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ANALYSIS AND MINING OF BIG NATURALISTIC DRIVING VIDEO

自然驾驶录像的数据分析和挖掘

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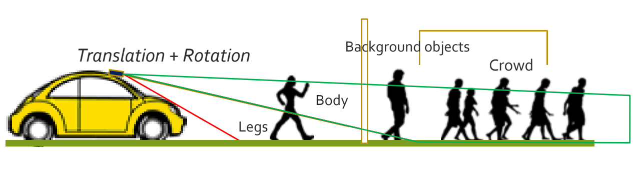
车	路	(驾车）人
轨迹，安全距离，周围交通.....	车道，路面，行人......	驾驶行为，分心，疲倦......

VEHICLE BORNE CAMERA RECORDING FRONT VIDEO

前向车载录像机记录整个行程

Toward autonomous driving



OVERVIEW　概要

- Naturalistic Driving Video
  - Infrastructure for recording, documenting, storing and retrieval of driving videos
- Vehicle Interaction with vehicles, pedestrians, and bicyclists
  - Computing TTC of vehicles to alarm potential collision
  - Detection of pedestrians and bicyclists in driving video – using motion and shape information
- Road Environment Sensing and Recording
  - Road profile to compact video to image for road assessment
  - Detection of road edge, road surface mark, etc.
  - Minding data of road edges under different weather and illuminations
- Traffic counting by moving cameras

视觉

形状，色彩，运动，事件

速度

加速度

TABLE I: MAJOR PROJECTS OF NATURALISTIC DRIVING STUDY IN THE WORLD

Project name	Conductor	Period	Mileage [mile]	Vehicle	Sensor	Drivers	Research topic
100 Car Naturalistic Driving Study [6]	Virginia Tech.	2001–2009	2×10^6	100 sedans	camera	109 primary drivers, 132 secondary drivers	Rear end collision
Automotive Collision Avoidance System [13]	University of Michigan	2004-2005	1.37×10^5	11 sedans	camera, radar	96 drivers	Forward collision warning (FCW)
Road Departure Crash Warning [14]	University of Michigan	2005–2006	8.3×10^4	11 sedans	camera, radar	11 drivers	Lane departure warning (LDW)
Sweden-Michigan Naturalistic Field Operational Test (SeMiFOT) [15]	University of Michigan	2008–2009	1.07×10^5	10 sedans, 4 trucks	camera, radar	39 drivers	FCW, LDW, blind spot information system, electronic stability control, and impairment warning
Integrated Vehicle-Based Safety Systems [16]	University of Michigan	2010–2011	sedans: 213&309; trucks: 601&944	16 sedans 10 heavy trucks	camera, radar	108 drivers for sedans; 18 professional truck drivers	Integrated warning
Safety Pilot Model Deployment [17]	University of Michigan	2012–2014	more than 3.4×10^7	2,800 various types of vehicles	camera, radar	2,700 volunteer drivers and several professional bus and truck drivers	Connected vehicle
Google driverless car [18]	Google	2012–present	more than 1.3×10^6	At least 50 sedans and SUVs	lidar, camera, radar	Google technicians and volunteers	Fully self-driven vehicle
Australian Naturalistic Driving Study or Australian 400-car Naturalistic Driving Study [19], [20]	Led by University of New South Wales	2015–present	4 months	400 vehicles	camera, CAN data, GPS	360 participants (180 in New South Wales and 180 in Victoria)	Safety at intersections; Speed choice; Interactions with vulnerable road users; Fatigue; Distraction and inattention; Crashes and near-crashes; Interactions with ITS
European naturalistic Driving and Riding for Infrastructure & Vehicle safety and Environ-ment(UDRIVE) [21]	the 7th EU Framework Programme and 20 partners	2012–2017	On going	200 vehicles (cars, trucks, and scooters)	cameras, IMU sensors, GPS, Mobil Eye smart camera, CAN data, and Sound level	On going	Crash causation and risk; Everyday driving; Distraction and inattention; Vulnerable road users; Eco-driving
China Naturalistic Driving Study	Tongji University; VTTI; General Motors	2012–2015	more than 1.0×10^5	5 vehicles	–	90 drivers; each drove vehicle for 2 months	Exploring Chinese moped-vehicle conflict configurations; Examining car driver responses to moped-vehicle conflicts
Japan Naturalistic Driving Study [22]	Ministry of Land, Infras-tructure, Transport and Tourism	2006–2008	–	60 vehicles (35 wagons & 25 sedans)	GPS, CAN data, acceleration sensor, camera	60 drivers (58 males & 2 females)	Accident causation research

NATURALISTIC DRIVING VIDEO COLLECTION

TASI110 NDV collected over a year

- North US region in 2012
- Different roads including urban, rural, local, and highway
- Road surfaces are asphalt mostly and are concrete occasionally
- Roadside ranges from grass, trees, dirt, concrete curb, barriers, etc.
- Cover four seasons such that roadside materials change color

All weather and illumination conditions

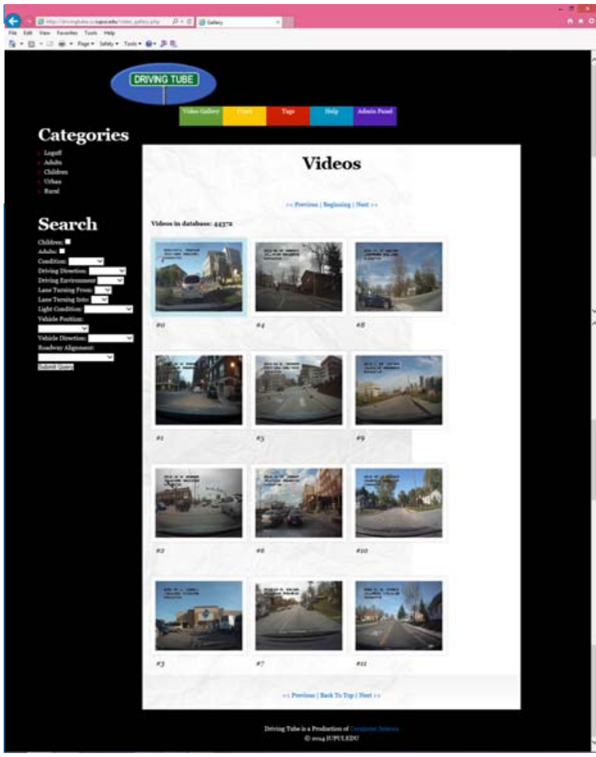
- Various weathers (illumination type and reflectance changes)
- All time under different illumination (directions and strength)

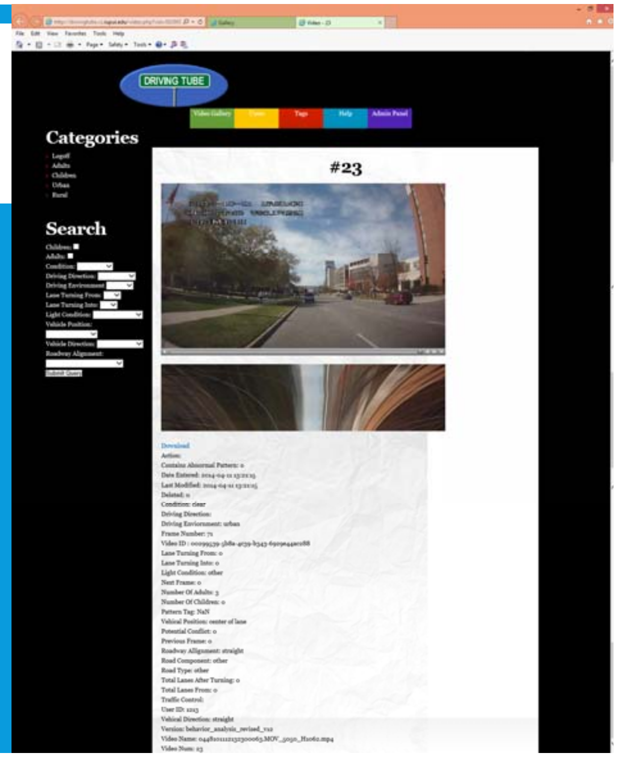
Data size for mining

- Five-minute driving has 9000 HD video frames
- 35TB video clips of five minutes

ONLINE DRIVING VIDEO DATABASE

- Video clips are sampled and put online in a database like Youtube
- Video clips are tagged with many attributes for query by keywords
- Video search and retrieval by attributes
- Browsing video and visualizing properties


