



UNIVERSITY OF WASHINGTON
ELECTRICAL ENGINEERING

NATIONAL CHIAO TUNG UNIVERSITY
DEPARTMENT OF
COMPUTER SCIENCE



电子电气工程学院

College of Electronic and Electrical Engineering

Camera Self-Calibration from Tracking of Moving Persons

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Agenda

- Introduction
- System Overview
- Computation of Vanishing Points
 - Object Tracking and Head/Foot Localization
 - Vanishing Points Estimation
- Self-Calibration by Optimization
- Experimental Results
- Conclusion

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Introduction

- Geometry of camera model

$$[u, v, 1]^T \sim \mathbf{P} \cdot [X, Y, Z, 1]^T$$

$$\mathbf{P} = \mathbf{K} \cdot [\mathbf{R} | \mathbf{t}]$$

$$\mathbf{K} = \begin{bmatrix} f_x & s & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \quad \mathbf{t} = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix}$$

$$\mathbf{R} = \mathbf{R}_Z \mathbf{R}_X \mathbf{R}_Y$$

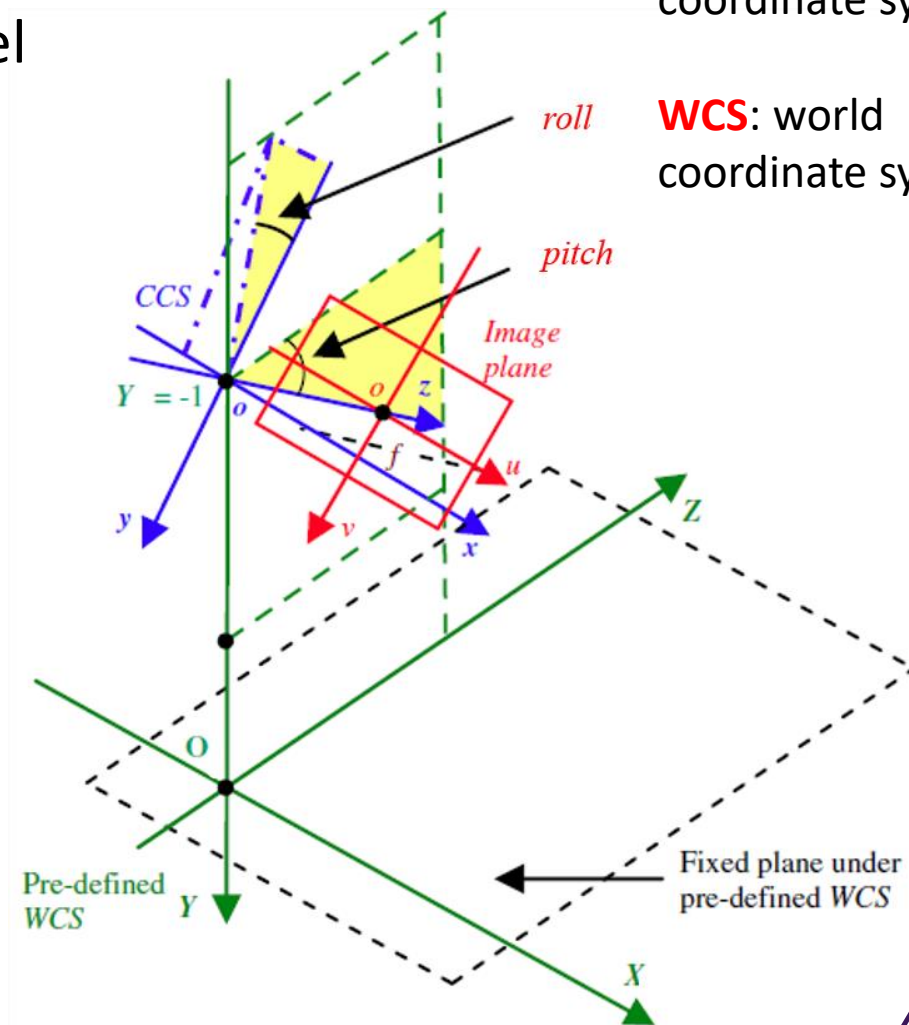
$$\mathbf{R}_Z = \begin{bmatrix} \cos(\text{roll}) & -\sin(\text{roll}) & 0 \\ \sin(\text{roll}) & \cos(\text{roll}) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{R}_X = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\text{pitch}) & -\sin(\text{pitch}) \\ 0 & \sin(\text{pitch}) & \cos(\text{pitch}) \end{bmatrix}$$

$$\mathbf{R}_Y = \begin{bmatrix} \cos(\text{yaw}) & 0 & -\sin(\text{yaw}) \\ 0 & 1 & 0 \\ \sin(\text{yaw}) & 0 & \cos(\text{yaw}) \end{bmatrix}$$

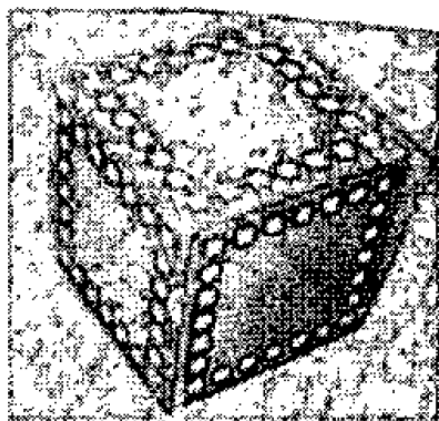
CCS: camera coordinate system

WCS: world coordinate system

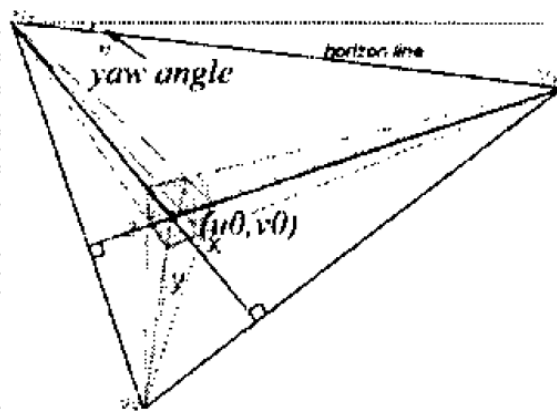


Introduction

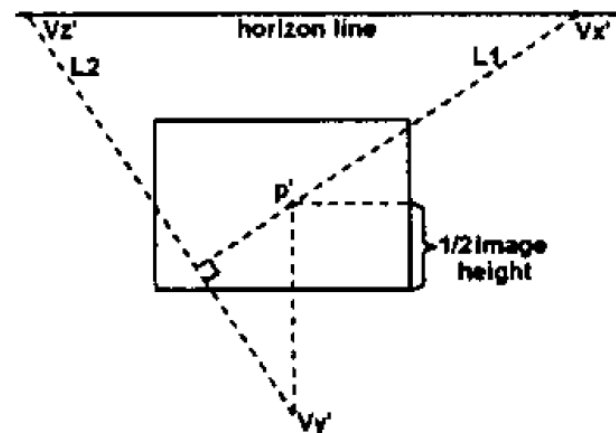
- Categories of camera calibration
 - Calibration using calibrated templates
 - Self-calibration/auto-calibration
 - Static scene structures
 - Object motion -> **Moving-person tracking**



