COLLISION AVOIDANCE OF MOVING OBSTACLES USING LIDAR SENSORS FOR AUTONOMOUS VEHICLES

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- The System Architecture
- Detection and Tracking of Moving Object
- Classification of Moving Object
- Path Planning
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INTRODUCTION

https://www.youtube.com/watch?v=Uqt_pRbR8rI

INTRODUCTION

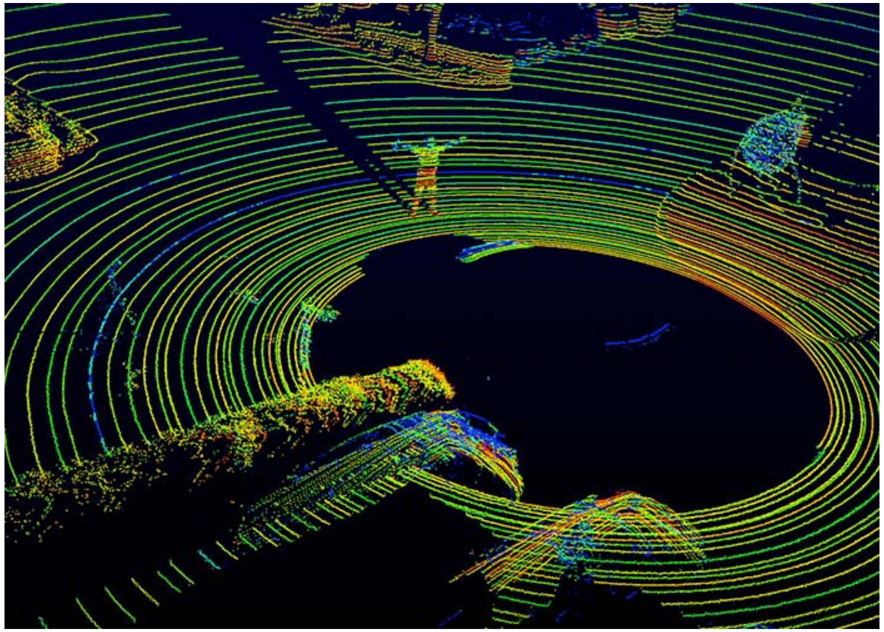
- Knowledge of the environment and obstacles
- Sensor Data : Radar, Lidar, and Camera (Monocular and Stereo) [8]

Sensing Modality	Perceived Energy	Raw Measurement	Moving Object Recognition
Radar	Millimeter-wave radio signal (emitted)	Distance (Meters)	motion characteristics
Lidar	600 and 1000 nm laser signal (emitted)	Distance (Meters)	Spatial and motion characteristics
Camera	Visible light (environment)	Light intensity(Pixels)	Appearance and motion characteristics

- Detection, tracking, and classification of moving objects
- Path planning (Based on higher path planning)

