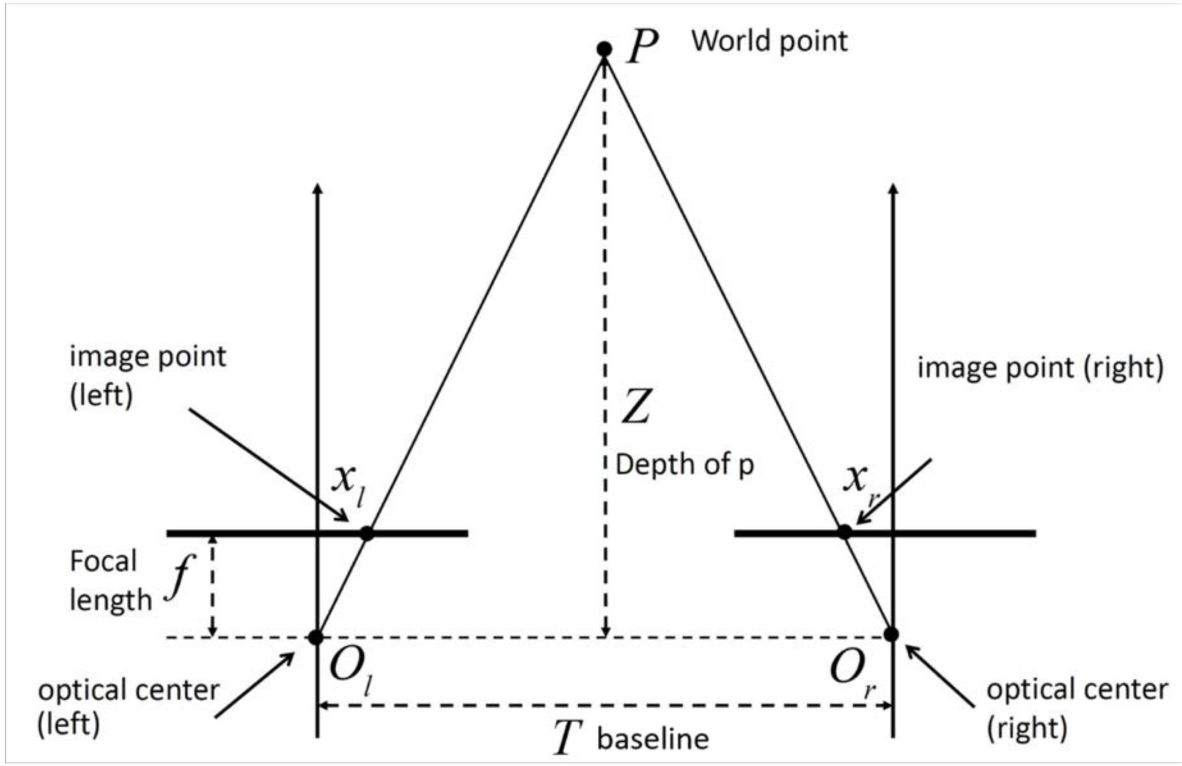
Z : depth

f : focal length

T : baseline

d : disparity

Depth map (Left)



VISUAL COMPUTING Lab

Evaluation

- For evaluation, we provided ground truth depth map. (gt_depthmap.mat)
- Drag and drop gt_depthmap.mat into your matlab.
- Then leftGtDepth will be on your workspace.

Ground-truth depth map (left)

SUBMISSION

Allowed Functions

- imfilter
- imguidedfilter
- svd
- lsqnonlin
- rotationMatrixToVector
- rotationVectorToMatrix
- normxcorr2

Forbidden Functions

If you use these functions, we will not score the part of your homework.