DRIVING TUBE
Categories
Search
Videos


DRIVING TUBE
Categories
Search
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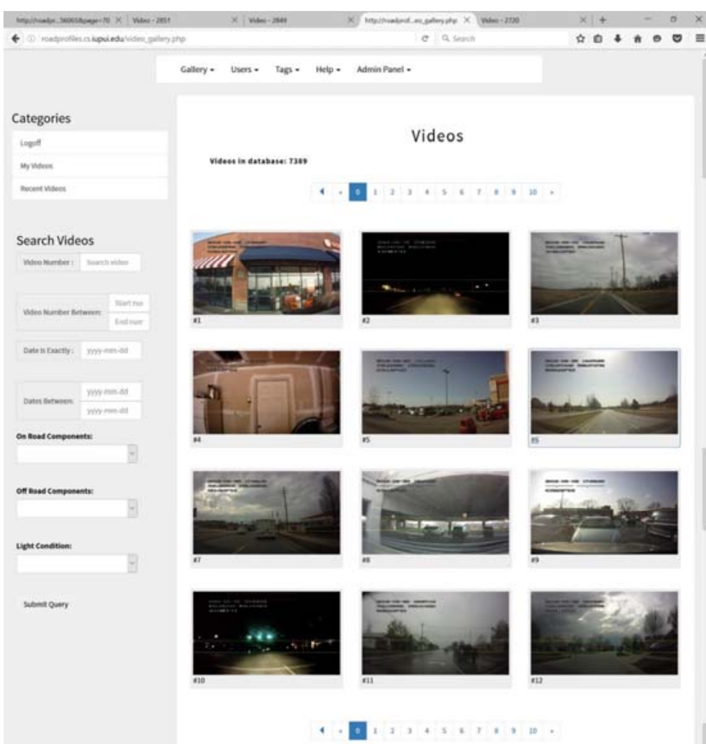
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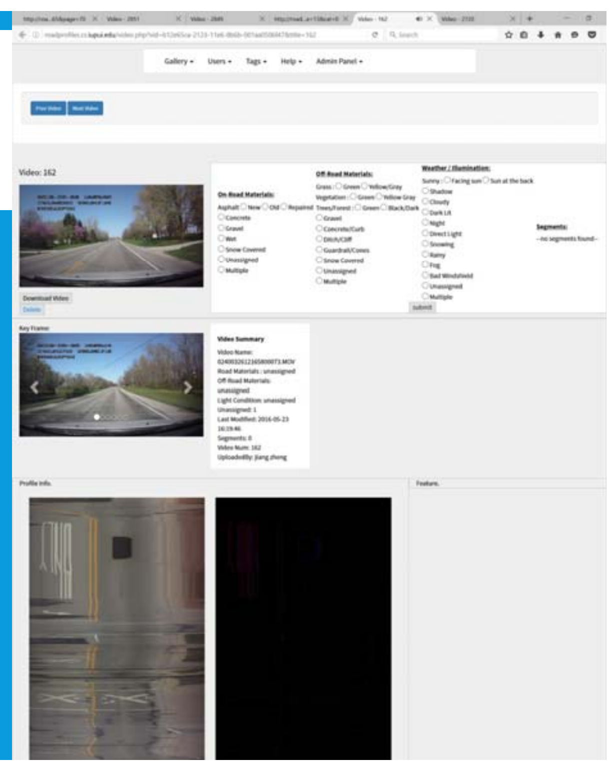

Video: 162

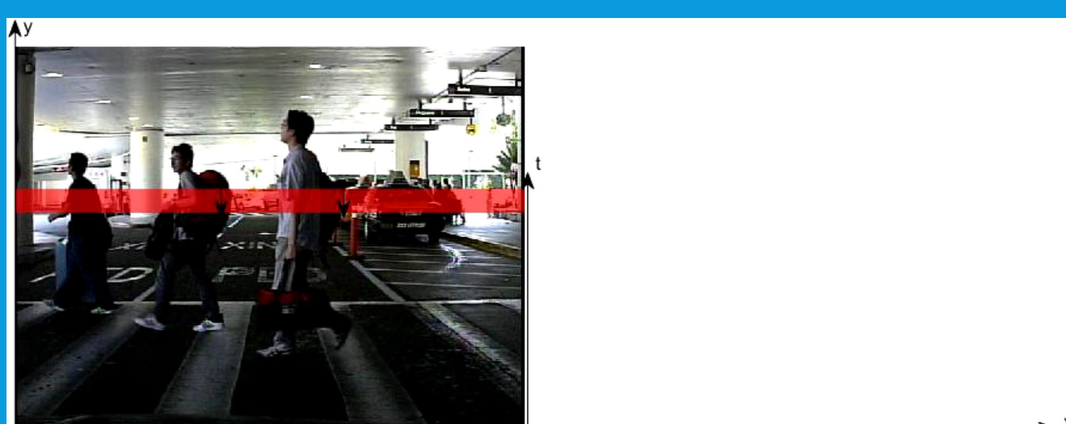
BIG-DATA -> DRIVING VIDEO PROFILE: MOTION AND ROAD

Road profile

Video frame

Motion profile

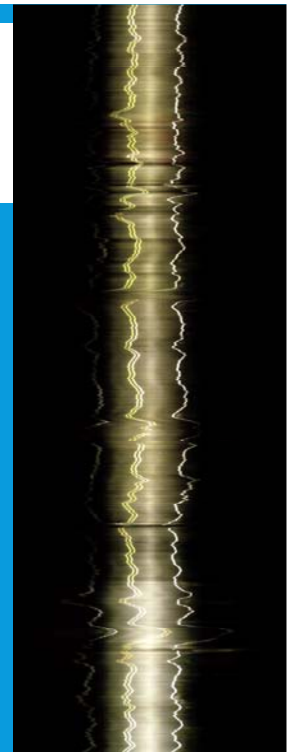
DYNAMIC GENERATION OF MOTION PROFILE



ROAD PROFILES

- Spatial-temporal images reflecting road appearance
- Waves from vehicle rolling
- Other vehicles involved partially
- Temporal lighting change also recorded

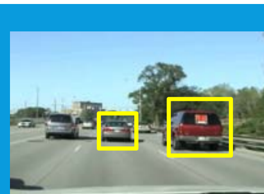
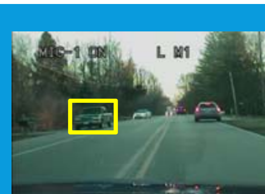