(a)

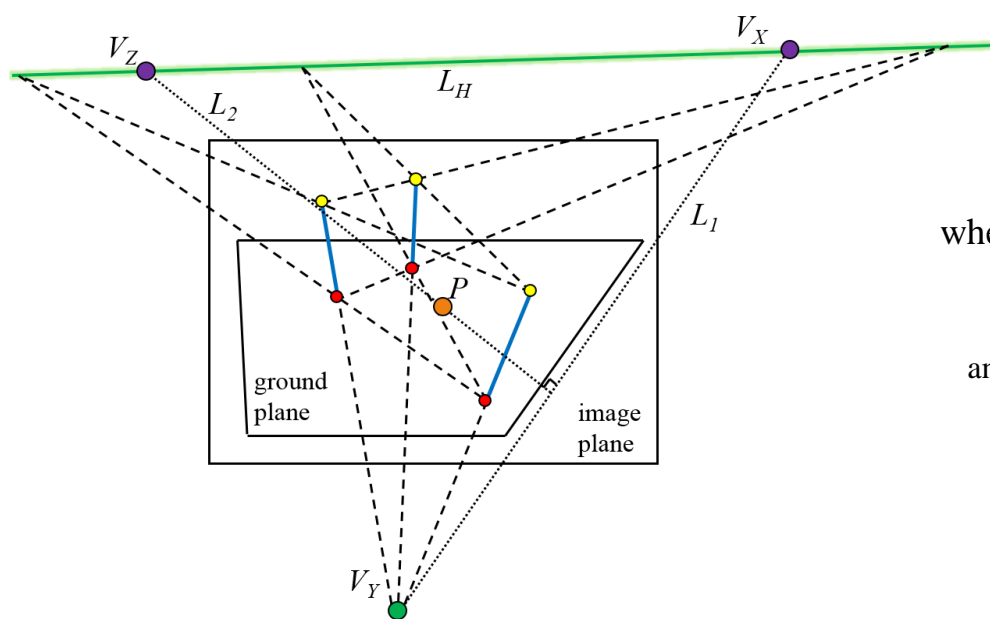


(b)



Introduction

- Self-calibration from tracking of moving persons [Lv *et al.*, 2002]



$$\text{roll} = \tan^{-1} \left(\frac{v_{V_Z} - v_{V_X}}{u_{V_X} - u_{V_Z}} \right)$$

$$f_x = f_y = \sqrt{-(v_{V_X}^{\text{rot}} \cdot v_{V_Z}^{\text{rot}} + u_{V_X}^{\text{rot}} \cdot u_{V_Z}^{\text{rot}})}$$

where $v_{V_X}^{\text{rot}} = \cos(\text{roll})(v_P - v_{V_X}) - \sin(\text{roll})(u_{V_X} - u_P)$,
 $v_{V_Z}^{\text{rot}} = \cos(\text{roll})(v_P - v_{V_Z}) - \sin(\text{roll})(u_{V_Z} - u_P)$,
 $u_{V_X}^{\text{rot}} = \cos(\text{roll})(u_{V_X} - u_P) + \sin(\text{roll})(v_P - v_{V_X})$,
 and $u_{V_Z}^{\text{rot}} = \cos(\text{roll})(u_{V_Z} - u_P) + \sin(\text{roll})(v_P - v_{V_Z})$,

$$\text{pitch} = \tan^{-1} \left(\frac{v_{V_X}^{\text{rot}}}{f_x} \right)$$

$$\text{yaw} = -\tan^{-1} \left(\frac{f_x}{\cos(\text{pitch}) \cdot u_{V_X}^{\text{rot}}} \right)$$

Original assumptions:

- (1) Central principal point
- (2) Unit aspect ratio
- (3) Zero skew

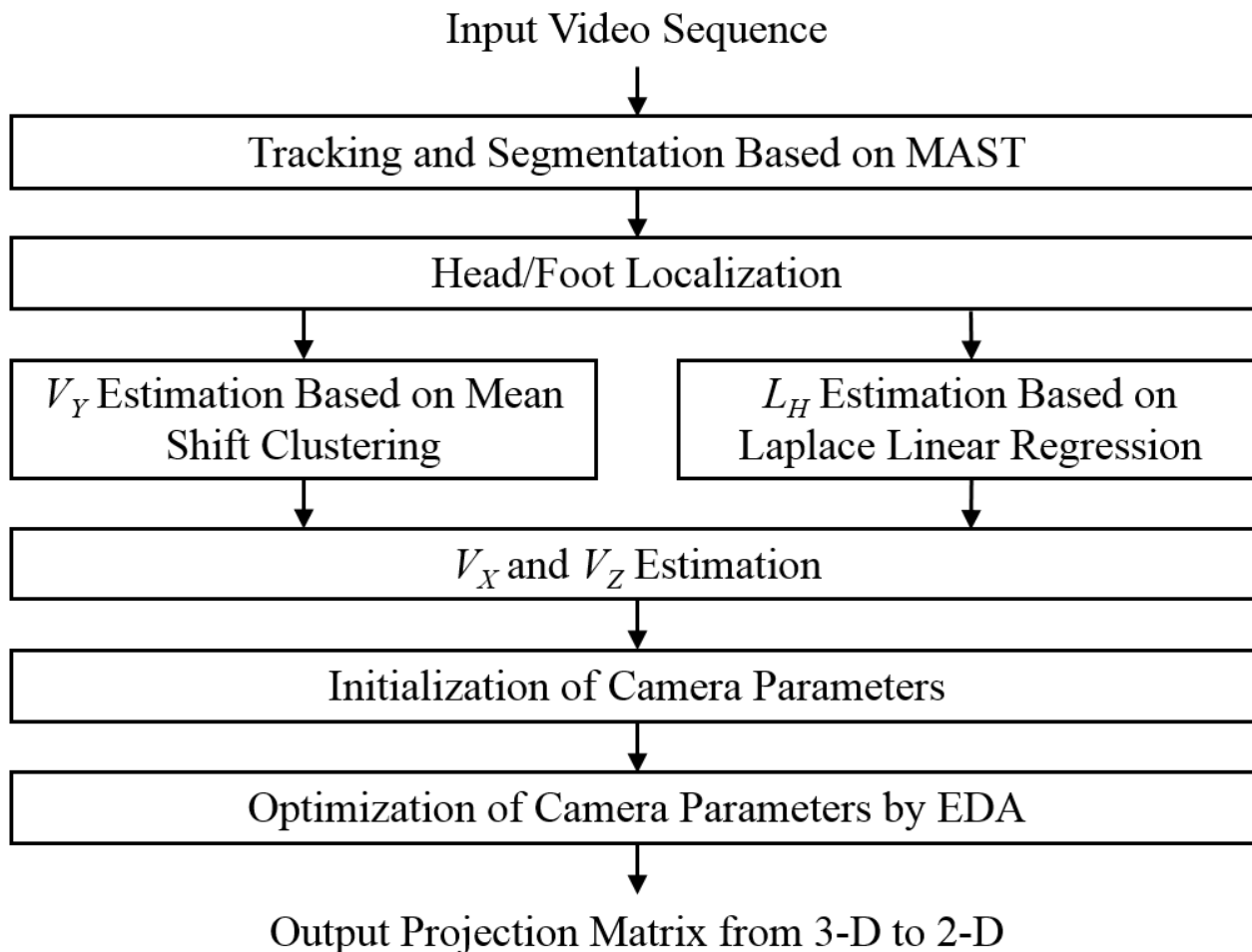
Challenges:

- (1) How to find the accurate V_Y and L_H ?
- (2) How can we optimize all camera parameters (relax original assumptions)?

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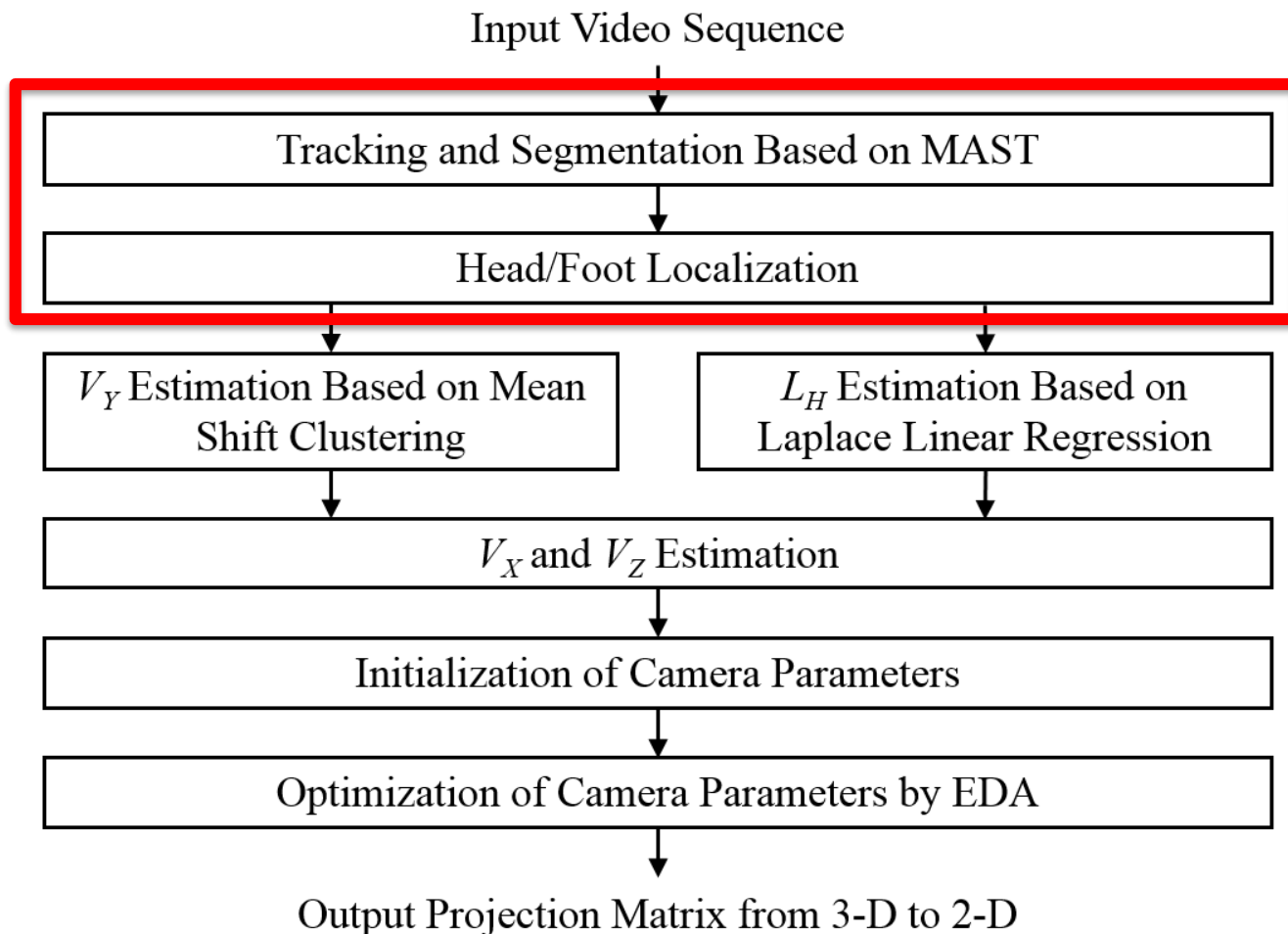
System Overview



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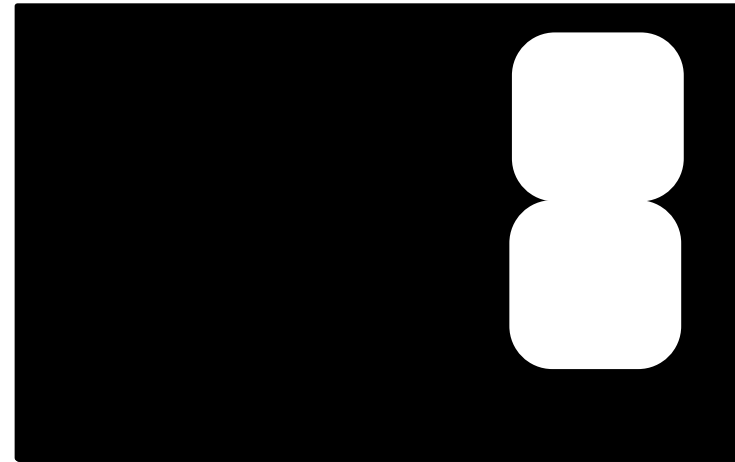
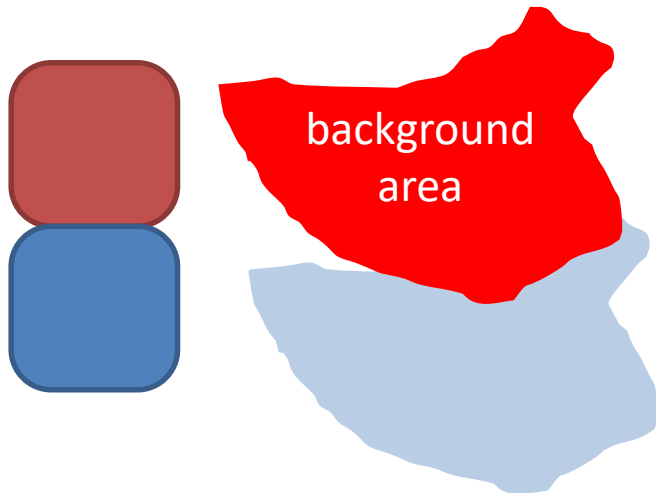