LIDAR SENSOR DATA

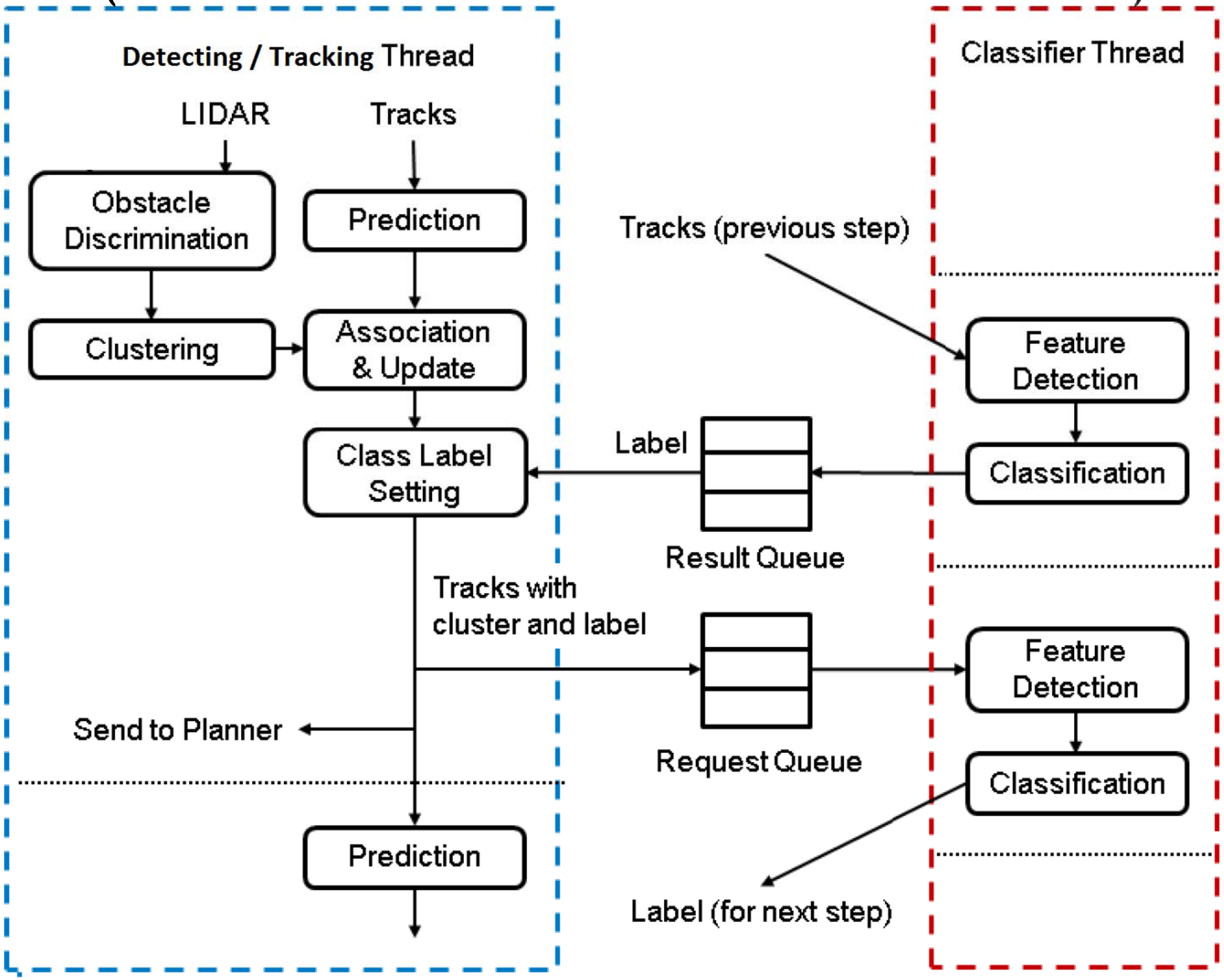
- Measures distance to a target by illuminating that target with a laser light
- 3D data of surrounding areas
  - 2D picture with the value of each pixel is the distance to a target
  - Scan: one round of Lidar sensor data



- Velodyne HDL-64E S3 [1]
  - Range >=120m
  - Horizontal FOV: 360°
  - Vertical FOV: +2.0° to −24.9°
  - 5 Hz – 20 Hz rotation rate

[1]