VEHICLE DETECTION BY MOTION

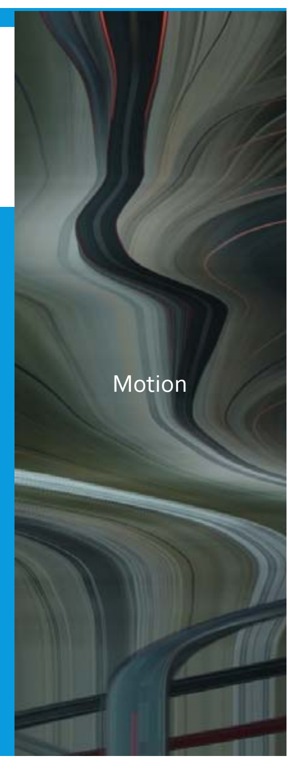
基于运动模型的汽车监测

- 形状检测法：图像小波分解，学习参数，模式识别
- 运动检测法：车辆平稳前行时景观移动模式，追踪运动轨迹，使用HMM统计模型判断

Demo video: http://www.cs.iupui.edu/~jzheng/

InCar Video: demovideo

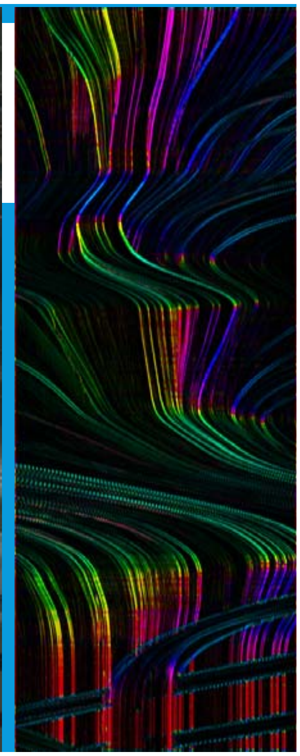


TIME-TO-COLLISION
撞击预测时间

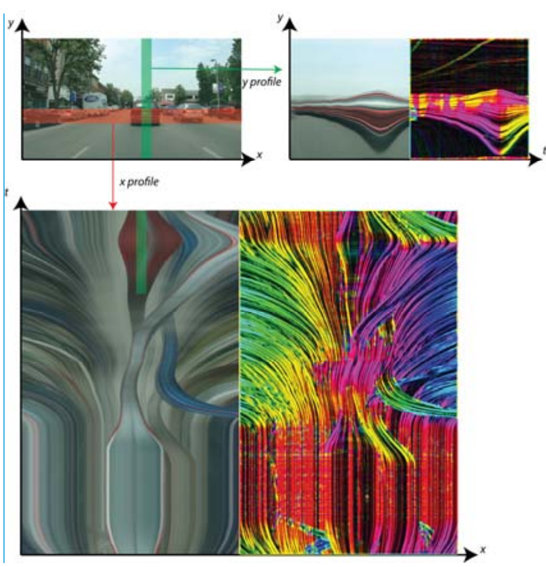
- 相撞可能的方向：零光流（沿视线运动）
- 撞击预测时间的图像推算：

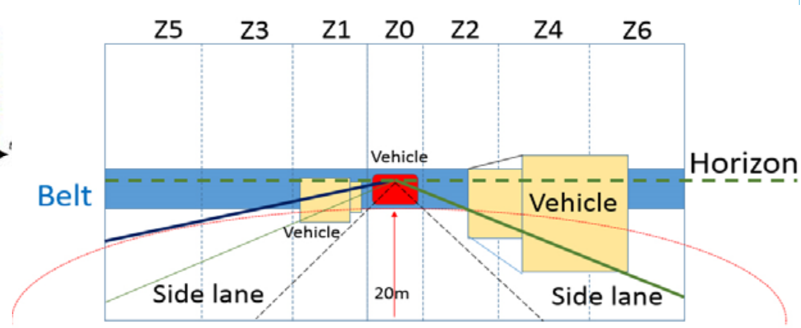
  TTC=距离 / 速度=物体尺寸/ 尺寸变化率

  测算纵向的轨迹变化率



MONITORING VERTICAL EXPANSION AT HORIZONTAL ZERO-FLOW LOCATION





Video

ZERO-FLOW AND MOTION EXPANSION RATE FOR TTC

EXAMPLES

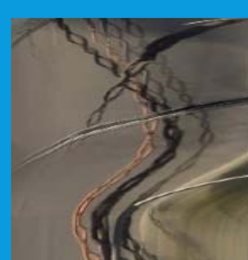
PEDESTRIAN DETECTION IN VIDEO

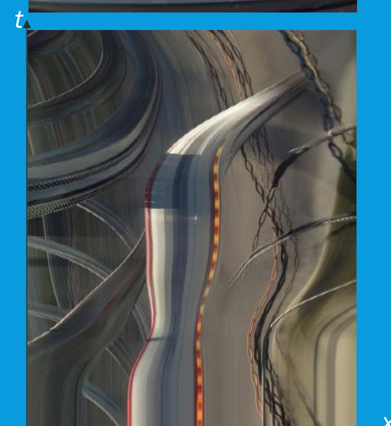
形状检测法

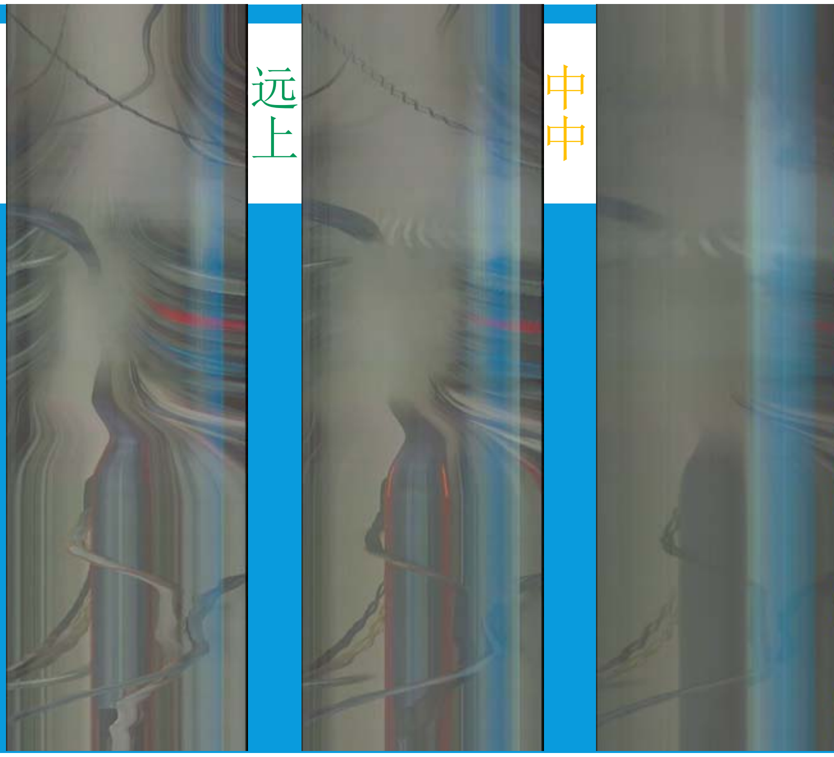
- 用不同尺度的窗在录像中搜寻人的边缘轮廓，最有效的是HOG（方向直方图）统计特征，加之分类算法分别行人与非行人。计算实时，运算量大

运动检测法

- 人的运动有明显的，有别于物体运动的特征。双脚交替形成链状轨迹，发现这样的轨迹便能判断行人存在







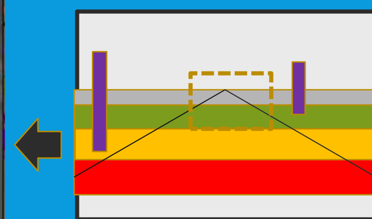
远
上

中
中

近
下

距离上
图像中

Video frame

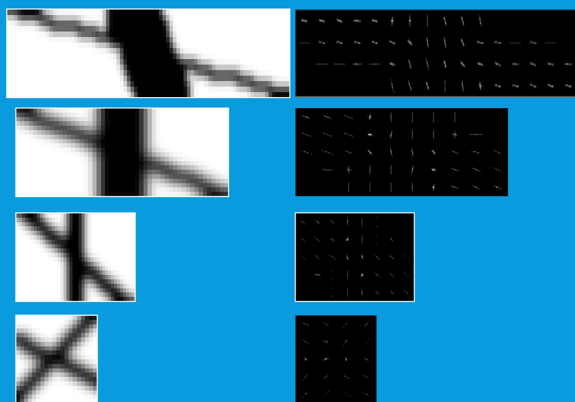


时间t

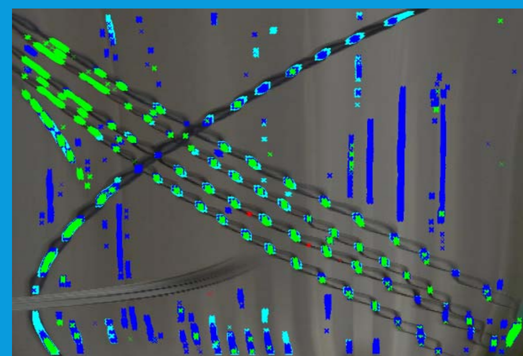
CLOSE PEDESTRIANS （近处行人）

HISTOGRAM OF ORIENTED GRADIENT FEATURES

Model of leg crossing



HOG feature based detection



20 degree – fast   40 degree – normal

60 degree – slow   80 degree – skewed

BICYCLIST DETECTION 自行车的视觉监测

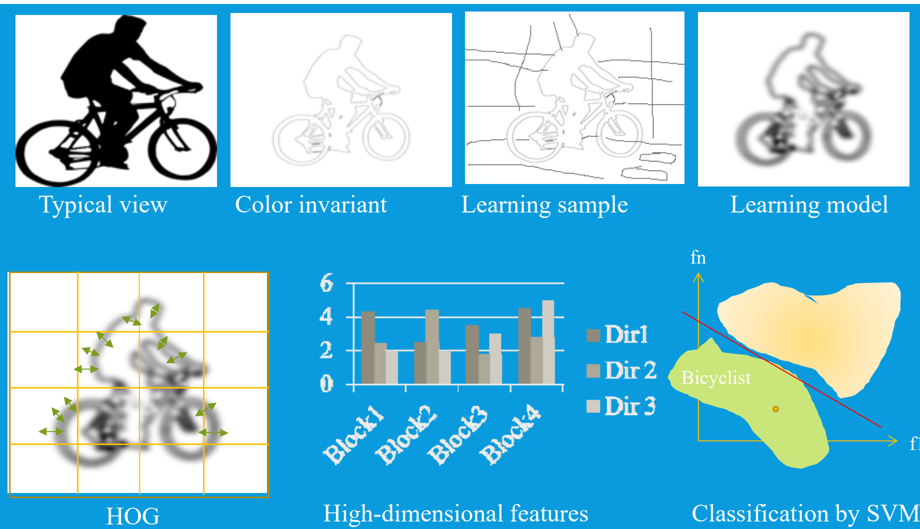
- 形状检测法： 对骑车人和自行车的不同侧面的HOG参数学习后，用不同尺度的视窗扫描图像空间，模式识别的分类方法判断骑车人或其他物体
  - Rear side   Side   Front side

  - Models flipped horizontally
  - Poses combined with above cases

Rear

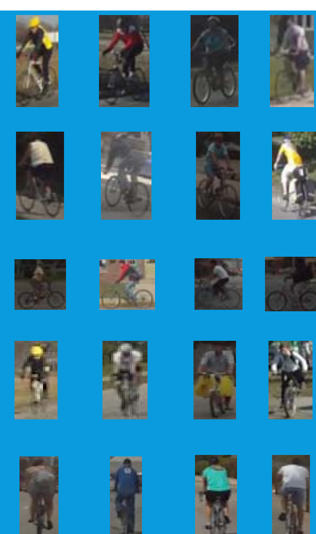
Front

APPEARANCE BASED RECOGNITION



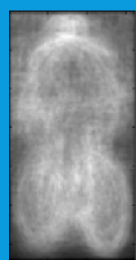
TRAINING SET EXTRACTED MANUALLY

- 45 degree front-side view
  - 922 cropped patches
- 135 degree rear-side view
  - 1628 cropped patches
- Side view
  - 733 cropped patches
- Front view
  - 173 cropped patches
- Rear view
  - 509 cropped patches

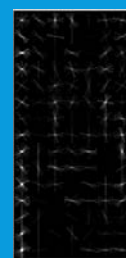


HOG BASED WINDOW REFINEMENT

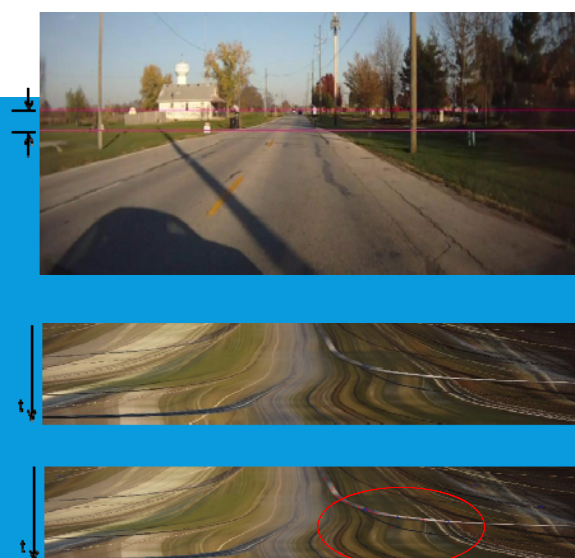
- Front and rear side views: 128x64 pixel window, block size 8x8, 2x2 shift cells, and 6 orientations, 630 dimensional feature
- Side view: 128x128 pixel window, block size 8x8, 2x2 shift cells, and 6 orientations, 1350 dimensional feature
- Supporting Vector Machine (SVM)/ Extreme Learning Machine (ELM) as classifiers for bicyclists


