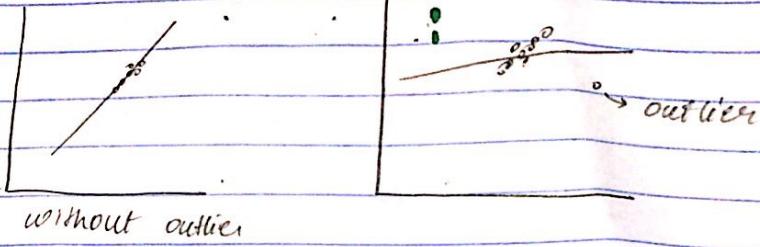


1 a) Outliers are points, which behave completely different with the existing points.

During line fitting, because of outliers it presented a completely wrong solution.



16) Objective function for Robust Estimation:-

$$E(\theta) = \sum_{i=1}^n \rho(d(x_i, \theta))^2$$

In standard least square \rightarrow we use $\rho = x^2$

where individual error is squared

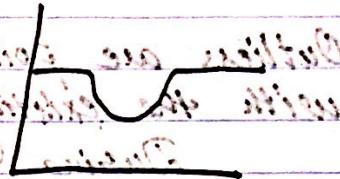
whereas, in robust estimation

we use $\rho = \frac{x^2}{x^2 + \sigma^2} \rightarrow$ called
Geman-McClure function

So, in robust if error is
big we give weight 1, whereas in
least square, we square all the error & sum it

1c) German McCleee function:-

$$S_\sigma = \frac{x^2}{x^2 + \sigma^2}$$



if σ is small, then it is called robust estimator.

→ due to straight line before & after the curve, the maximum weight an outlier can get is 1.

if $\sigma \gg 0$

$$S_\sigma = 1$$

if $\sigma \ll 0$

$$S_\sigma = \frac{\sigma^2}{\sigma^2 + x^2}$$

if σ is small, too less points are considered
and σ is large, too many points are selected
thus giving wrong answers, in both the cases.

∴ since large σ gives consider many

$$((0, \infty) \setminus \{0\}) \ni \frac{1}{\sigma} = (0, \infty)$$

Since small σ considers less points & large σ considers too many points. Right σ is estimated by considering a large σ then iteratively reduce it. and.

$$\rightarrow \sigma_n = 1.5 \times \text{median}(d(x_i, \sigma))$$

- 1) Draw a large subset of points uniformly at random.
- 2) Fit the model using robust estimation.

1d) Principle of RANSAC Algorithm.

: We try to do many small experiments and hope one of them is a right model.

The number of points drawn at each attempt should be small, possibility to get inliers and not outliers is high, ~~so we are~~ so high hope to get one good experiment.

1 e) Parameters:-

n = no. of points to draw at each evaluation

d = minimum no. of points needed.

κ = no. of trials

t = distance to identify outliers.

κ can be estimated as:-

$$\kappa = \frac{\log(1-p)}{\log(1-w^n)}$$

where

w = Probability that a point is an outlier (initial guess $w=0.5$)

$1-p$ = Probability that experiment fails

1P) Objective of the segmentation :-

The main objective of segmentation, is to separate object from background.

Merge approaches :- Here, we start with each pixel in separate cluster iteratively merge clusters

split approach :- start with all in one cluster then iteratively split clusters (by some distance)

1g)

K-means

- Select k initial x_i 's from image as cluster centers.
- Start with initial guess of k means $\{m_j\}_{j=1}^k$.
- repeats

$$l_i^* = \underset{j \in [1, k]}{\operatorname{argmin}} \|f_i - m_j\|$$

for each pixel we chose cluster with closest center.

$$m_j = \frac{\sum_{i \in S_j} f_i}{\# S_j}$$

where S_j is set of pixels labeled l_i^* when $f_i \rightarrow$ all the pixels in the image labelled l_j .
- Stop when m_j don't change.