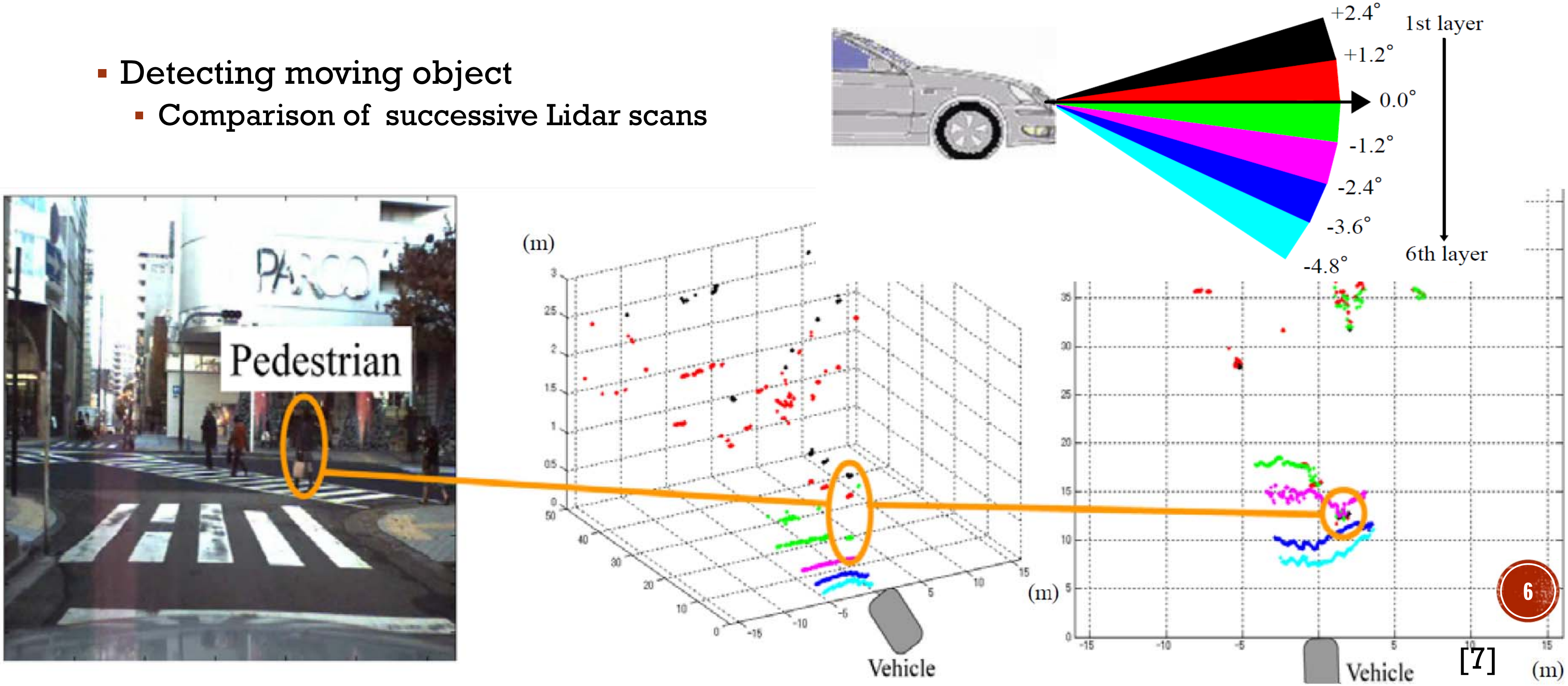
THE SYSTEM ARCHITECTURE
(DETECTION/TRACKING/CLASSIFICATION MODULES)



[4]

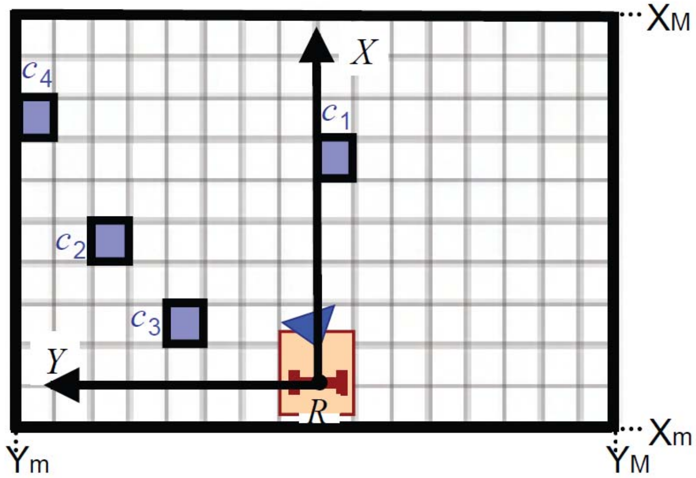
DETECTING OF MOVING OBJECT

- Detecting moving object
  - Comparison of successive Lidar scans



THE OCCUPANCY GRID METHOD

- Create 2D grid map:



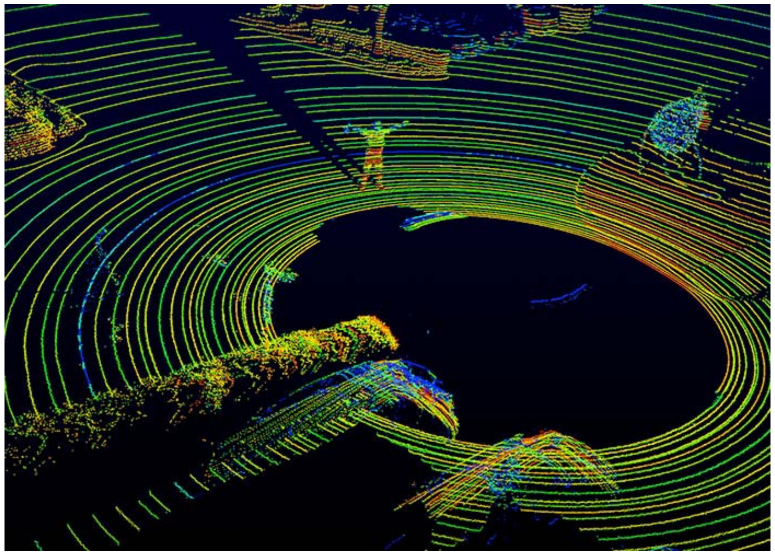
[2]