Average gradient


SVM Positive weights


SVM Negative weights

TRACKING BICYCLISTS


Procedure of making temporal profile and overlaying bicyclist positions

ROAD ENVIRONMENT SENSING AND RECORDING
道路环境的感知和记录

Road maintenance and assesment

Safety function of vehicle

Autonomous driving

Road departure prevention

Accident examination

ROAD PROFILE FROM VIDEO FOR ROAD EDGE
获取道路表面图以显示道路边缘的视觉特性

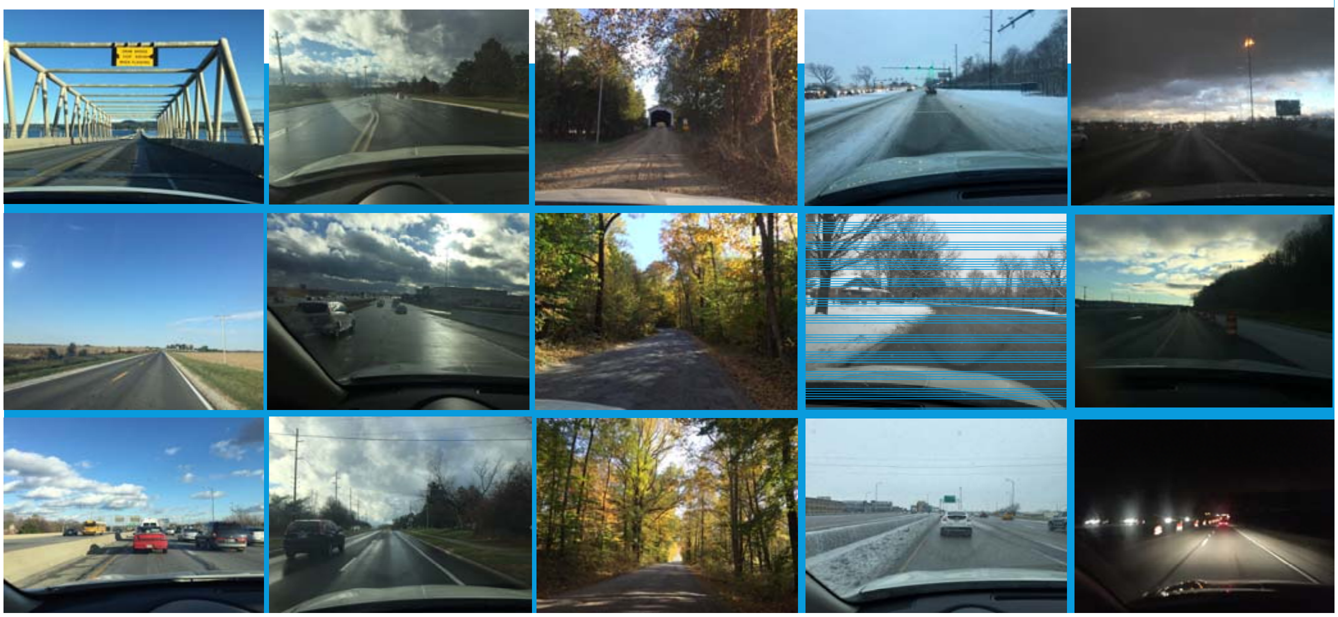
Much more difficult than lane detection

- Road edge detection is critical to the safety driving, in additional to the lane mark detection
- Vision algorithm is the best approach for detecting various road edges
- Significant amount of variation of roads in visual appearance under different illuminations
- Data mining and machine learning method is used to cluster different classes of road and understand

比车道标识线更困难的任务

- 道路边缘是路面标识外最重要的防止车辆偏离道路的线索
- 视觉方法仍然是最佳的边缘抽取的方法（马等动物都能做到）
- 由于路上和路边材料的多样性，加之照明状况不同，照相机测到的色彩变化很大
- 采取数据挖掘和机器学习等统计方法归纳道路边缘的分布

IMAGE COLOR{RGB} = REFLECTANCE{DR, SR} × ILLUMINATION(RGB, D}



PHYSICAL AND OPTICAL MODELING OF IMAGES

- Too complicated to model all parameters of light and reflection on road

照相机的图像亮度 = a_1 环境散射光+ a_2 $R_d \bullet$ 阳光 +a_3 $R_s \times$ 阳光 +a_4阳光

  - 阳光 : incident light vector – exists in a sunny day and is related to vehicle direction, or is from vehicle headlight and street lights in night. It may directly enter camera in sun set and sun rise, sunny facing the sun, and occasionally from other vehicle headlight.
  - 环境散射光: ambient light existing in shadow, cloudy, raining, fogy, snowy days, etc.
  - R_d: diffused reflectance 散射– exists mostly except on watering surface
  - R_s: specular reflectance 镜面反射– exists on asphalt road surface, wet road surface
- Influenced from materials on road and off-road, roadside scenes, vehicle driving direction, etc.
- Some components exist simultaneously but not all

FACTORS INFLUENCING ROAD APPEARANCES

Road Materials	Off-road Materials	Seasons	Weather	Illumination	Camera sensitivity
Asphalt new, old, repaired	Grass	Spring	Rainy, wet	Specular reflection	Dirty windshield
Concrete	Soil, dirt	Summer	Heavy rain	Dark lit	Normal
Gravel	Gravel	Fall	Snowing, snow-covered	Direct lighting	auto-exposure
Soil/dirt	Vegetation, field	Winter	Sunny	Shadow	
	Concrete, curb		Cloudy	Night	
	Cliff, ditch		Fog		
	Tree, forest				
	Construction cone				
	Guardrail, barrier				
	Other vehicles				

21,000 Combinations

FUSING TO THREE FACTORS - 924 CASES ARE STILL TOO MANY

On-road materials	Off-road materials	Weather/illumination
Asphalt new	Grass green	Sunny – facing sun
Asphalt old	Grass yellow/gray	Sunny – back to sun
Asphalt repaired	Vegetation green	Shadow
Concrete	Vege yellow/brown	Cloudy
Gravel	soil/dirt	Direct light
Snow covered	Tree/forest green	Dark lit
Wet	Tree/forest brown	Night
	Gravel	Fog
	Concrete/curb	Snowing
	Ditch/cliff	Raining
	Snow-covered	
	Guardrail, barrier, cones, vehicle	Dirty windshield

RAINING ON WET ROAD – GRAPHICS REFLECTANCE MODEL

Spray around car

Raining blurs the scene

BIG DATA MINING OF ROAD APPEARANCES

Material properties

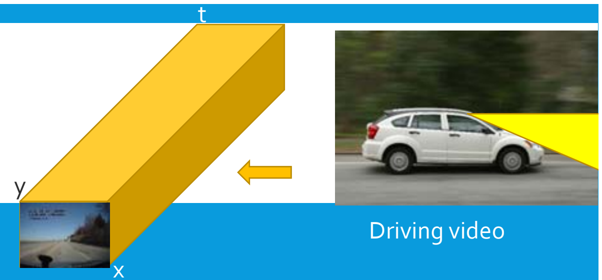
- Counting most frequently passed road materials for vehicle testing

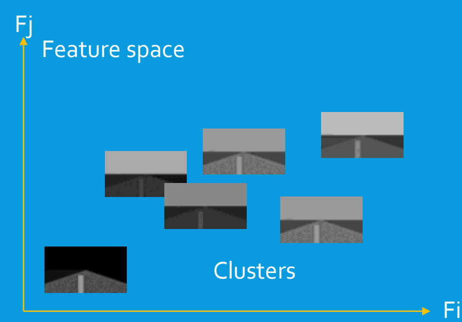
Visual appearance

- Clustering various road edges for sensing algorithm development

OBJECTIVES

- Investigating the visual appearance of road edges thoroughly in different weather and illumination conditions
- Using rich naturalistic driving video to perform big-data mining
- Clustering weather and illumination categories in terms of visual features on road and off road in video
- Classifying video frames to these categories in order to guide road edge detection algorithms.
- Understanding weather and illumination helps road edge detection
- The results will benefit autonomous driving and vehicle safety