K-means can be improved by using mixture of gaussians :-

This is similar to K-means, but here we replace

$$d = \|f_i - m_j\|^2$$
 with

with

$$d = (f_i - m_j)^T \Sigma^{-1} (f_i - m_j)$$

where

$$m_j = \frac{\sum_{i \in S_j} f_i}{\# S_j}, \quad \Sigma = \frac{\sum_{i \in S_j} (f_i - m_j)(f_i - m_j)^T}{\# S_j}$$



So a point in one (p_1) in C_1 will be included now in cluster C_1 even if distance from centre of C_2 is small because variance in this direction (C_1) is more; thus this example will be success in mixture of Gaussian but fail with K-means.

1h) Mean Shift

This algorithm is similar to 'K' means, with a minor change here:-

$$m_j = \frac{\sum_{i \in S_j} f_i}{\# S_j} \rightarrow m_j = \frac{\sum_{i \in S_j} w_i(f_i - m_j)}{\sum_{i \in S_j} w_i}$$

Here \rightarrow weight is given to each example based on distance of sample from m_j .

- function ' w ' - determines value of weight.
when far from center \rightarrow low w value.
 - here cluster centre are peaks of histogram.

Qa)

Camera Calibration

we find 3D point for image from point in 3D-world space

$$\text{equation } (p = Mp^*) \quad (1)$$

if we are given p (3D point) & M (projection matrix)

In reconstruction, \rightarrow given 2D \rightarrow we find 3D.

Reconstruction is more difficult, as we have to add an unknown dimension here whereas in other cases we simply remove it which is easy.

2(b) The inputs for camera calibration are:

→ 2D image points (x_i, y_i)

→ and 3D world points (X, Y, Z) .

Q) STEPS in the non-coplanar calibration algorithm:-

- (i) Estimate projection matrix, M
- (ii) Find intrinsic & extrinsic parameters (K^* , R^* , T^*)

$$2D \leftarrow P_i = MP_i$$

$$\begin{bmatrix} x_i \\ y_i \\ w_i \end{bmatrix} = \begin{bmatrix} m_1^T \\ m_2^T \\ m_3^T \end{bmatrix} P_i \rightarrow x_i = \frac{x_i}{w_i} = \frac{m_1^T P_i}{m_3^T P_i} \quad \text{--- (1)}$$

$$y_i = \frac{y_i}{w_i} = \frac{m_2^T P_i}{m_3^T P_i} \quad \text{--- (2)}$$

To solve these we need min '6' points.

$$\underbrace{\begin{bmatrix} P_i^T & 0 & -x_i P_i^T \\ 0 & P_i^T & -y_i P_i^T \\ 1 & 1 & 1 \end{bmatrix}}_A \begin{bmatrix} m_1 \\ m_2 \\ m_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

+ this is M .

We can also find $M \rightarrow$ by SVD of $A \rightarrow$

\rightarrow now

$$K^* [R^* | T^*] = S \hat{M}$$

$$\text{so } K^T T^* = S \begin{bmatrix} q_1^T \\ q_2^T \\ q_3^T \end{bmatrix}$$

$$K^T T^* = S b$$

$$M = \begin{bmatrix} q_1^T & b \\ q_2^T & b \\ q_3^T & b \end{bmatrix}$$

$$\rightarrow \text{solving we get } |S| = \frac{1}{|q_3^T|}$$

$$U_0 = S^2 q_1 \cdot q_3$$

$$V_0 = S^2 q_2 \cdot q_3$$

2(a) - Projection Matrix $\begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 0 & 3 & 4 \\ 1 & 1 & 1 & 1 \end{bmatrix}$

$P_i = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 1 \end{bmatrix} \rightarrow \text{homogeneous form}$

$P_i = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 0 & 3 & 4 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \\ 1 \end{bmatrix}$

volume $= \begin{bmatrix} 18 \\ 14 \\ 7 \end{bmatrix} \rightarrow \text{so } 2D = \begin{bmatrix} 18/7 \\ 14/7 \\ 2 \end{bmatrix}$

2c)

$$\text{world point} = (1, 2, 3) \Rightarrow (x_i, y_i, z_i) \quad \text{at } (i)$$

image point = $(100, 200) \Rightarrow (x_i, y_i)$

so for matrix A :-

$$\left[\begin{array}{ccccccccc} X, Y, Z, 1, 0, 0, 0, 0, -xiX, -xiY, -xiZ, -xi \\ 0, 0, 0, 0, X, Y, Z, 1, -yiX, -yiY, -yiZ, -yi \end{array} \right]$$

$$= \begin{bmatrix} 1, 2, 3, 1, 0, 0, 0, 0, -100, -200 & -300 & -100 \\ 0 & 0 & 0 & 0 & 1 & 2 & 3 & 4 & -200 & -400 & -600 & -200 \end{bmatrix}$$

$\kappa_f)$

The minimal number of joints required is 6 to able to find unique solution.

