# Automatic Traffic Data Collection Using Surveillance Videos Cameras

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#### **Presentation Outline**

- Background
  - Introduction
  - Available approaches
- Methodology
  - VVDC1: Video-based Vehicle Detection and Classification System, Version 1
  - VVDC2: Video-based Vehicle Detection and Classification System, Version 2
  - Demo
- Conclusions

### Introduction

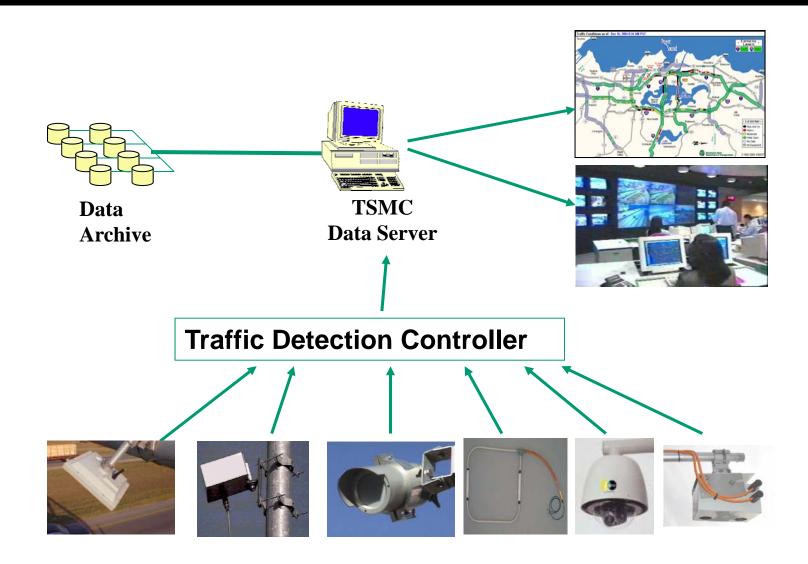
- Manage Demand
  - Too many cars, not enough road
- Monitor Movements
  - Ensure a safe and mobile network
- Data Collection
  - Can't manage what you can't measure

## **Data Collection Infrastructure**

- Thousands of inductance loops
- Measure occupancy, volume
- Can classify cars and trucks
- Certain percentage malfunctioning
- Damage pavement
- Require lane closure for onsite maintenance



# **Data Collection Infrastructure**



## Surveillance Video Infrastructure





- Hundreds of available cameras
- Mainly used for traffic surveillance
- Low resolution
- Varying mounting angles
- Changing environments

# Surveillance Video Cameras as Video Image Processors (VIP)



Surveillance video



Video Image Processor (VIP)

Source: http://www.metroactive.com/papers/metro/02.06.97/traffic-camera-9706.html http://www.iteris.com/rs/products.html

## **Video Benefits**

- Why Surveillance Video? Aren't loops and VIPs OK?
  - Cheap
    - Nothing proprietary, network already there
  - Easy
    - No pavement damage, lane closures
  - Verifiable
    - "See it in action"

## Video Issues – Project Motivation

- Proprietary algorithms, equipment
  - High cost, limited deployment potential
- Extreme sensitivity to environmental impacts
  - Inconsistent error rates, depending on conditions
- Sensitivity to congestion
  - Occlusions between vehicles cause issues

#### **DOT Benefits**

- Collaboration with Washington State DOT (WSDOT)
  - Testbed evaluation
    - Future sensor studies
  - Live surveillance feeds through 2 fibers
- Benefits to WSDOT
  - Capability to collect volume data through surveillance cameras

### **Video Detection Basics**

- Detection
  - Distinguish objects from background
- Classification
  - Determine which objects are of interest
- Tracking
  - Find these objects in the next frame

# State of the Art

- Background Subtraction
- Motion Features
- Scan-line approaches

# **Background Subtraction**

- Obtain background frame
  - Average, median, etc...
- Subtract background from current frame
  - Remaining pixels are thresholded to form binary image
  - Blobs are objects of interest
- Examine blobs for size/proportion to find vehicles
- Assume blobs do not change shape, size and color distributions and can be found nearby in the next frame

# **Background Subtraction**



# **Background Subtraction Issues**

- Blobs merge when objects get near or occlude one another
- Camera movement is interpreted as object movement
- Non-static noise is a source of error
  - Lighting, trees, shadows

#### **Motion Features**

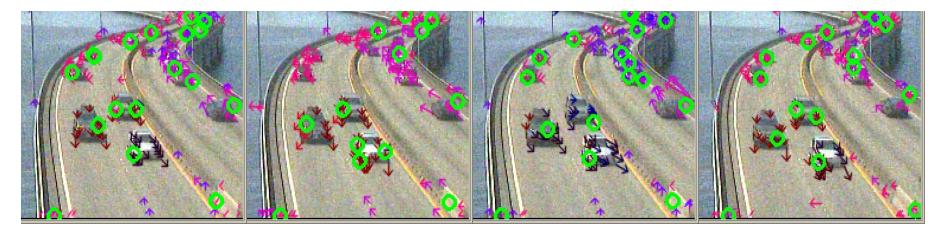
- Find unique points in an image
  - Gradient is high in both directions
- Assume small displacements
  - Assume the closest unique point in the next frame is the same point
- Cluster features to form objects