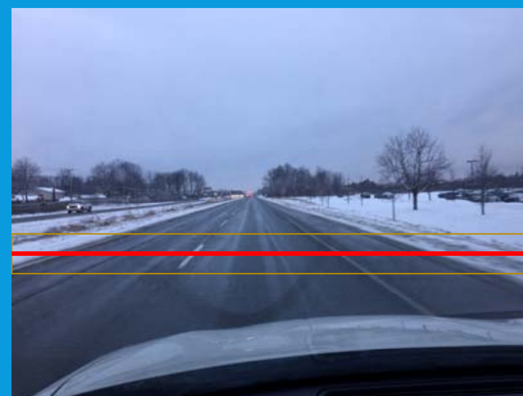
DATA MINING APPROACH FOR ROAD APPEARANCES

Obtain qualitative and quantitative conclusion

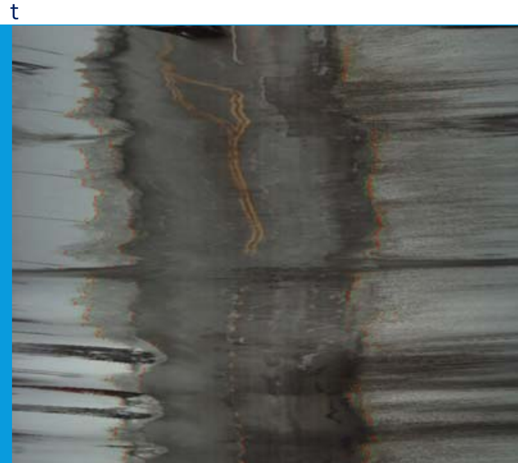
1. Computing on road and off-road features from Naturalistic Driving Videos（数据压缩）
2. Clustering feature samples close in properties by K-mean algorithm (数据聚类定义照明）
3. Classifying input video frames into clusters obtained in clustering（识别照名）
4. Road edge detection for different weather and illuminations

ROAD PROFILE ACQUISITION FROM VIDEO
从录像获得道路的表面图

- Sampling color on a line in the video frames to create road profile
- Computing linearity and homogeneity at the same time
- Clustering visual appearance parameter according to on-road and off-road materials, illuminations, and camera sensitivity



VIDEO DATA REDUCTION TO ROAD PROFILE FOR FEATURE MINING



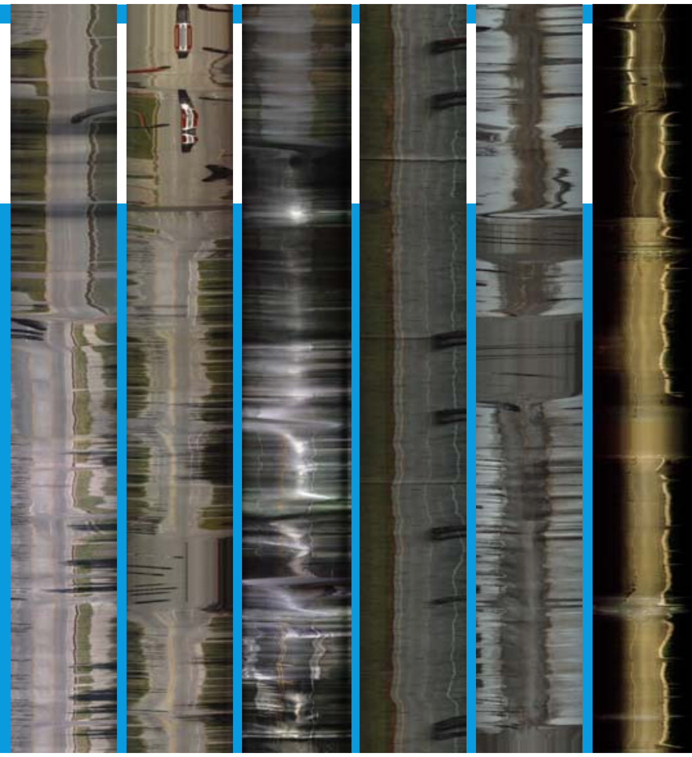
Road profile P(x,t)

- Road profiles
- Intensity and chroma in four focused regions – 8 features
- Standard deviation in color on road surface – one feature

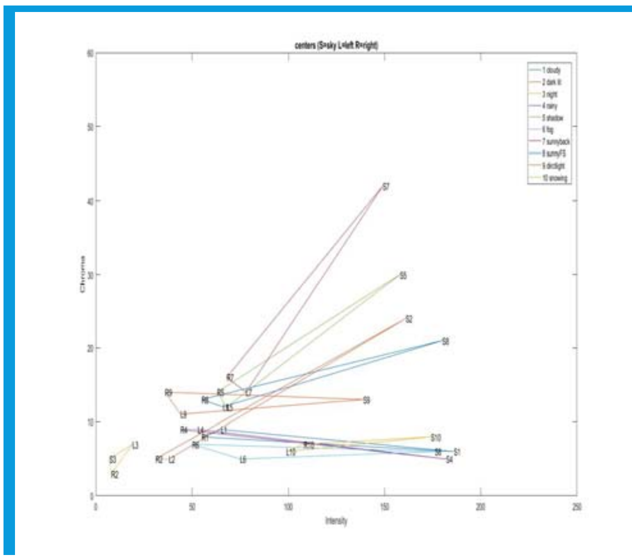
ROAD PROFILES

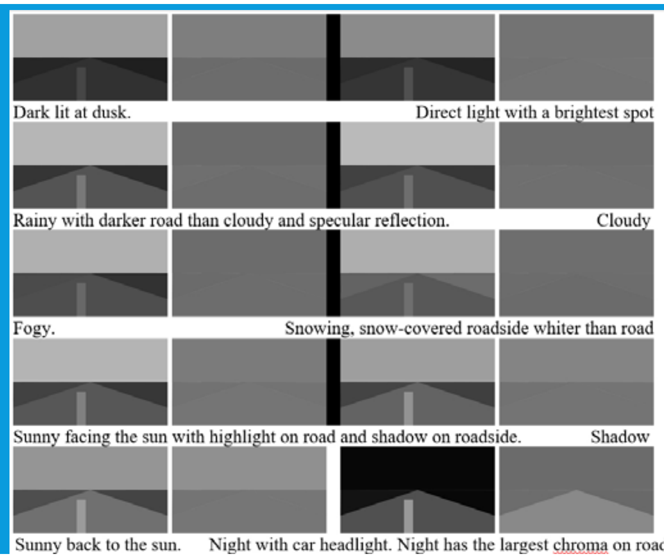
Visualization

- Snow-covered roadsides are brighter than road surface
- Night road has no edge visible unless lit by vehicle headlight
- Lane mark is the most reliable sign in night
- Most roadsides are darker than road surface in daytime except new asphalt road
- Specular reflection appears on wet road surface but less appears roadsides due to rough materials (grass, dirt, tree, …) there
- Passing or parked vehicles have dark boundary at shadow and tires
- Many more …



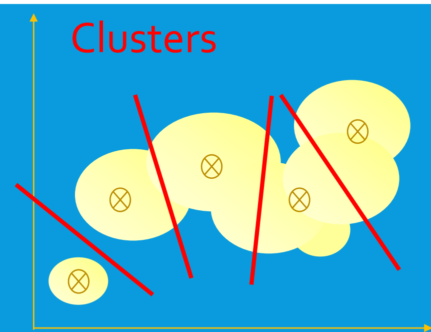
EXAMINE HUMAN TAGGED WEATHER AND ILLUMINATION



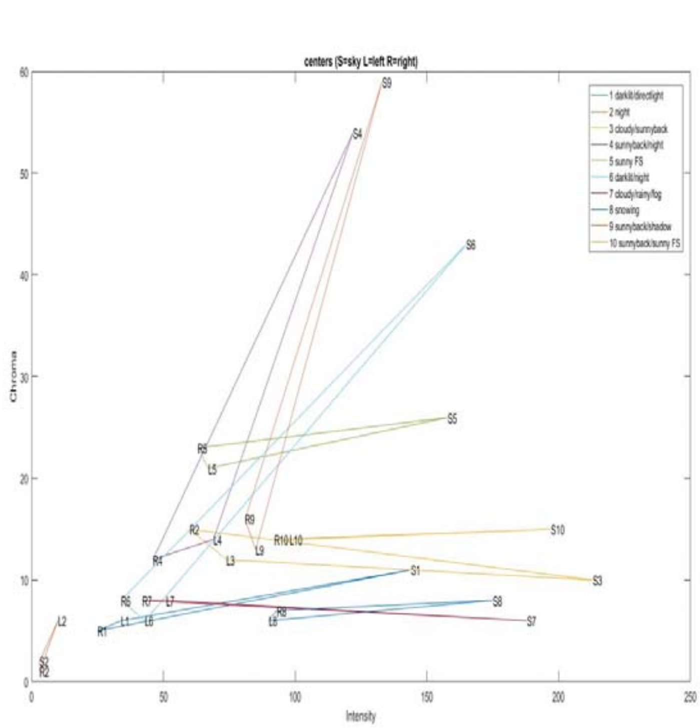


CLUSTERING VIDEO SAMPLES FOR WEATHER AND ILLUMINATION

- Feature space tagged by humans from big-video data is ambiguous
- Data are mostly of continuous nature but not necessary to be Gaussian



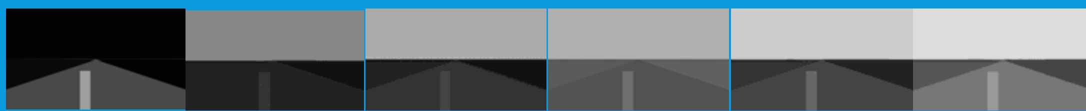
- Typical views generated from clusters
- Give each cluster a Reference Name from the most contributed category tagged by humans