Object Tracking and Segmentation Based on MAST

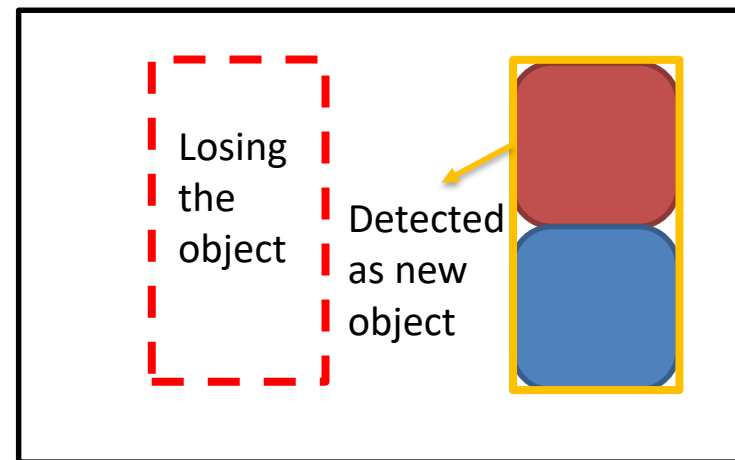
Multiple-kernel Adaptive Segmentation and Tracking

Segmentation result

- Object merging



Tracking result

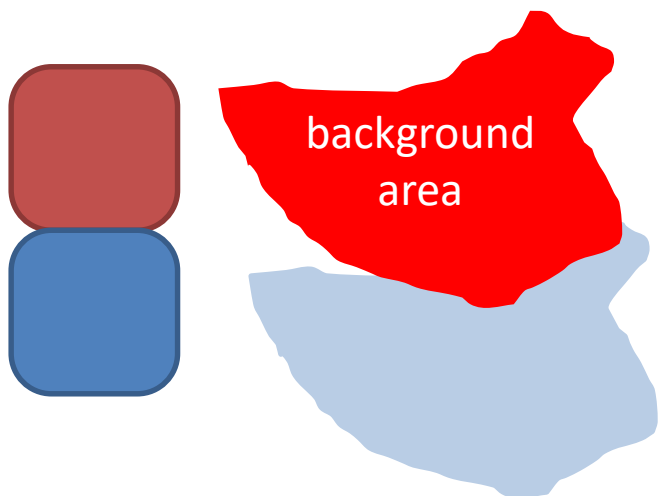


Object Tracking and Segmentation Based on MAST

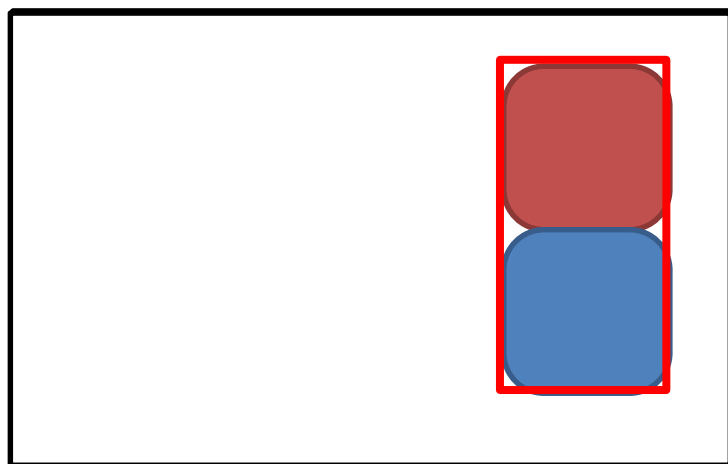
Multiple-kernel Adaptive Segmentation and Tracking