# **Motion Features**



## **Motion Features Issues**

Clustering is difficult



- Several clusters may form per vehicle
- Clusters form on shadows, glare, etc...
- Speeds may be too similar

# Scan-line Approaches

- Scan-lines simplify the scene significantly
  - Examines changes along a single, user-defined line
  - Background subtraction, 1D data analysis
  - Good example of relaying certain challenges to the user

### Scan-line Issues

- 1D data does not take full advantage of available information
- Similar drawbacks to background subtraction
  - Sensitivity to environmental effects

# VVDC: Video-based Vehicle Detection and Classification System

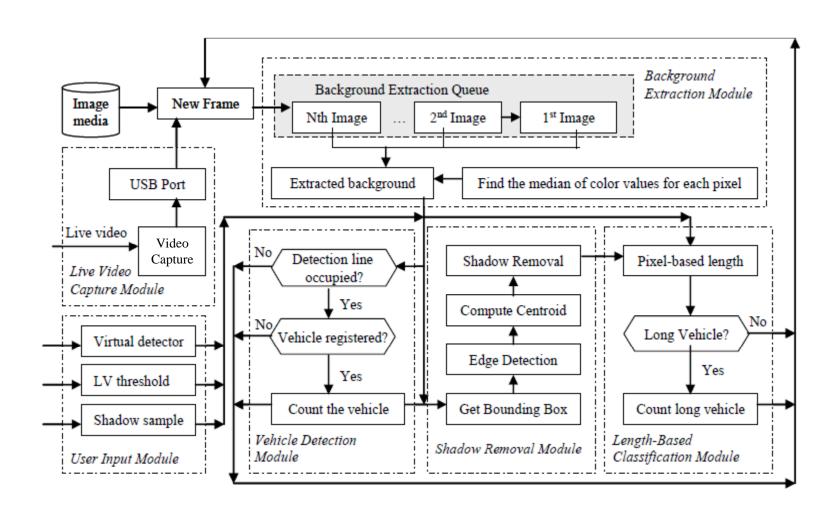
- Development Guidelines
- Overview
- Shadow mitigation
- Vehicle Classification
- System Setup
- Demo
- Results

# **VVDC Version 1 Development**

- Focus on:
  - Collect data such as volume, occupancy, headway, speed
  - Analyze traffic composition (LVs and SVs)
  - Shadow removal

- Ignore:
  - Occlusions
  - Night-time detection
  - Inclement weather
  - Camera vibration
  - Tracking