- Using 300 × 9000 frame for K=10
- Seeds from each category human tagged

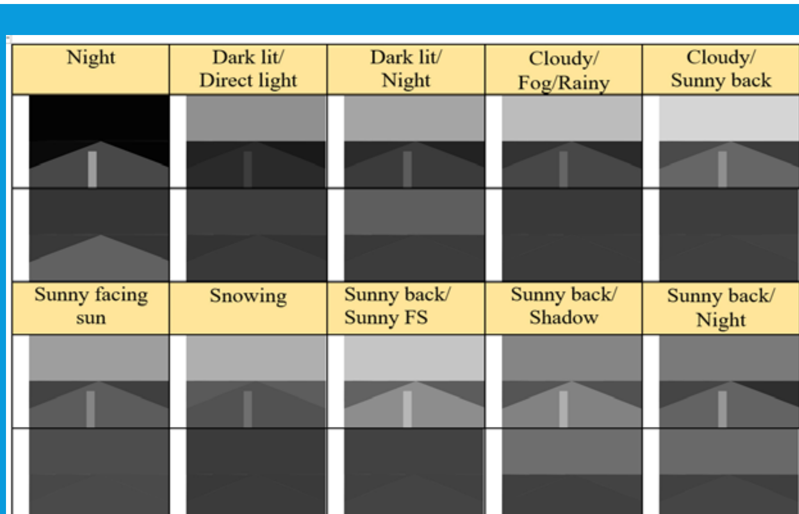
10 CLUSTERS

Night	Direct light	Dark Lit	Snowy-cloudy	Cloudy-rainy-fogy	Sunny facing sun



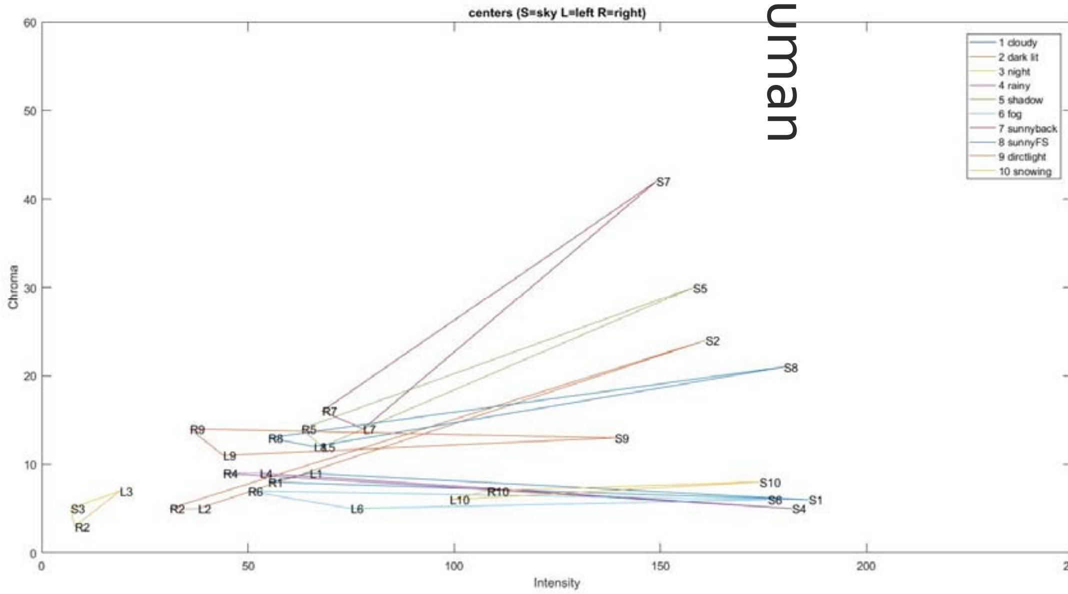
		Sunny back to sun Dark lit	Sunny back to sun	Shadow	Sunny back to sun Sunny facing sun

REPRESENTATIVE VIEWS OF K-MEAN CLUSTERS

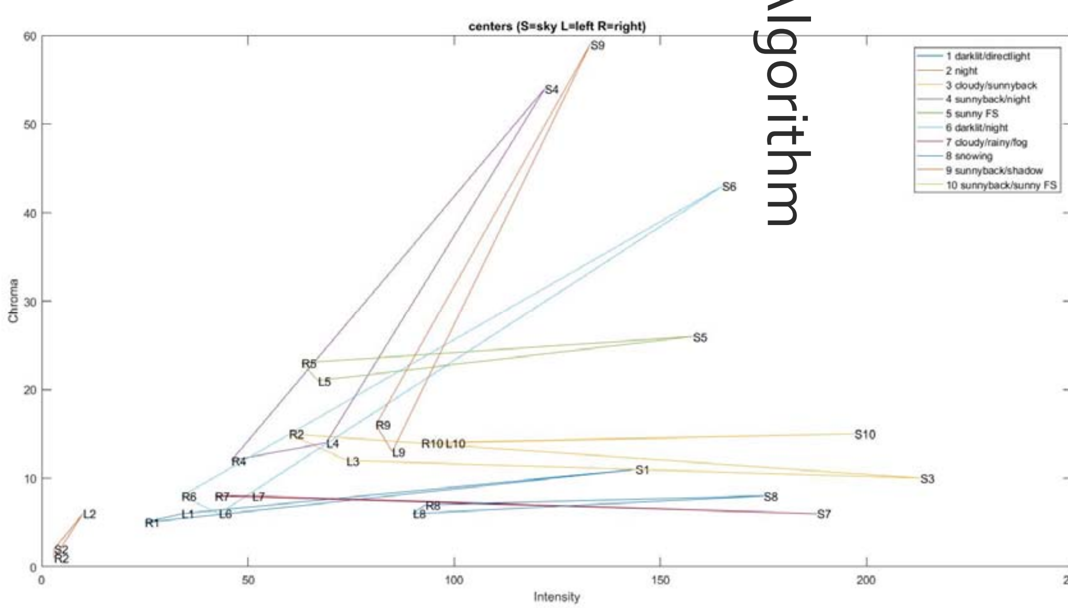


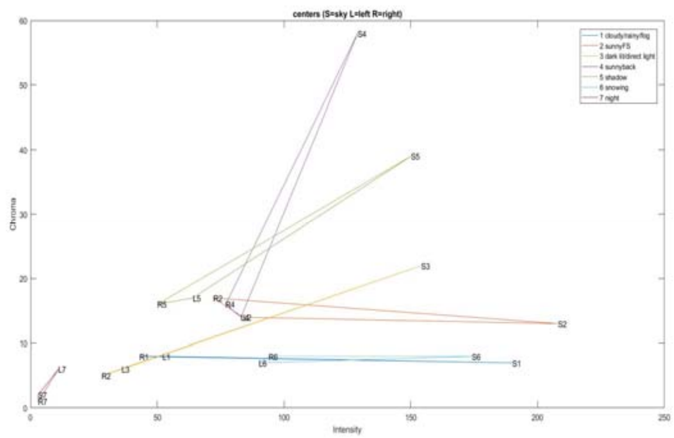
Quantitative Results

Human



Algorithm

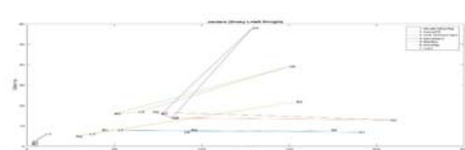




K=7

Very distinct clusters

Means in three regions for all clusters



Sunny back to the sun

Shadow

Sunny facing the sun

Cloudy/raining/fog

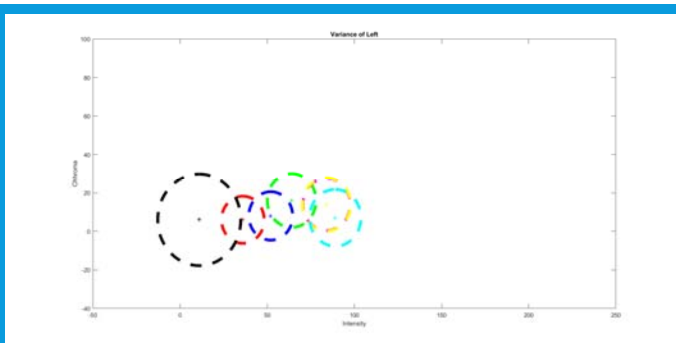
Snow

Dark lit / direct light

Night

LEFT ROADSIDE

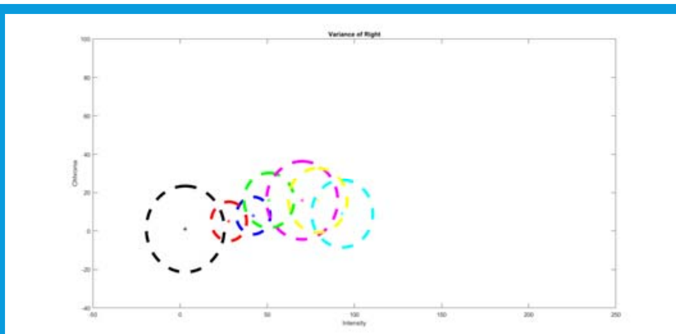
Variations for all clusters



Sunny back to the sun
Shadow
Sunny facing the sun
Cloudy/raining/fog
Snow
Dark lit / direct light
Night