Segmentation result

- Motivation

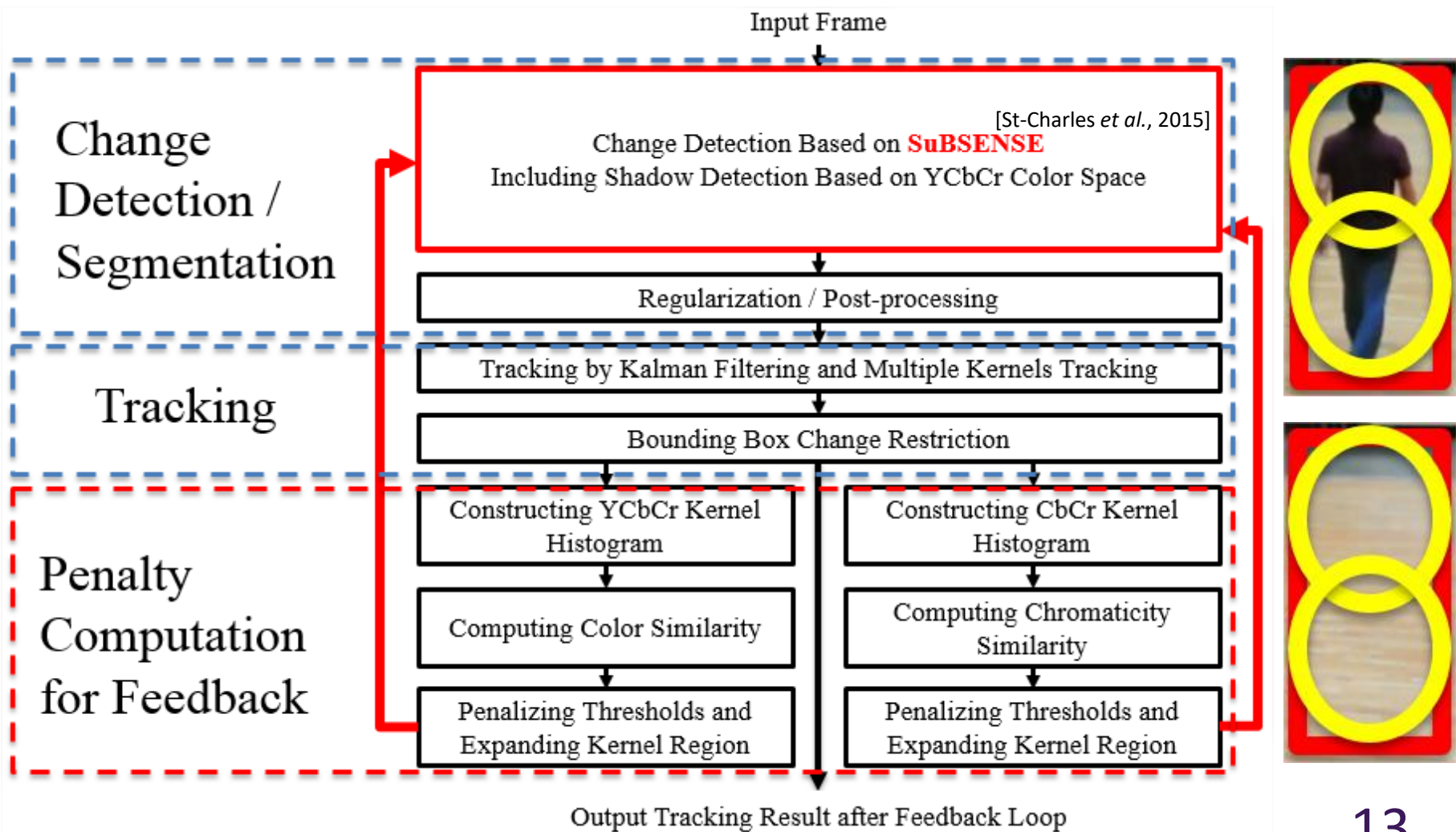


Tracking result

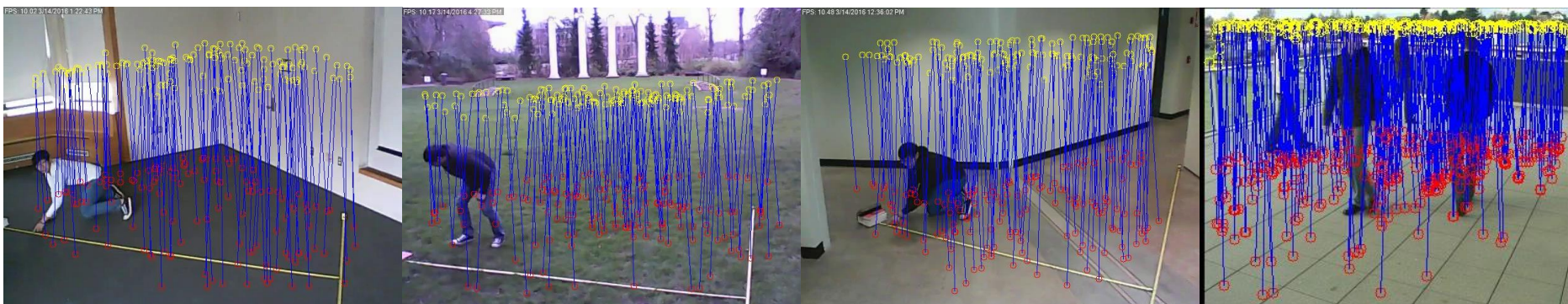


Object Tracking and Segmentation Based on MAST

Multiple-kernel Adaptive Segmentation and Tracking [Tang et al., 2016]



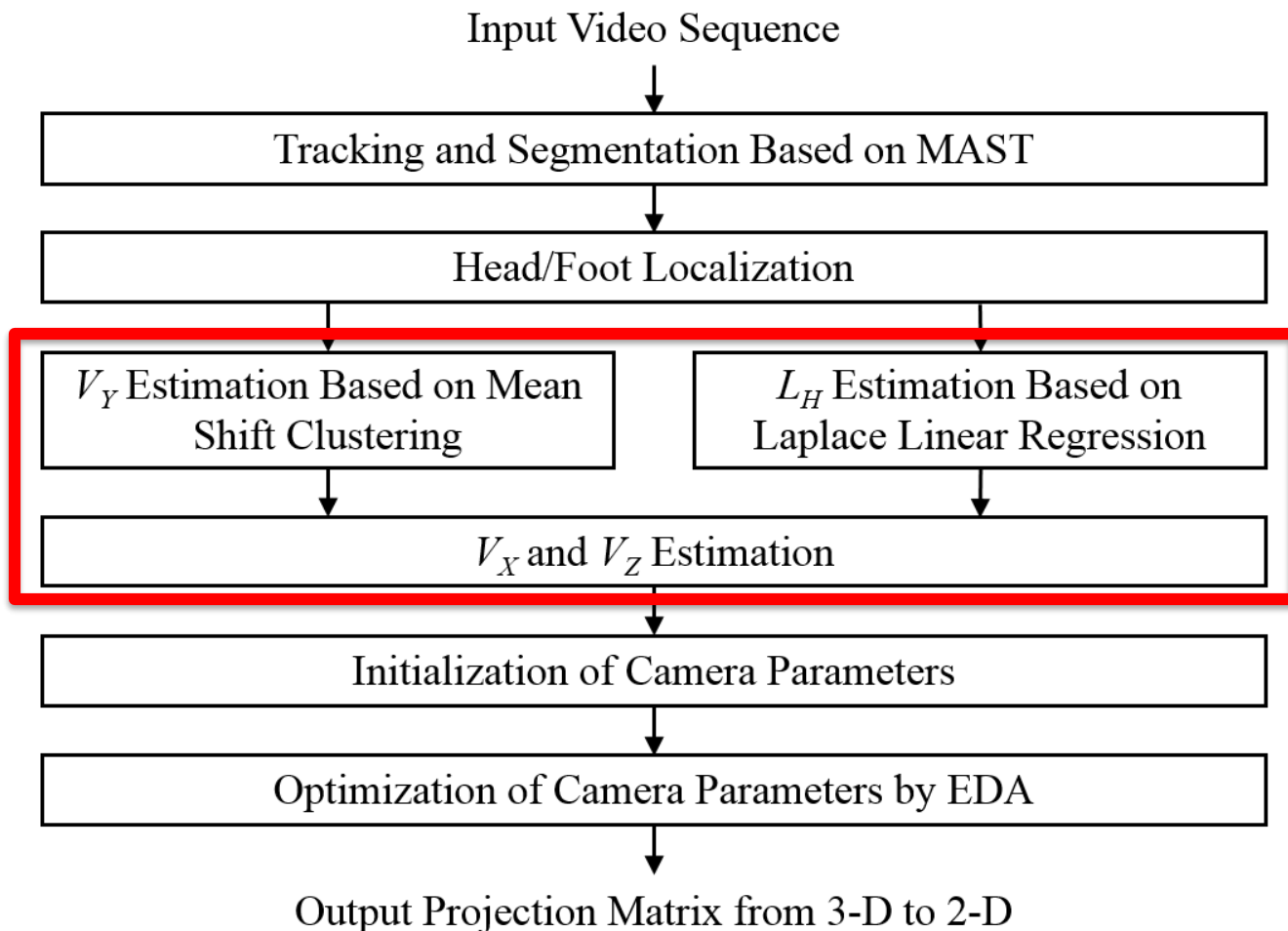
Head/Foot Localization



Agenda

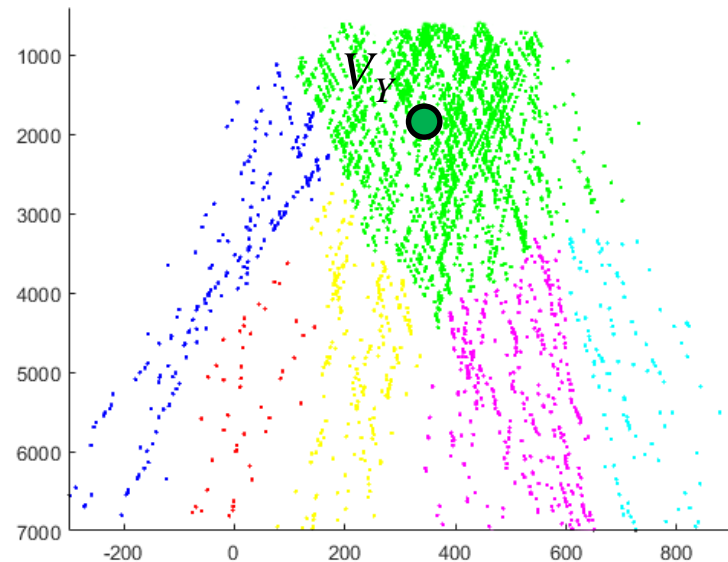
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System Overview