- Motion compensation for the ego-vehicle motion
- Determine moving grid cells
  - Counting successive occupied time
  - For example: if K <= 7, the cell is the moving cell

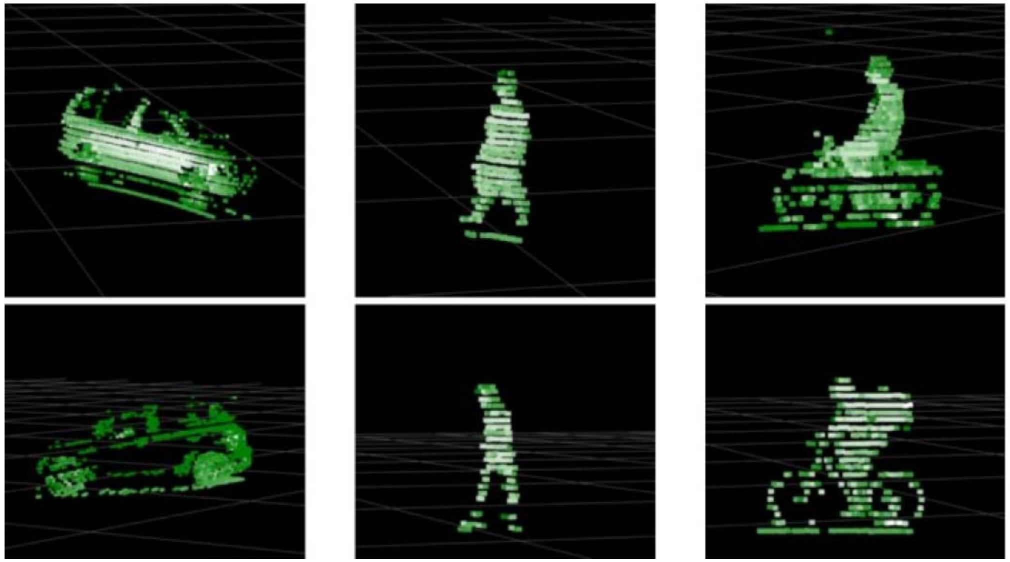
[7]

CLUSTERING

- **Moving Lidar scan point:** measurement points in moving cells
- **Static Lidar scan point:** measurement point in the static cells
- **Clustering**: group measurement points belong to the same object
- Using depth information



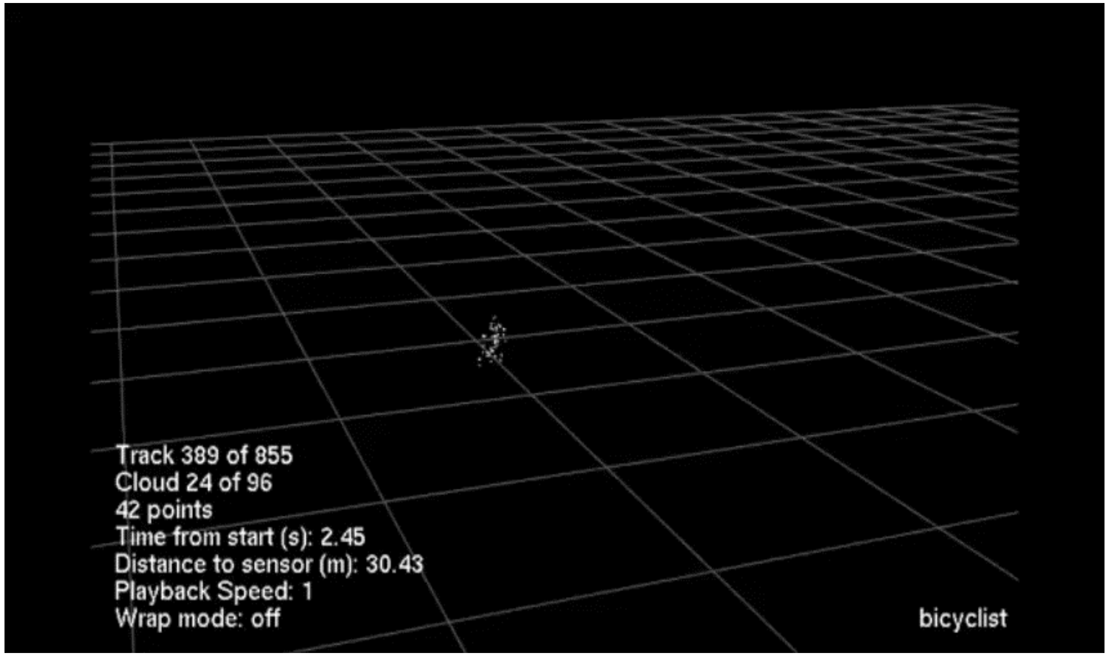
[1]