# **VVDC1** Overview



# **Shadow Mitigation**

Region growth shadow removal





Explore low-texture areas between gradients

# **Shadow Mitigation**

Region growth shadow removal failure

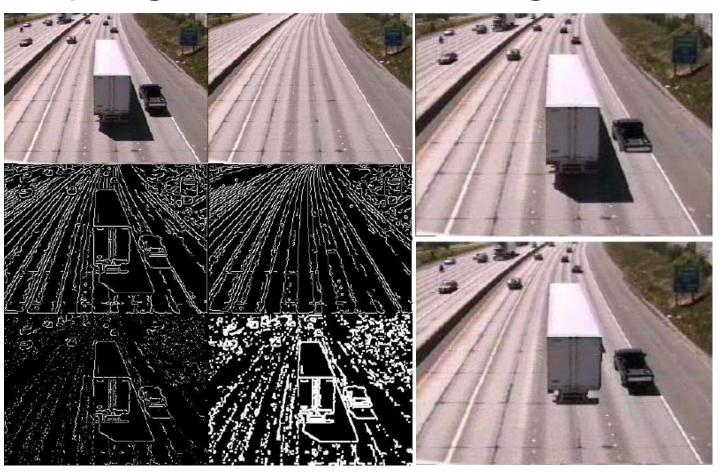




Pavement texture prevents full removal

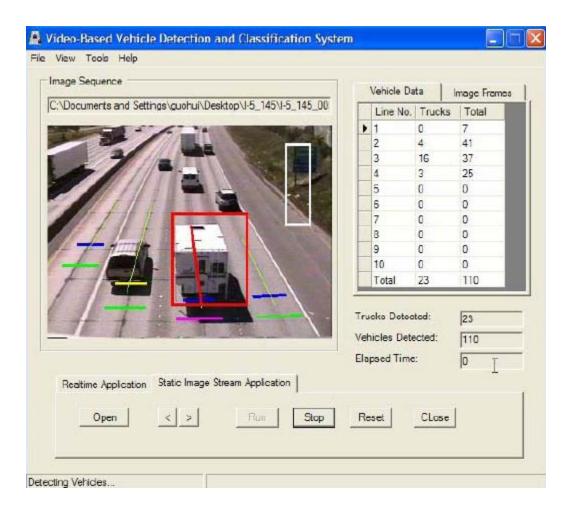
# **Shadow Mitigation**

Canny-edge based shadow mitigation



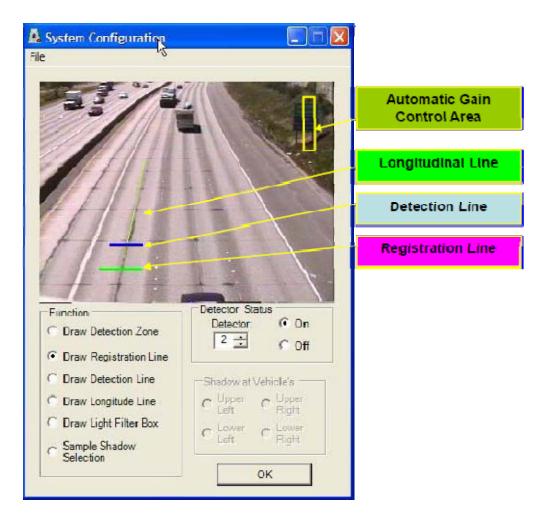
## **Vehicle Classification**

- Length-based
- User-defined
- 2-bin system

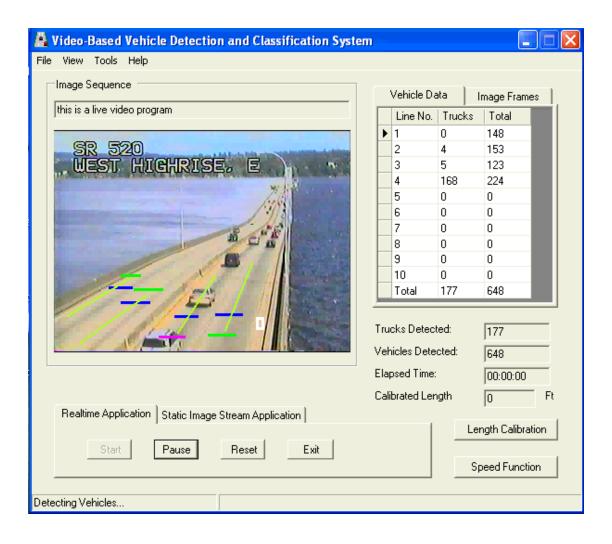


# System Setup

- User defines detection lines
- User defines classification lines
- Selects gain area
  - For background adjustments



## **VVDC1** Demo



# **VVDC1** Testing



**Test Site 1** 



**Test Site 2** 



**Test Site 3** 

**VVDC1** System Test Sites

# I-5 at NE 145<sup>th</sup> Street

#### Off-Line Test Results at the I-5 Test Location

	Location: Southbound I-5 near the over bridge										
Time Period 12 minutes		Lane 4		Lane 3		Lane 2		Lane 1		Subtotal	
Ground-truth	Trucks	5		4		37		12		58	
	Total vehicles	149		409		335		244		1136	
System Detected	Trucks	5		4		35		12		56	
	Total vehicles	154		412		335		245		1146	
Comparison Error	Trucks	0 <sup>a</sup>	0ь	0	0	2	5.41%	2 <sup>c</sup>	16.67 %	4	6.89%
	Total vehicles	5	3.36%	3	0.73 %	0	0	3 <sup>d</sup>	0.82%	10	0.88%

<sup>&</sup>lt;sup>a</sup> absolute error, <sup>b</sup> relative percentage error, <sup>c</sup> one was missed and one was over-counted. <sup>d</sup> two cars missed and one truck over-counted.

# I-5 at NE 145<sup>th</sup> Street

#### Error Cause Investigation for the I-5 Test Location

Lane	Error descriptions	Explanations						
Lane 4	Five vehicles over-counted	Both Lane 3 and Lane 4 had false alarms. These false						
Lane 3	Three vehicles over-counted	alarms were likely caused by the reflection of vehicle head lights from Northbound I-5 traffic.						
Lane 2	Two trucks missed	The two false dismissals were because of that the						
		colors of the two trucks were too similar to the						
		background to have its length properly measured.						
		Figure 5-5 shows one of the two trucks to illustrate the						
		problem.						
Lane 1	1. One truck missed	1. The reason was the same for that of Lane 2.						
	2. One truck over-counted	2. A truck occupied both Lane 1 and Lane 2 was						
	3. Two vehicle missed	counted by both the Lane 1 and Lane 2 detectors. A						
		snapshot of this truck is shown in Figure 5-6.						
		3. Two lane-changing vehicles did not trigger any of						
		the two virtual loops. See the black car in the lower						
		right corner of Figure 5-7 for example.						