For do obtain solution,

$$M_x = 0$$

where

$$M = \begin{bmatrix} X Y Z & 1000 & -x_i X & -x_i Y & -x_i Z & -x_i \\ 0 & 0 & 0 & X Y Z & -y_i X & -y_i Y & -y_i Z & -y_i \end{bmatrix}$$

for 1 point

so all points this is find

$$Mx = 0$$

now take syd. for M.

then obtain vector V → which is

12×12 matrix.

$V^T \rightarrow$ last column will provide

z values

4) will provide reshape provide
projection next.

ans:-

$$\begin{bmatrix} P^T & 0 & -x \\ \vdots & \vdots & \vdots \\ 0^T & P_n^T & -y_n^T \end{bmatrix} \begin{bmatrix} M_1 \\ \vdots \\ M_{2n} \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

12x1 2nx1

this ~~P~~ will provide projection matrix after reshaping.

g)

To find the camera parameters from projection matrix:-
we will find SVD of projection matrix ($M_P = 0$)
Then for $V \rightarrow$ matrix $\rightarrow V^T \rightarrow$ the last column
will provide projection matrix.

$$= \begin{bmatrix} m_{11} & m_{12} & m_{13} & m_{14} \\ m_{21} & m_{22} & m_{23} & m_{24} \\ m_{31} & m_{32} & m_{33} & m_{44} \end{bmatrix}$$

P also divided as:-

$$P = K^* X [R^* | E^*]$$

where $K^* R^* = \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix}$, $K^* E^* = \begin{bmatrix} m_{14} \\ m_{24} \\ m_{44} \end{bmatrix}$

Q1) To compute the quality of projection matrix M :

$$\{P_i\}_{i=1}^n \rightarrow \{P_i\}_{i=1}^3$$

image points (3D)
world point (3D)

For the camera calibration, we will parameters K^* , R^* , T^* , ϵ will find error, with the correct one.

$$Err(K^*, R^*, T^*) = \sum_{i=1}^n \left(\frac{x_i - m_i^T P_i}{m_3^T P_i} \right)^2 + \left(\frac{y_i - m_{2,i}^T P_i}{m_3^T P_i} \right)^2$$

smaller the error \rightarrow better quality of projection matrix
smaller the distance \rightarrow smaller the error.

Q2) Principal of Planar Camera Calibration:-

Here, to perform camera calibration minimum of three views we have shown three views, for processing.

- Estimation of 2D homography, between calibration target and image
- calculate intrinsic parameters from different views & then calculate extrinsic parameters.

Non-coplanar

→ use 3D image for calibration target, which is in more than one plane. we calculate pixel coordinate (image point) & based on these camera calibration was done.

Planar

→ Here a single image (planar points) is used with different views, to be used for camera calibration.

Q2) Homography (H) → 2D projective map is used for transformation from one plane to other, it is (3x3)

Whereas Projection matrix (M) is used to project 3DH points to get image 2DH points
it is (3x4)

→

$$x' = Hx$$

$$\begin{pmatrix} x'_1 \\ x'_2 \\ x'_3 \end{pmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

(Homography)

$$p_i = M \cdot p_i$$

$$\begin{pmatrix} x_i \\ y_i \\ z_i \\ 1 \end{pmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} & m_{14} \\ m_{21} & m_{22} & m_{23} & m_{24} \\ m_{31} & m_{32} & m_{33} & m_{34} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

2DH

3DH

$$p_i = K^T [R^* | T^*] p_i$$

$$\begin{pmatrix} u_i \\ v_i \\ w_i \end{pmatrix} = K^T [\lambda_1 \lambda_2 \lambda_3 T^*] \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}$$

$$= K^T [\lambda_1 \lambda_2 T^*] \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}$$

2D
Homography