[9]

TRACKING OF MOVING OBJECT

- Results of clustering are considered moving objects
- Tracking moving objects using following step: [3]
  - Step 1: the centroid coordinates $Z(t)$ is derived for each object
  - Step 2: the current and previous object centroids are pairwise matched according to their distance and previous Kalman filter prediction
  - Step 3: for matched objects, a Kalman filter is used for tracking
  - Step 4: for unmatched objects, creating a new tracking

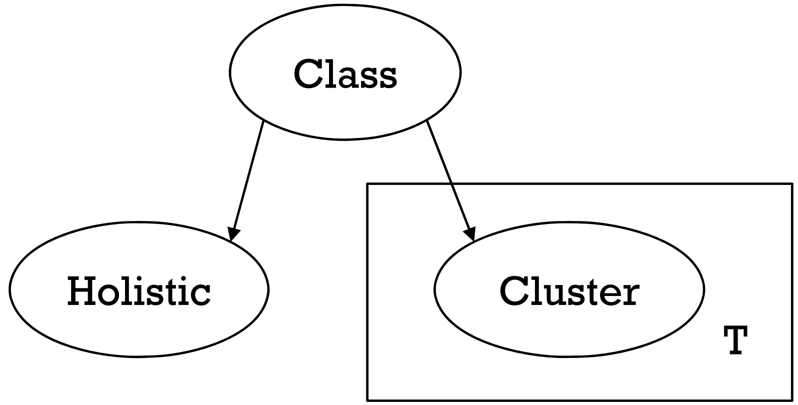


http://cs.stanford.edu/people/teichman/stc/

CLASSIFICATION OF MOVING OBJECT

- Cluster: result from clustering
- Track: result of tracking
- Holistic: statistics of a track

- Goal: determine the class label of each track.
- Using the Augmented Discrete Bayes Filter [3]
  - Based on naïve Bayes assumption
  - Compensations for conditional independence



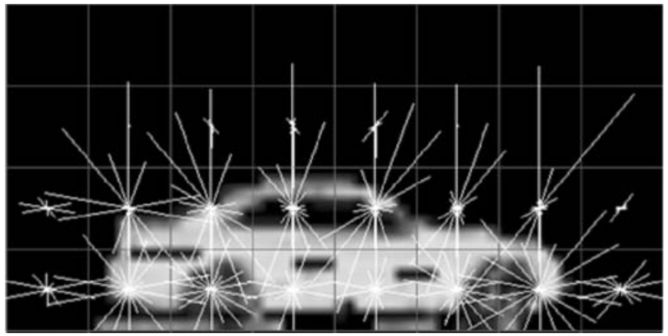
[3]

FEATURE EXAMPLES

- Cluster feature examples
  - Spin Images

[4]