# SR-99 at NE 41<sup>st</sup> Street

#### Off-Line Test Results at the SR-99 Test Location

Time Period 12 minutes		Location: Northbound SR-99 near the									
		Lane 3		Lane	2	Lan	e 1	Subtotal			
Carry d tarrella	Trucks	8		7		15		30			
Ground-truth	Total vehicles	270		244		192		706			
System Detected	Trucks	7		6		15		28			
	<b>Total vehicles</b>	270°		245		194		709			
Comparison Error	Trucks	1ª	12.5%b	1	14.28%	0	0	2	6.67%		
	<b>Total vehicles</b>	2	0.74%	1	0.41%	2	1.04%	5	0.41%		

<sup>&</sup>lt;sup>a</sup> absolute error, <sup>b</sup> relative percentage error, <sup>c</sup> one vehicle missed and one over-counted.

# I-5 at NE 92<sup>nd</sup> Street

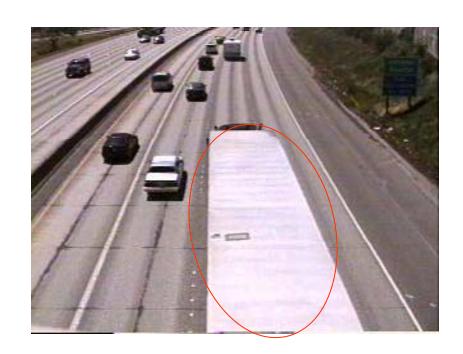
#### **Test Results for Test Site Three**

Time Period 12 minutes		Location: Southbound I-5 near the 92 <sup>nd</sup> Street Over Bridge									
		Lar	ne 4	Lane 3		Lane 2		Lane 1		Subtotal	
Observation Results	Trucks	13		36		5		5		59	
	Total vehicles	38	38	378		380		170		1316	
System Results	Trucks	14		37		6		5		62	
	Total vehicles	397		387		389		173		1346	
Comparison Error Results	Trucks	1 <sup>a</sup>	7.69% b	3 <sup>c</sup>	8.33%	1	20%	0	0	5	8.47%
	Total vehicles	9	2.31%	9	2.38%	9	2.36%	3	1.76%	30	2.27%

<sup>&</sup>lt;sup>a</sup> absolute error, <sup>b</sup> relative percentage error, <sup>c</sup> one truck missed and two trucks double counted.

# I-5 at NE 145<sup>th</sup> Street

#### These vehicles generated errors. Why?



a) Adjacent lane overlap



b) Missed lane-changing vehicle

# I-5 at NE 145<sup>th</sup> Street

#### These vehicles generated errors. Why?



a) Fragmentation



b) Containers counted separately

# I-5 at NE 145<sup>th</sup> Street

These vehicles generated errors. Why?



a) Occlusion error

#### **VVDC1** Conclusions

- The VVDC1 system demonstrated that surveillance cameras can be used for traffic data collection
- Detection error rarely exceeds 3% and is suitable for planning and analysis purposes
- Length-based vehicle classification is acceptable, error rate below 10% at the test sites
- The VVDC program provides a good base from which to expand

#### **VVDC Version 2**

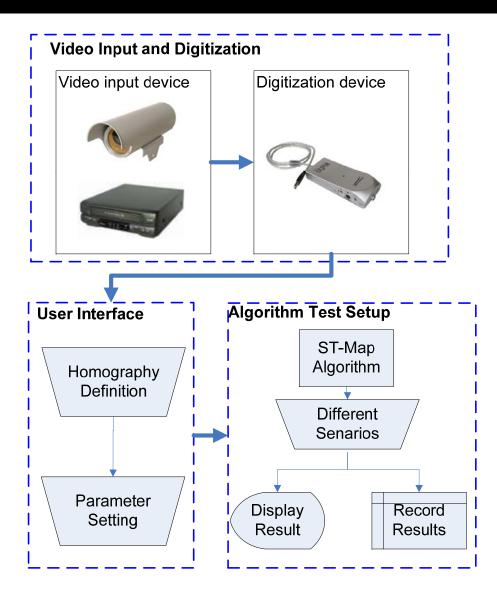
- Development Guidelines
- Overview
- Spatiotemporal Maps
- Perspective Transformation
- Hough Transform
- Graph Based Clustering