Vertical Vanishing Point (V_Y) Estimation Based on Mean Shift Clustering

- Disadvantage of RANSAC
 - Failure when the number of outliers is significantly large
- Proposed method
 - Mean shift clustering among all the candidate points of V_Y
 - Choosing the mean point of the largest cluster as the estimated V_Y



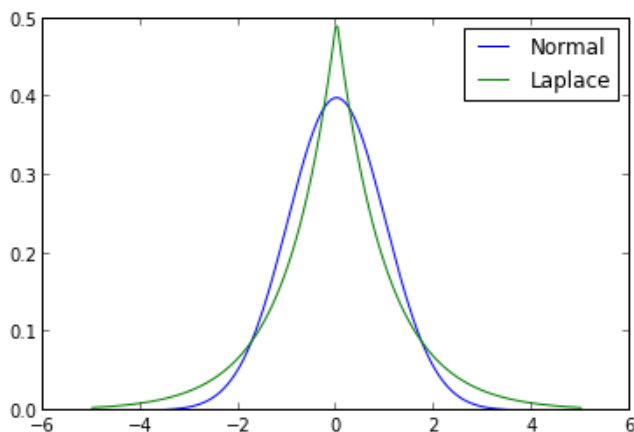
Horizon Line (L_H) Estimation Based on Laplace Linear Regression

- Disadvantage of RANSAC

- Setting of threshold parameter for inliers

- Proposed method

- Formulating as convex optimization by Laplace linear regression



$$p(\mathbf{y}|\mathbf{x}, \mathbf{w}) = \text{Laplace}(\mathbf{y}|\mathbf{w}^T \mathbf{x}) \propto \exp(-|\mathbf{y} - \mathbf{w}^T \mathbf{x}|)$$



$$\min_{\mathbf{w}, \mathbf{r}} \sum_i r_i = \min_{\mathbf{w}, \mathbf{r}^+, \mathbf{r}^-} \sum_i (r_i^+ + r_i^-)$$

$$\text{s.t. } r_i^+ \geq 0, r_i^- \geq 0, \mathbf{w}^T \mathbf{x}_i + r_i^+ - r_i^- = y_i$$



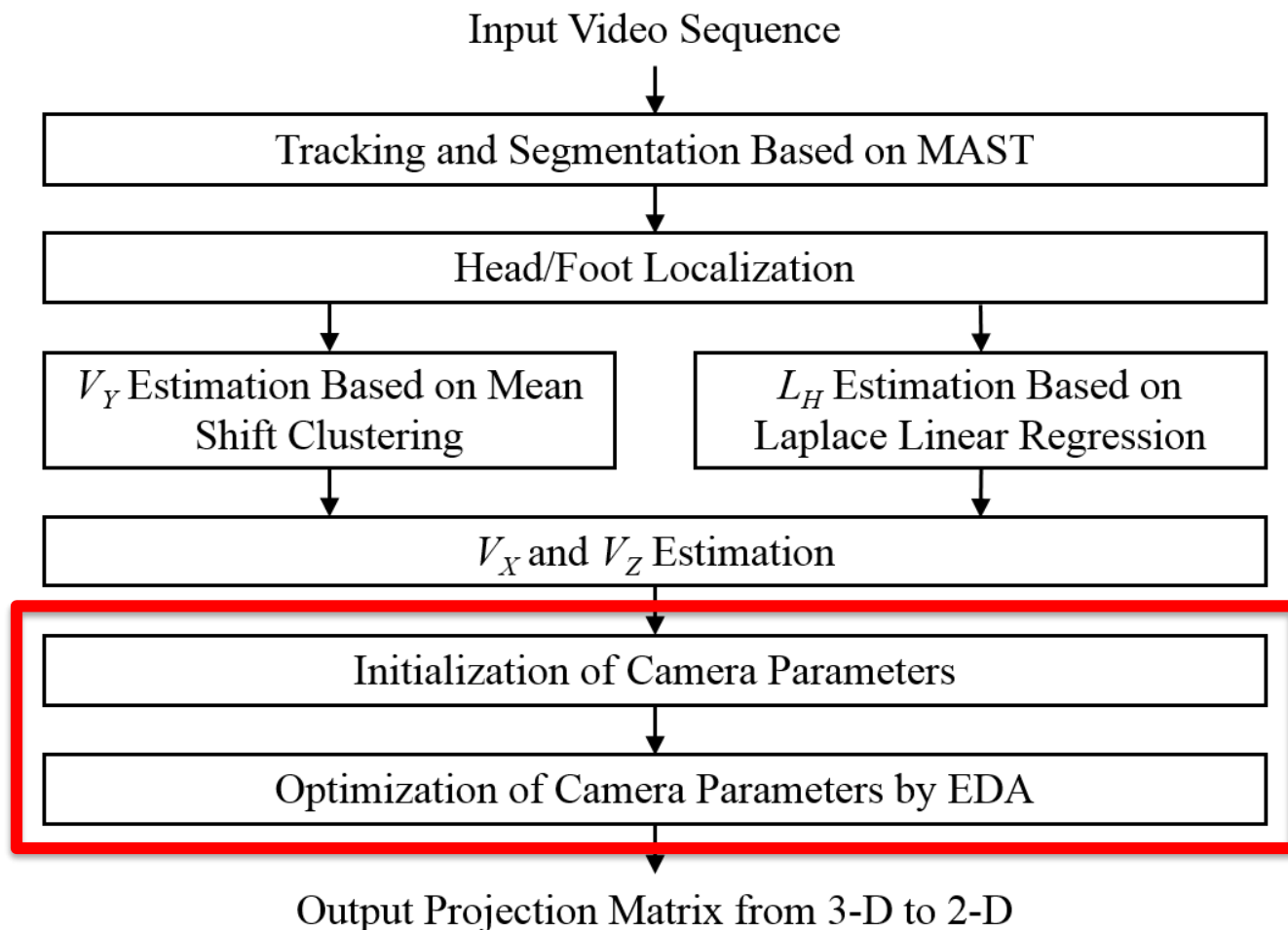
$$\min_{\boldsymbol{\theta}} \mathbf{f}^T \boldsymbol{\theta} \quad \text{s.t. } \mathbf{A}\boldsymbol{\theta} \leq \mathbf{b}, \mathbf{A}_{eq}\boldsymbol{\theta} = \mathbf{b}_{eq}, \mathbf{l} \leq \boldsymbol{\theta} \leq \mathbf{u}$$