HOG (Histogram of Oriented Gradients) Features

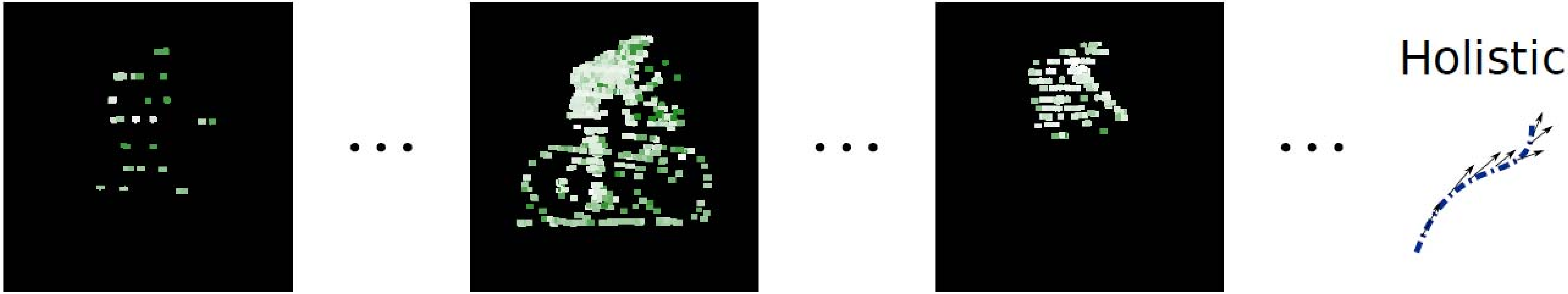


[4]

- Holistic feature examples
  - 1) maximum velocity, 2) average velocity, 3) maximum acceleration, and 4) average acceleration

[4]

CLASSIFICATION OF MOVING OBJECT



$$\begin{bmatrix} car \\ ped \\ bike \end{bmatrix} \begin{bmatrix} -11.60 \\ 0.36 \\ 1.27 \end{bmatrix} \cdots \begin{bmatrix} -20.31 \\ -6.42 \\ 4.01 \end{bmatrix} \cdots \begin{bmatrix} -5.28 \\ -3.67 \\ -0.28 \end{bmatrix} \cdots \begin{bmatrix} -0.06 \\ -6.23 \\ 1.29 \end{bmatrix}$$

$$[-30.98 \quad -14.68 \quad 11.42]$$

[3]

PATH PLANNING

- Using the occupancy grid
- Based on the output of tracking and classification

$$\hat{x}(t) = \left[\hat{X}(t), \hat{Y}(t), \hat{\dot{X}}(t), \hat{\dot{Y}}(t)\right]^T$$

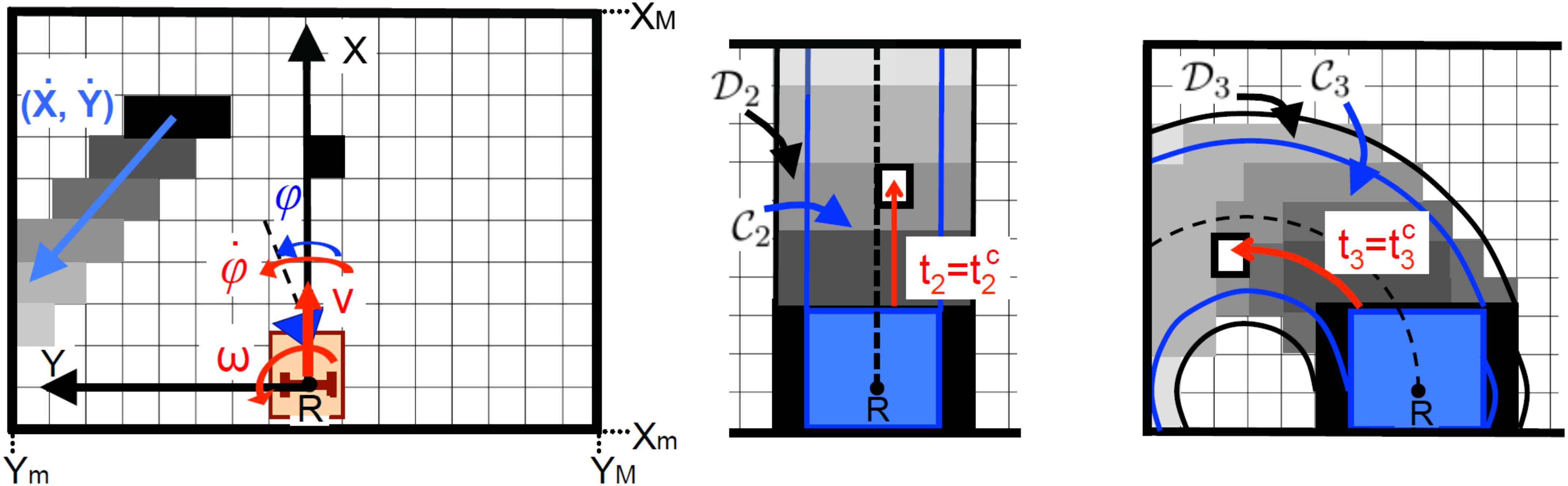
The object centroid coordinates and of its velocities