### **VVDC Version 2 Development**

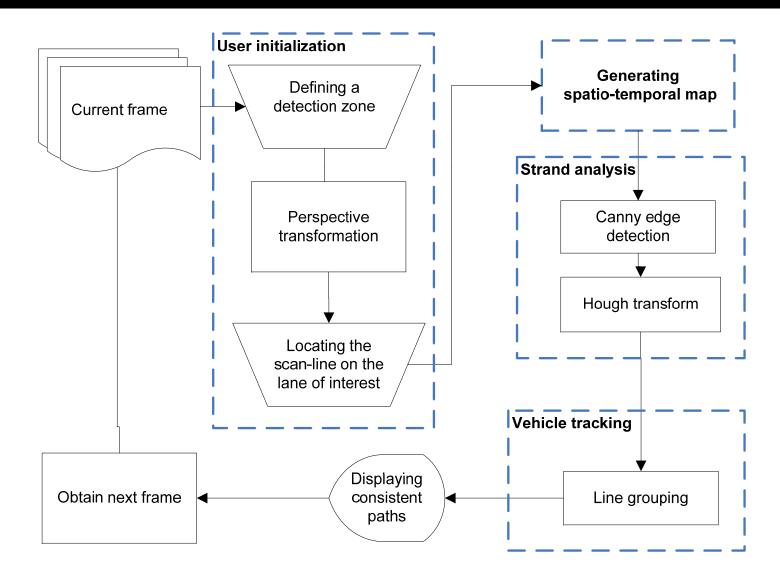
- Focus on:
  - Counts
  - Occlusions
  - Night-time detection
  - Inclement weather
  - Camera vibration
  - Tracking

- Ignore:
  - Classification
  - Volume/Occupancy
  - Headway
  - Speed

#### **VVDC2** Overview

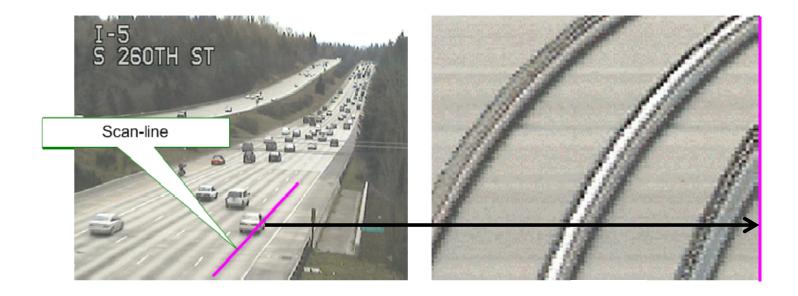


#### **VVDC<sub>2</sub> Overview**



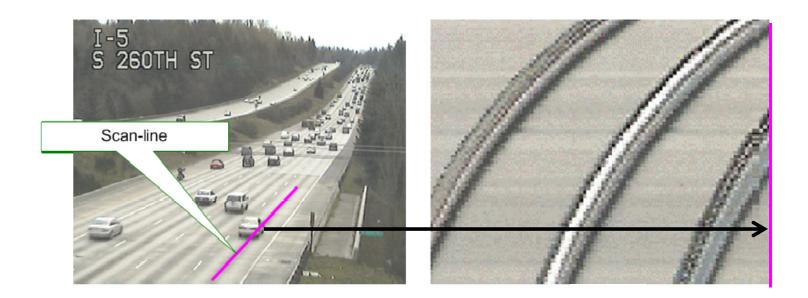
# **Spatiotemporal Maps**

Capture pixels along scan-line



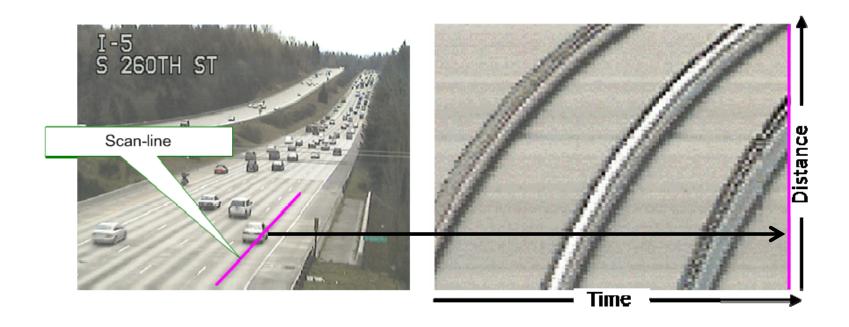
## **Spatiotemporal Maps**

Append to previous captured scan-line pixels



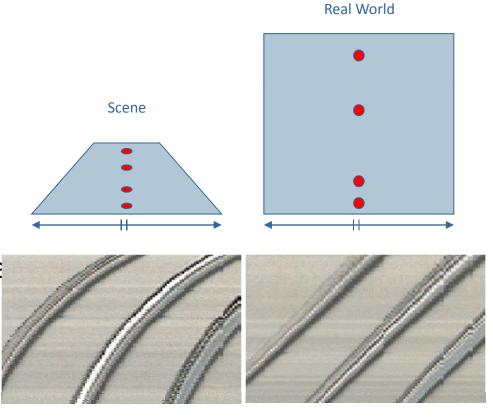
## **Spatiotemporal Maps**

Vertical scan-lines accumulated every frame

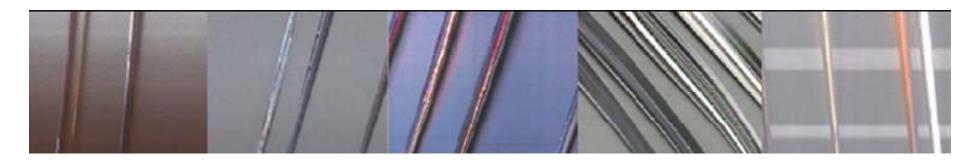


### **Perspective Transform**

- Perspective distorts relative spatial relationships
- Only four user-defined points are necessary for transformation
- Transformation does not have to be exact