RIGHT ROADSIDE

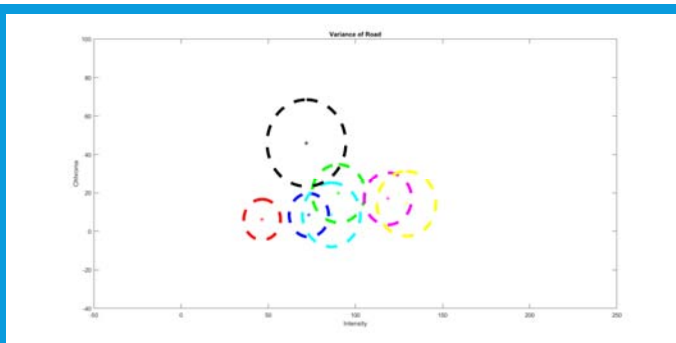
Variations for all clusters



Sunny back to the sun
Shadow
Sunny facing the sun
Cloudy/raining/fog
Snow
Dark lit / direct light
Night

ROAD SURFACE

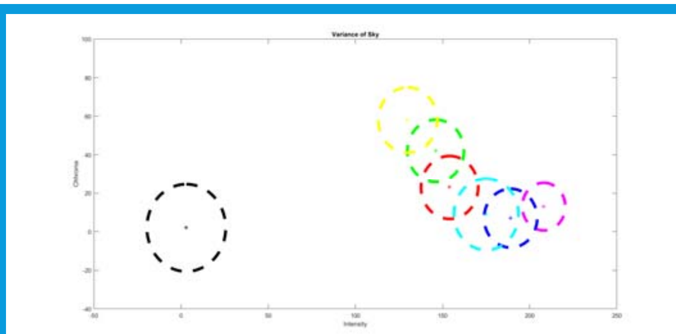
Variations for all clusters



Sunny back to the sun
Shadow
Sunny facing the sun
Cloudy/raining/fog
Snow
Dark lit / direct light
Night

SKY

Variations for all clusters



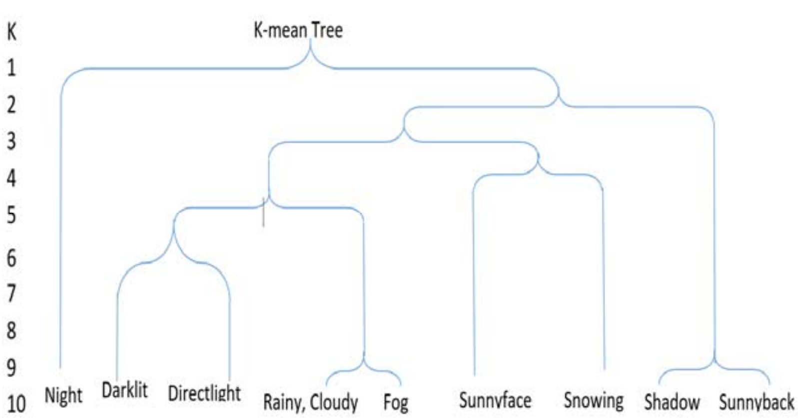
Sunny back to the sun
Shadow
Sunny facing the sun
Cloudy/raining/fog
Snow
Dark lit / direct light
Night

CONSISTENCY BETWEEN CLUSTERS AND TAGGED CATEGORIES

- Compute Euclidian distances from cluster centroids to classify new frame

	C1	C2	C3	C4	C5	C6	C7	%
	Cloudy/rainy/ fog	Sunny facing the sun	Dark lit/ direct light	Sunny back to the sun	Shadow	Snowing	Night	
K=7	93%	80%	91%	87%	80%	96%	98%	90%

- How many clusters (K=?) for classification or weather understanding



K=30 Still can not be separated

K-MEAN TREE

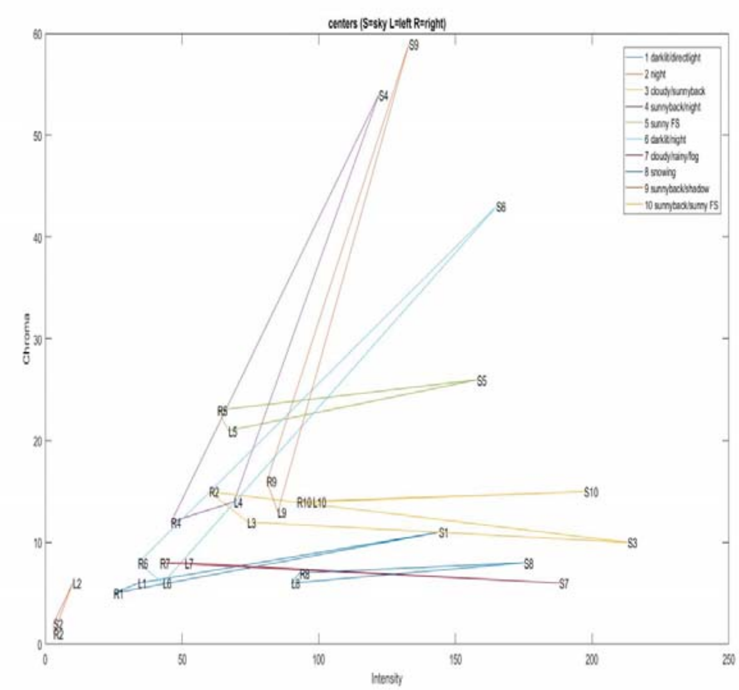
- Built from reference names for various K = 1, …., 10
- K up to 30 unable to provide distinct clusters of rain and cloudy
- K=7 is stable in terms of major Reference Name

Illumination	K=10	K=7	K=3
Night			
Dark lit/ Direct light			Night
Dark lit/ Night			
Cloudy/ Fog/Rainy			Dark daytime
Cloudy/ Sunnyback			
Sunny FS			
Snowing			
Sunnyback/Sunny FS		Sunny back sun	
Sunnyback/Shadow			Bright daytime
Sunnyback/Night			showdow

For different Ks

ILLUMINATION CLUSTERING IN FEATURE SPACE

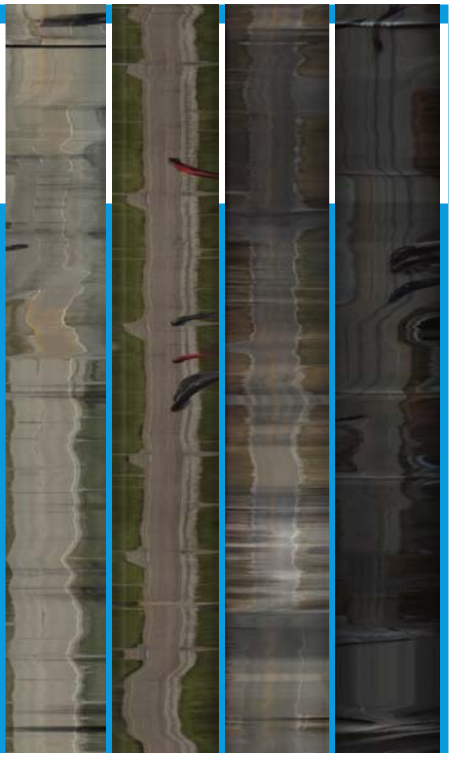
Intensity and chroma from sky, road, and off-road regions are averaged for each cluster of weather and illumination conditions



ROAD PROFILES

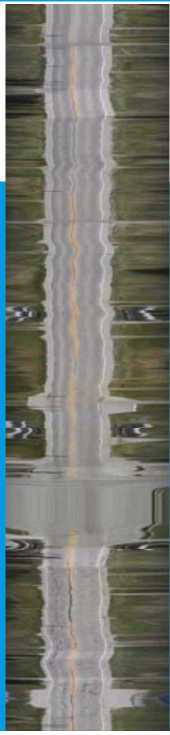
- Sunny back to the sun
- Sunny facing the sun
- Shadow
- Cloudy
- Rainy
- Snowy
- Fogy
- Dark lit
- Direct light
- Night

5 min video condensed to a long profile image

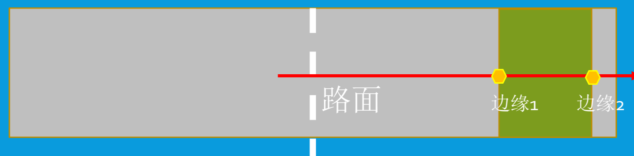


WEATHER AND ILLUMINATION CONDITIONS

- Weather and illumination change the road appearances drastically.
- After converting video to road profiles, we have visual maps of roads under various weather and illumination conditions.
- This provides information to develop vision algorithms to detect road margins in order to prevent vehicle road departure in poor weather conditions.
- Data mining is performed to obtain the visual parameters across the road edges.