in which $\boldsymbol{\theta} = (\mathbf{w}, \mathbf{r}^+, \mathbf{r}^-)$, $\mathbf{f} = [\mathbf{0}, \mathbf{1}, \mathbf{1}]$, $\mathbf{A} = []$, $\mathbf{b} = []$, $\mathbf{A}_{eq} = [\mathbf{x}, \mathbf{I}, -\mathbf{I}]$, $\mathbf{b}_{eq} = \mathbf{y}$, $\mathbf{l} = [-\infty \mathbf{1}, \mathbf{0}, \mathbf{0}]$ and $\mathbf{u} = []$.

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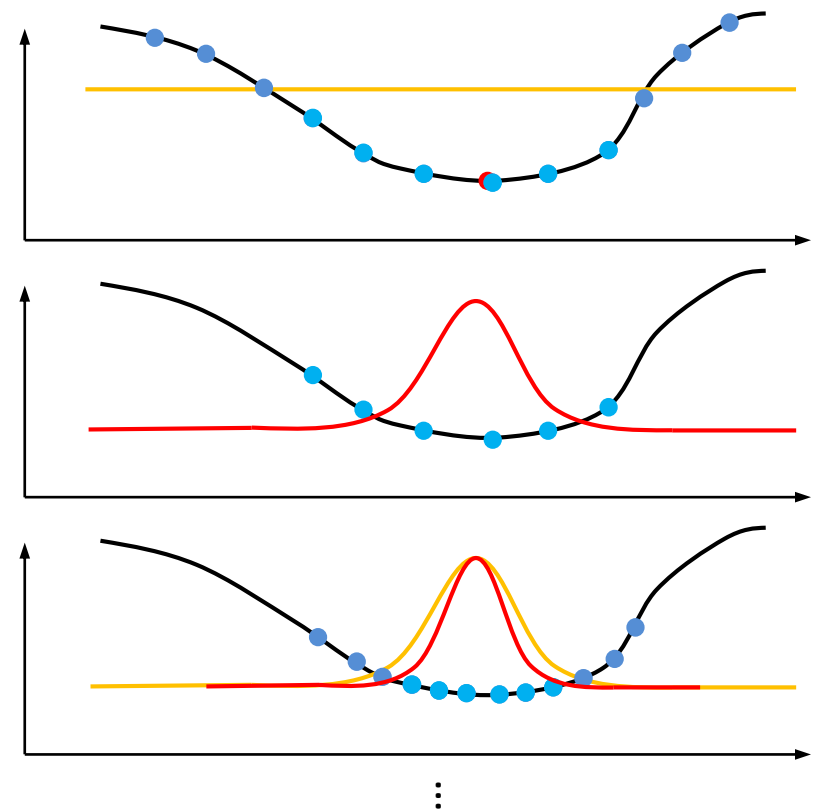


Estimation of Distribution Algorithm (EDA)

Consider $\arg \min_x f(x)$

1. Randomly generate R samples.
2. Calculate $f(x_i)$ of each sample, and sort the results.
3. Use the best N results to generate a *pdf* with normal distribution.
4. If stopping criterion is not met, use the *pdf* to generate new R samples, jump to 2.

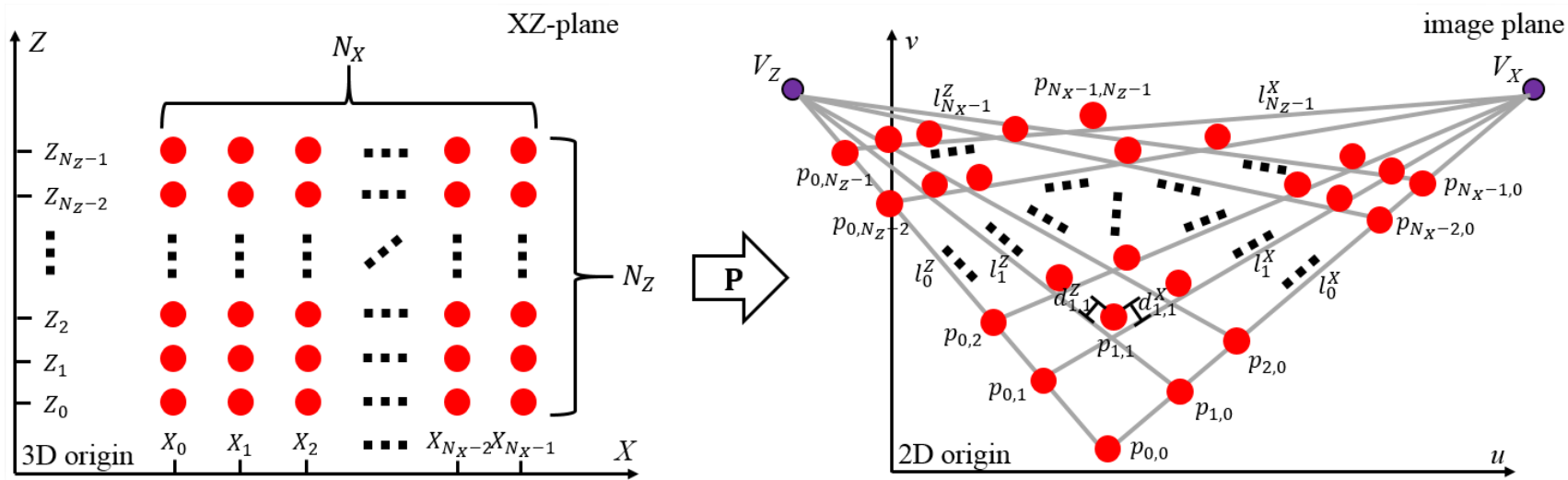
In this example, $R = 12, N = 6$



until stopping criterion is met

Optimization of Camera Parameters by EDA

Estimation of **Multivariate Normal Algorithm**—global [Larrauaga *et al.*, 2002]



- Extending from univariate EDA, for multivariate scenario (8 parameters)
 - Using **multivariate normal density function** as *pdf*
- Each **projection matrix** formed by a set of camera parameters is regarded as a sample.
- Using **reprojection error** on the ground plane as the evaluation
- Stopping criterion
 - Change of reprojection error between generations is small enough
 - Number of generations is too large

Advantages of the Proposed Formulation

- Optimizing all camera parameters simultaneously by EMNA_global
- Relaxing original assumptions on intrinsic camera parameters by allowing them to be optimized within given ranges
- Advantages of EDA [Hauschild *et al.*, 2011]
 - Ability to adapt their operators to the structure of the problem
 - Prior knowledge exploitation
 - Reduced memory requirements
 - Implementation of parallel computation