- The goal is to:
  - Generating a collision-free trajectory to the goal
  - Decelerating to prevent collision when bypassing is impossible

- Using tentacles to reduce computational complexity
  - Tentacles: a set of drivable paths
  - Constrained by the robot kinematics

[3]

PATH PLANNING



Tentacles (dashed black), with for D_i dangerous areas and C_i for collision areas of tentacles i.

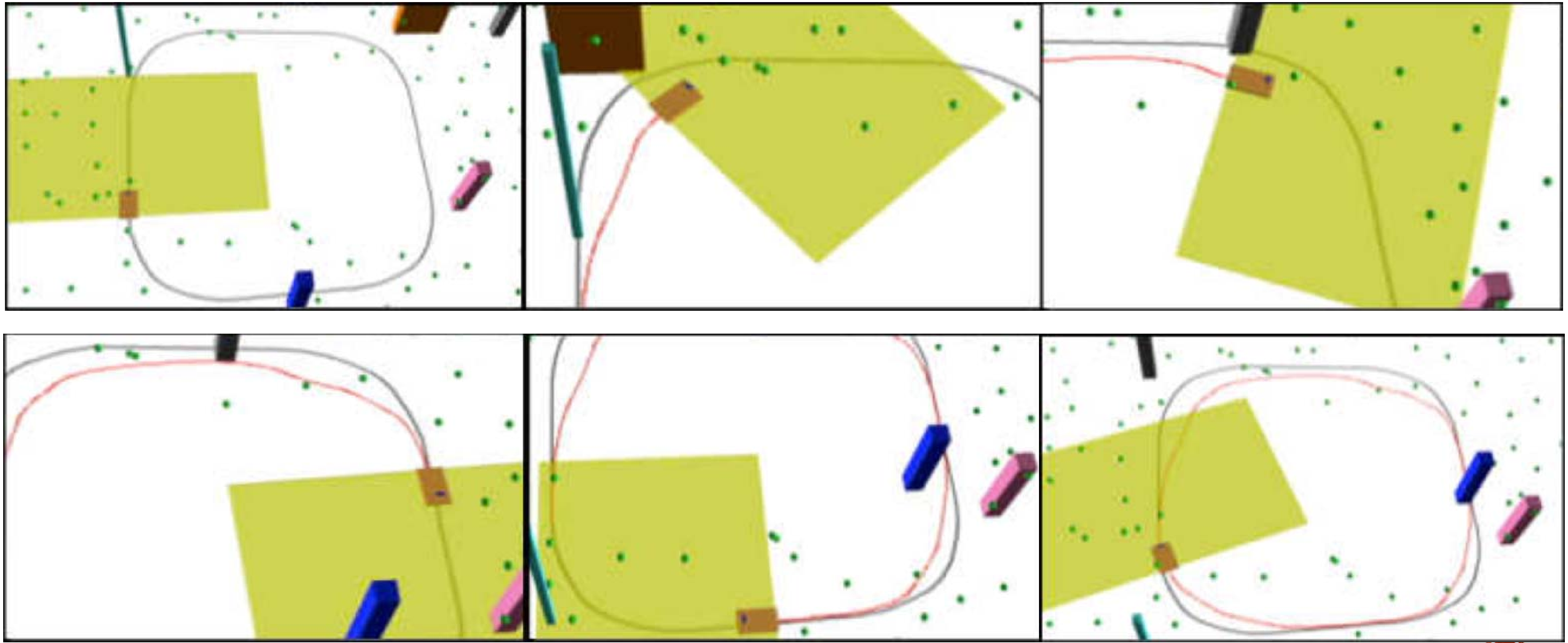
[3]