- estimateCameraParameters
- generateCheckerboardPoints
- disparity

[WARNING] Plagiarism Policy

KAIST

- ***First, no grade for copied codes (such as your friends or codes on Internet) is given!***
- ***Second, you will get F accordingly!***
- ***Your cheating will be reported to the school.***
- ***Do not cheat by copying others' codes!***
- ***Our TA are using an advanced code plagiarism detection software!***

VISUAL COMPUTING Lab

Grading Criteria

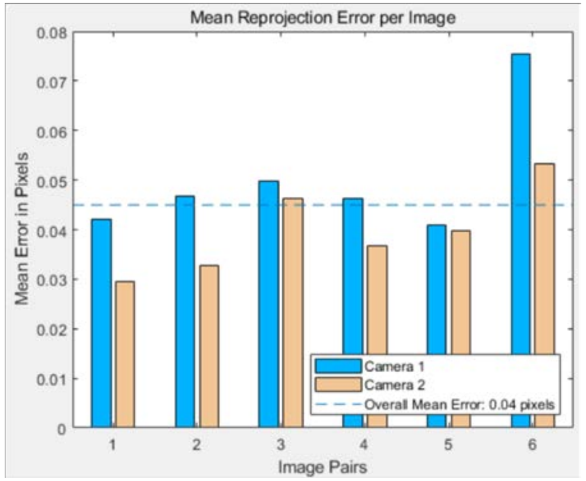
- Homography estimation: 10%
- Camera calibration: 50%
  - Mean Y-coordinate error should be lower than 1px
- Depth estimation: 30%
  - Mean depth error for scene1 should be lower than 50cm
  - Mean depth error for scene2 should be lower than 1m
- Writeup: 10%

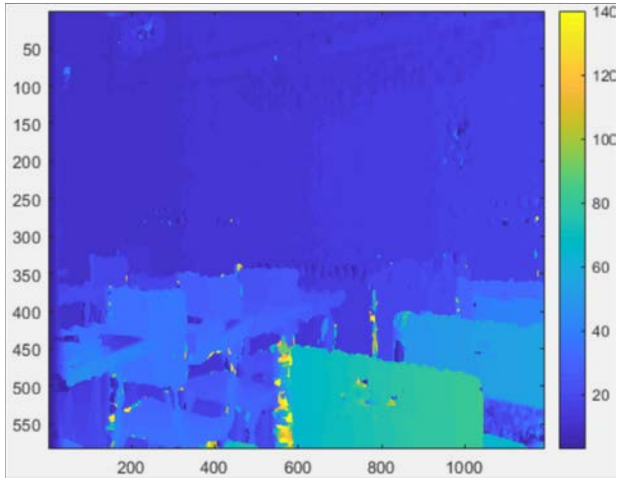
Functions to implement

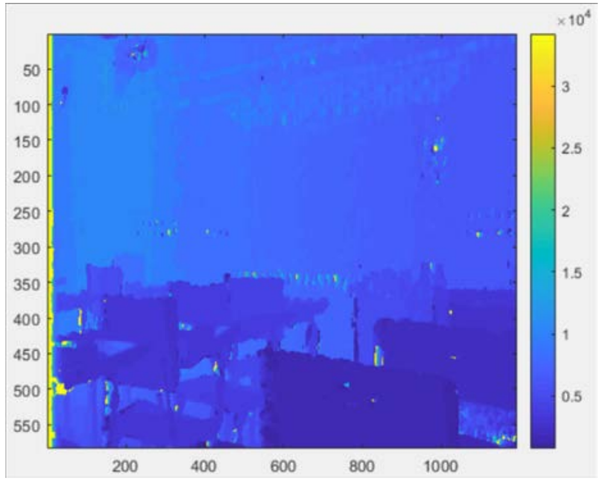
- *estimateDepth.m*
- *estimateSingleCameraParameters.m*
- *func_calibration.m*
- You have to fill in 10 empty code blocks.
- Do not change *main.m*

Writeup

- Briefly explain each step of your implementation.
- Include reprojection error of camera parameters.
- Include mean difference values and discuss about the results
  - Difference of y coordinate of rectified images
  - Difference of depthmap
- Include color coded disparity and depth images and discuss why depth estimation of some region is not working well.







Submission

- Due date: April 14th, Sunday, 23:55
- Zip your files 'cs576_hw1_studentid_name.zip'
  - Matlab codes
  - Writeup file (writeup.tex)
- Submit your homework to KLMS