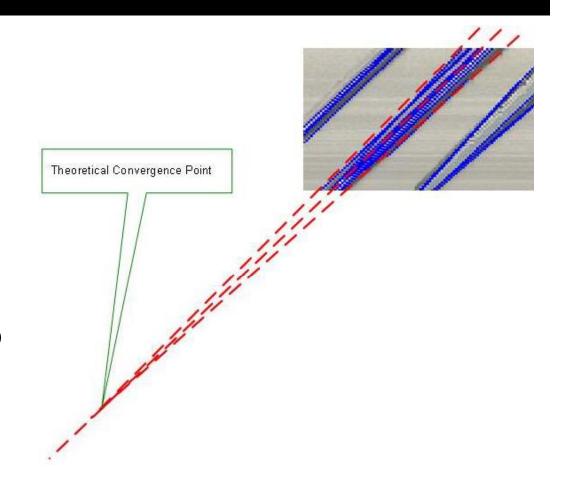


#### **Assumptions**

- Constant speeds
  - Linear strands
- Gaps between following vehicles
  - Varying speeds
  - Camera mounting
- Lane changing vehicles require additional scan-lines

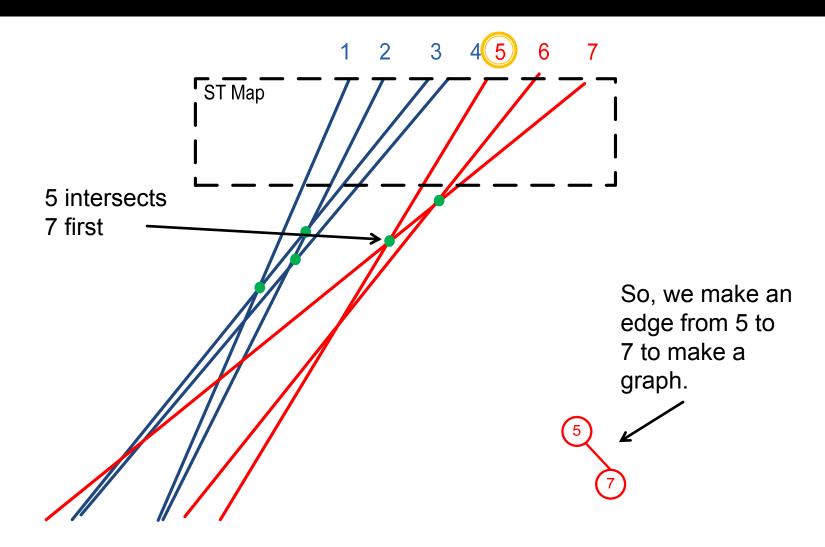
# Hough Transform

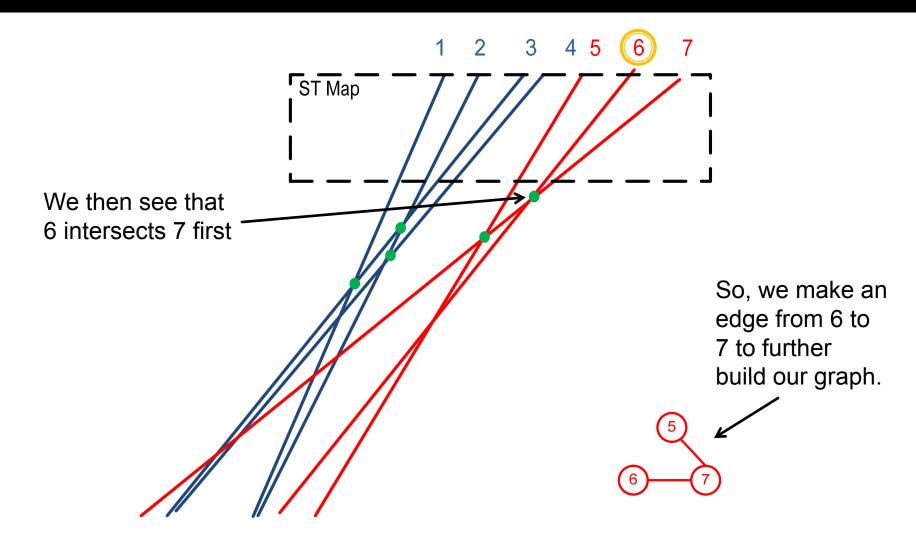
- Finds parameterized lines in images
- Lines indicate traces left by the vehicles
- Lines converge due to height distortion