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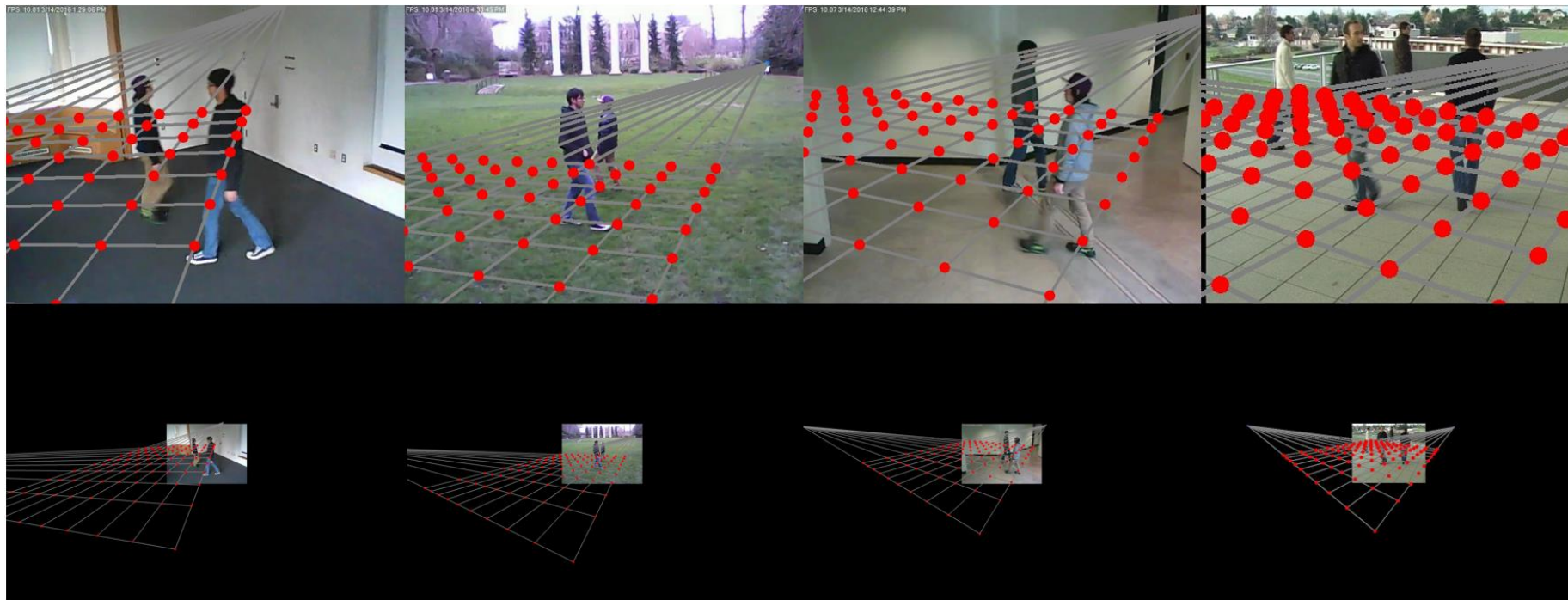
Experimental Results

- 3 captured video sequences
 - Length: ~ 1 min 30 sec
 - Resolution: 640 * 480
 - Frame rate: 10 fps
 - Ground truth: Extracted using linear method based on 52, 52, and 38 measured 3-D points
- 1 video sequence from EPFL dataset
 - Length: 3 min
 - Resolution: 360 * 288
 - Frame rate: 25 fps
 - Ground truth: Extracted using Tsai's method

Experimental Results

Seq. #	f_x (pix.)	f_y (pix.)	c_x (pix.)	c_y (pix.)	roll (deg.)	pitch (deg.)	yaw (deg.)	μ_{err} (pix.)
1. Ground Truth	731.3880	728.2518	322.1298	237.2676	-3.1371	16.2676	-78.3065	N/A
1. Method in [6]	611.5239	611.5239	320.0000	240.0000	5.7439	22.4758	-64.9974	11.7954
1. Method in [10]	638.2676	638.2676	320.0000	240.0000	3.8800	23.2010	-71.8167	8.7750
1. Proposed w/o EDA	738.7650	738.7650	320.0000	240.0000	5.0689	17.6076	-79.0154	6.0133
1. Proposed	730.9167	735.9371	322.9955	236.1948	-5.0345	17.4224	-79.1491	2.50E-5
2. Ground Truth	731.3880	728.2518	322.1298	237.2676	-1.8887	11.0081	-68.7126	N/A
2. Method in [6]	618.7858	618.7858	320.0000	240.0000	2.3671	8.7161	-71.5302	4.9334
2. Method in [10]	647.4640	647.4640	320.0000	240.0000	1.8874	9.8994	-71.7033	5.0624
2. Proposed w/o EDA	679.6617	679.6617	320.0000	240.0000	1.7928	10.7818	-70.3027	4.6445
2. Proposed	727.6335	728.1606	321.4372	241.1506	-2.2546	10.3345	-70.3032	3.12E-5
3. Ground Truth	731.3880	728.2518	322.1298	237.2676	-0.3459	18.3846	-63.8778	N/A
3. Method in [6]	606.8088	606.8088	320.0000	240.0000	-0.8635	13.2525	-67.1697	2.1670
3. Method in [10]	662.9474	662.9474	320.0000	240.0000	-0.2164	22.4663	-57.6830	0.5403
3. Proposed w/o EDA	719.8882	719.8882	320.0000	240.0000	0.2693	17.4219	-64.7125	0.3398
3. Proposed	720.6649	729.5090	319.8556	240.6065	-0.2658	17.2493	-64.7081	1.17E-4
4. Ground Truth	437.2689	437.8792	173.7693	142.7878	1.5466	14.1153	-54.5257	N/A
4. Method in [6]	406.8041	406.8041	180.0000	144.0000	-0.2633	22.4482	-63.5813	0.5051
4. Method in [10]	432.0973	432.0973	180.0000	144.0000	-0.2062	20.8494	-45.6322	0.4321
4. Proposed w/o EDA	440.5366	440.5366	180.0000	144.0000	-0.4297	16.2182	-55.8775	0.1858
4. Proposed	442.4795	440.9664	176.2516	142.1498	0.4313	15.9846	-55.6434	2.74E-5

Experimental Results



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Conclusion

- We proposed a robust single camera self-calibration method based on moving persons tracking.
- **Contribution (1)**: Combining the state-of-the-art change detection (**SuBSENSE**) and tracking (**MAST**) to generate accurate head/foot localization
- **Contribution (2)**: Introducing **mean shift clustering** and **Laplace linear regression** to the estimation of vanishing points
- **Contribution (3)**: formulating the problem of camera parameters optimization by **EDA** that can relax the assumptions on unknown intrinsic parameters.

Thank you!

Q&A