DETECTING ROAD EDGES FROM FEATURES



中值滤波将车道线消除

数据挖掘中取得各种天气合照明的（路-路边）色彩差异

X方向一维边缘检测

基于贝叶斯分布的路边缘选择

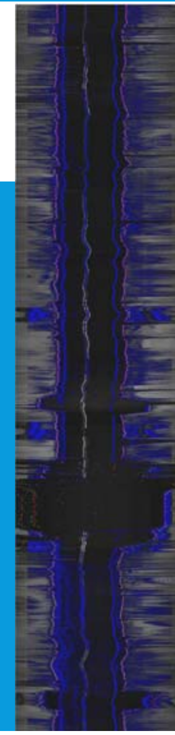
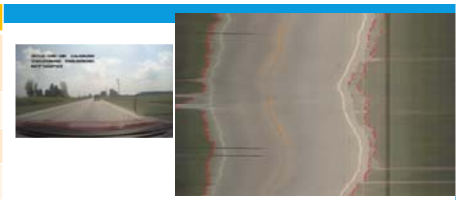
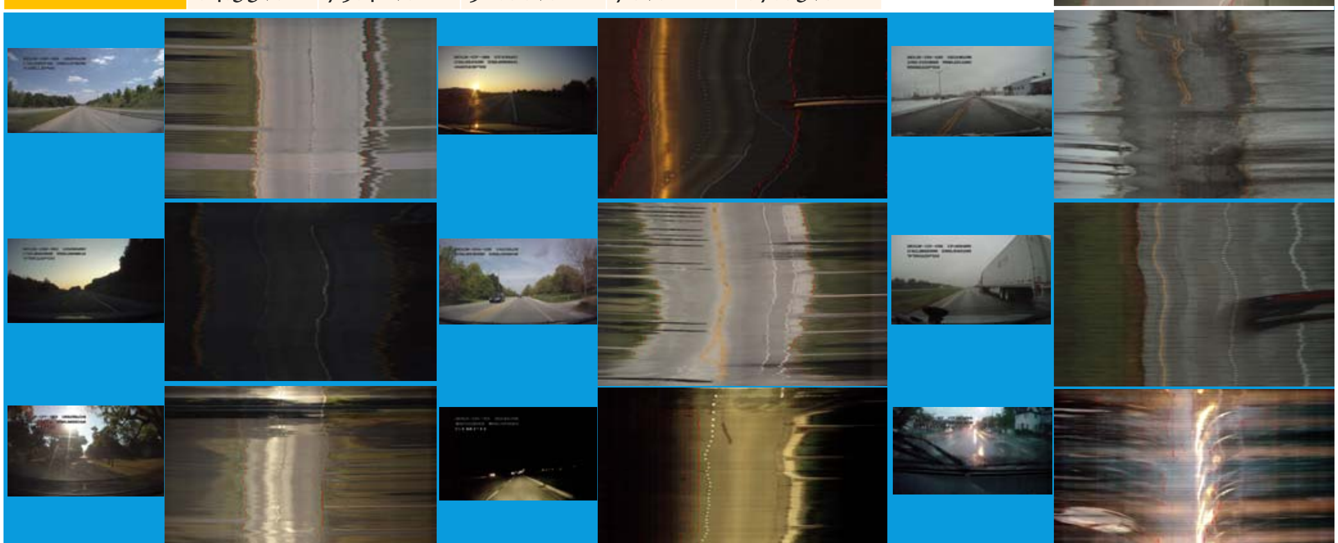


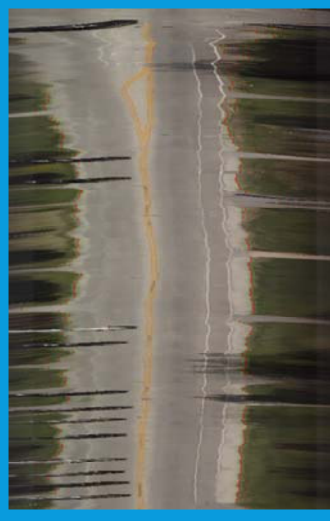
Table III Accuracy of road edge detection

Weather/ illuminations	Night	Dark lit	Direct light	Rainy	cloudy
Accuracy	90.58%	81%	63.63%	54.36%	88.04%
	Fogy	Snowy	Sunny FS	Shadow	Sunny bS
	84.53%	79.42%	91.08%	70%	87.03%

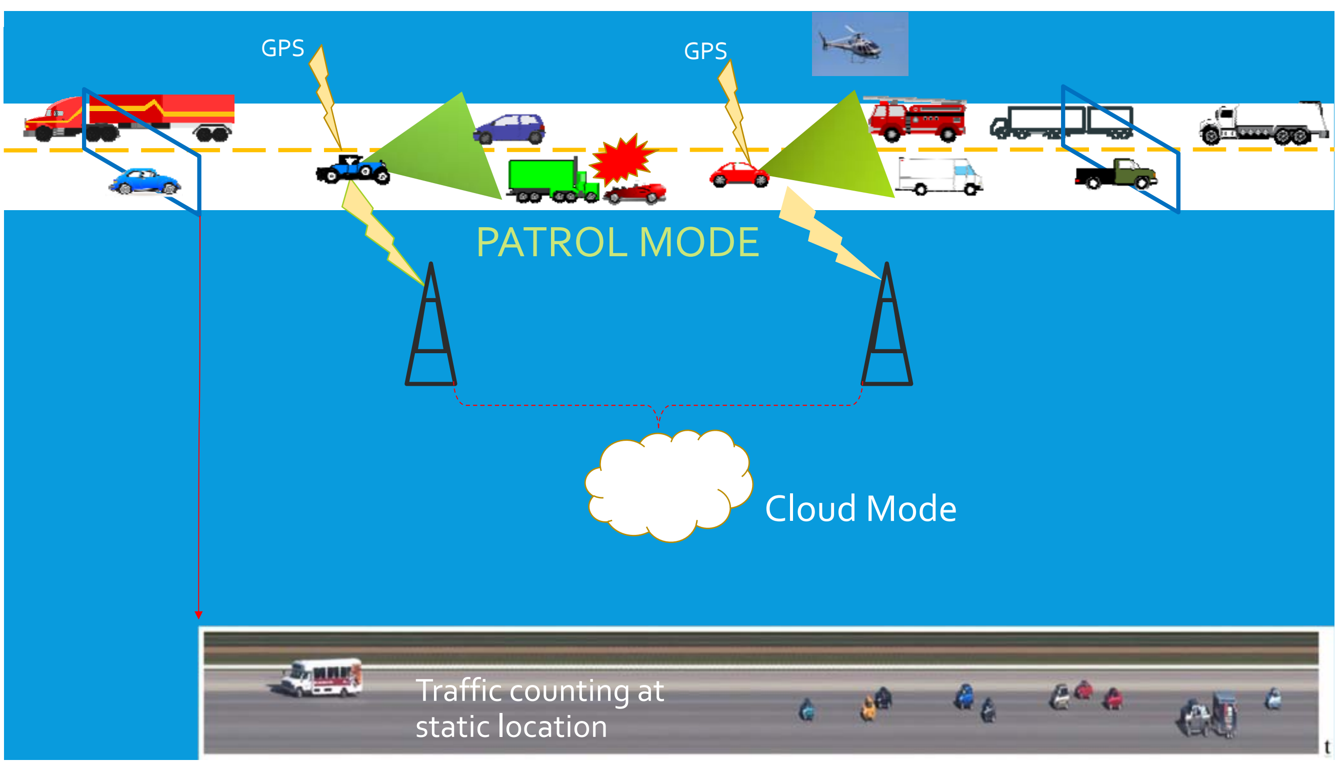




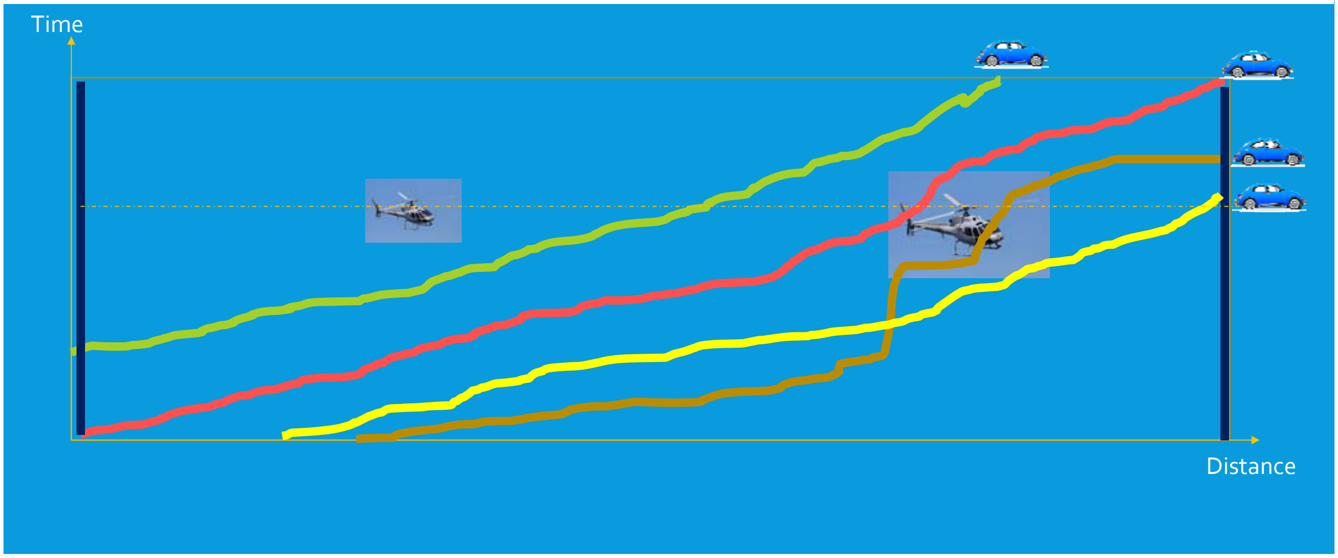
TRAFFIC COUNTING VIA PATROL MODE



- Opposite lanes
- Adjacent lanes



CELL PHONE TRANSMITTED TRAFFIC INFORMATION



CONCLUSION ON USING NATURALISTIC DRIVING VIDEO

- Traffic flow from patrol
- Driving behavior
- Accident recording
- Road environment survey
- Autonomous driving
- Data mining for advanced function