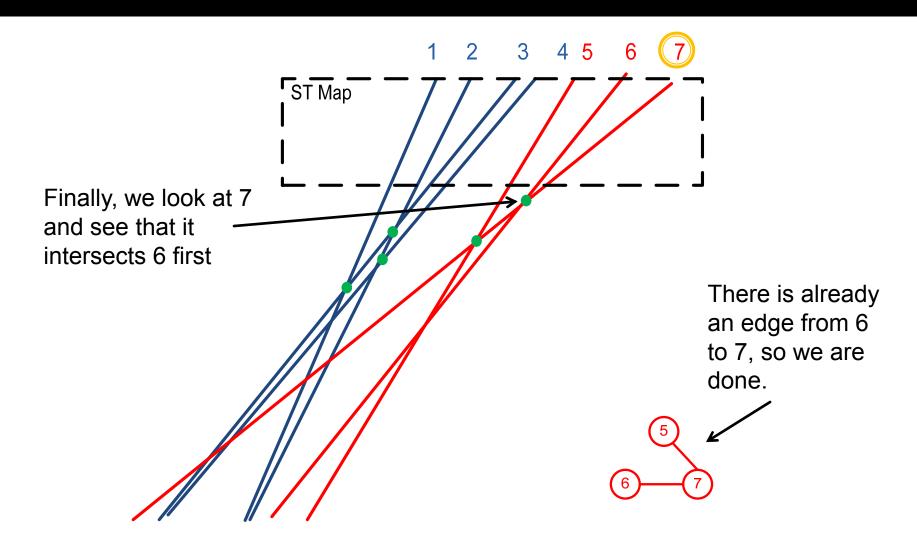


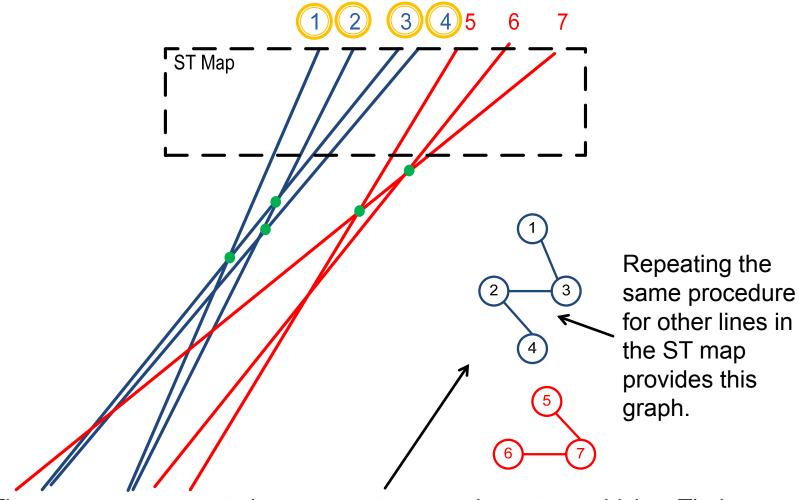
#### Graph Based Clustering

- Use the first intersection as metric
  - For each line, the first intersection is the first line that is encountered from the bottom of the ST-map
- Construct graph based on the first intersection relationship
- Search for connected components



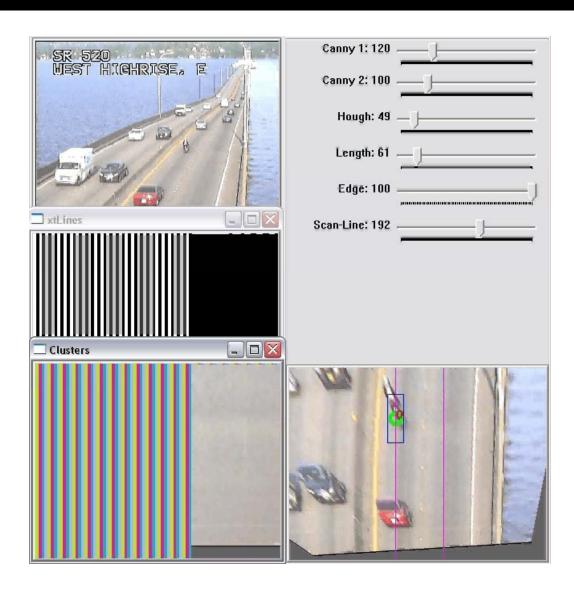




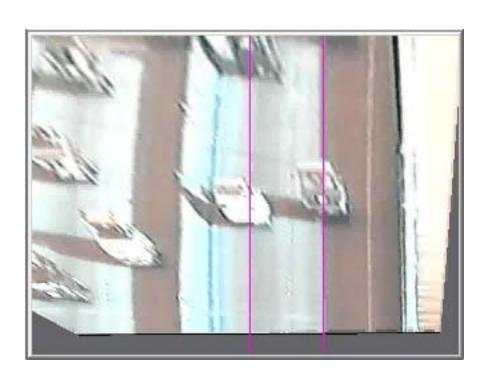


There are two connected components, so we have two vehicles. Their trajectories are the average slopes of all the Hough lines in the group.