PATH PLANNING

- Calculate obstacle occupation times
  - for each cell: t_{i0} and t_{if}
  - within a range
- Calculate robot occupation times
  - each grid cell in tentacles: t_{ij}
- Check dangerous instants and collision instants
  - $t_j = inf_{c_i \in D_i}\{t_{ij}: t_{i0} \leq t_{ij} \leq t_{if}\}$
  - $t_j^c = inf_{c_i \in C_i}\{t_{ij}: t_{i0} \leq t_{ij} \leq t_{if}\}$
  - generate a tentacle risk: H_j
- Calculate controls
  - For example translational velocity v
  - $v = (1 - H)v_s + Hv_u$

[3]

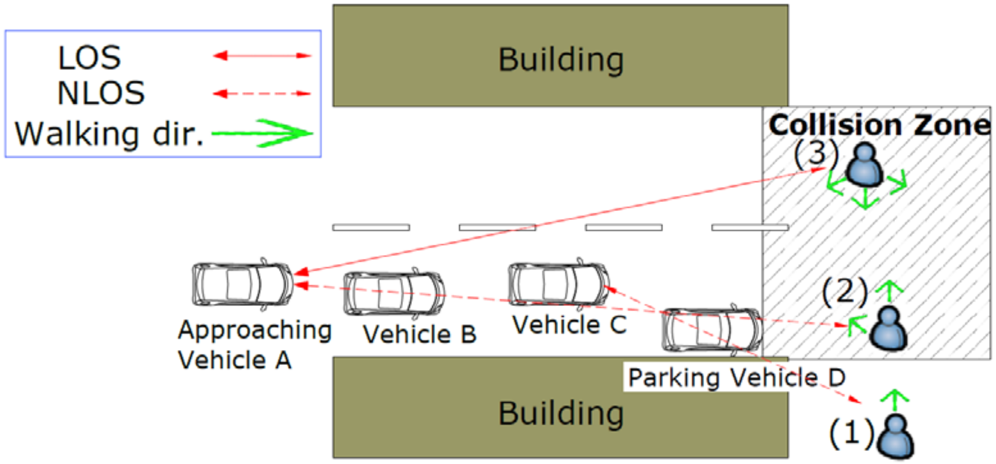
PATH PLANNING



[3]

CONCLUSION

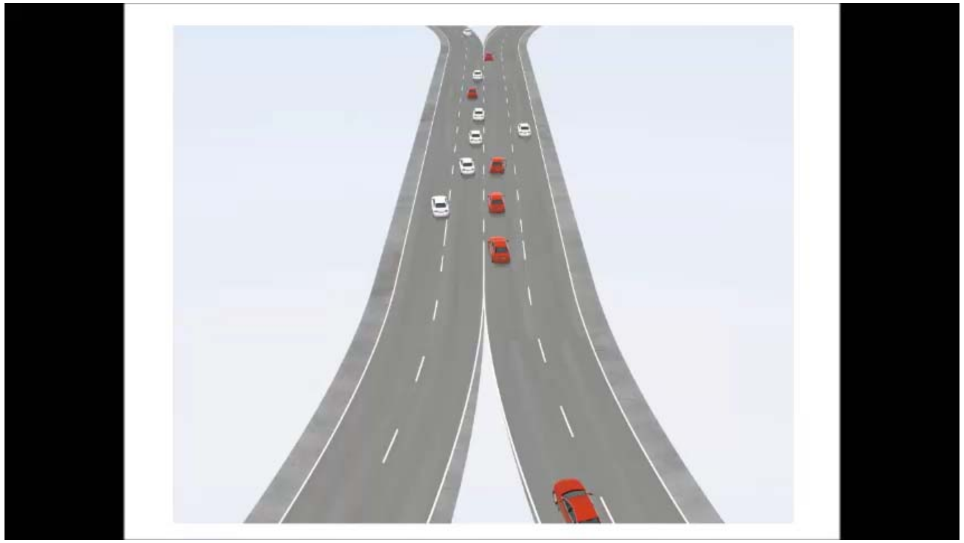
- The preceding method works well under most case [6][10]
- There still exist some problems to solve:
  - Line-Of-Sight (LOS) moving objects [5]



[5]

CONCLUSION

- Path planning under circumstances need negotiation between vehicles [11]
  - For example two way merge



[11]

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