#### **VVDC2 Ideal Conditions**



## **VVDC2 Adverse Conditions**



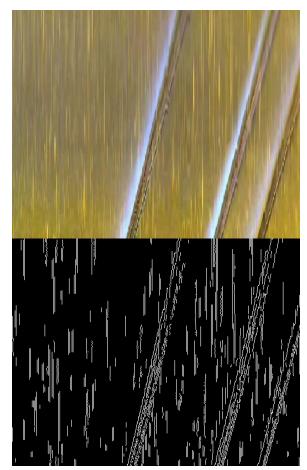


#### **More Adverse Conditions**

- Snow + Incline
  - No difference due to incline
  - Noise
  - Blurs some edges
  - Snow like heavy rain



Original snow video courtesy of Trafficon Inc.



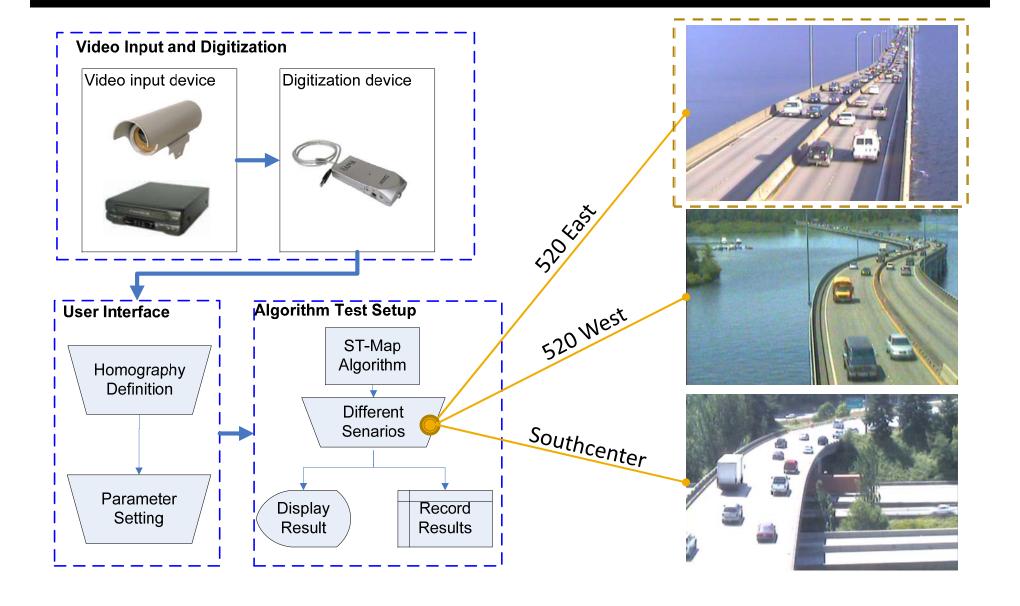
#### **Effects of Adverse Conditions**

- Weather Effects
  - Inconsistent noise trajectories
  - Blurring of certain edges
    - Dense fog or snow
    - Sensitivity must be adjusted if too blurred
- Camera effects
  - Small perturbations in vehicle trajectories
    - Usually not enough to change overall linearity

#### **Experimental Results**

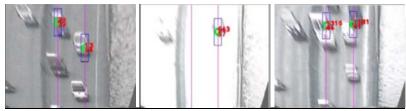
- Experiment Setup
- Hour-long Tests
- 10-minute Tests
- Findings

## **Experiment Setup**



## **Hour-Long Tests**

#### 11:30 pm – 12:30 pm, June 4, 2008

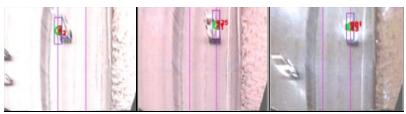


Performance measure	Left lane	Right lane
Manual count	1556	1302
ST-map count	1328	1194
Error rate	14.7%	8.3%



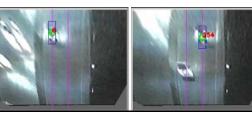
Performance measure	Left lane	Right lane
Manual count	1944	1499
ST-map count	1949	1588
Error rate	-0.26%	-5.94%

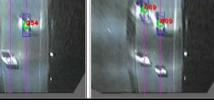
#### 8:30 pm – 9:30 pm, June 4, 2008



Performance measure	Left lane	Right lane
Manual count	871	841
ST-map	882	833
Error rate	-1.3%	1.0%

#### 8:30 pm - 9:30 pm, October 27, 2008





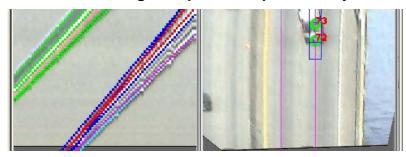
Performance measure	Left lane	Right lane	
Manual count		760	822
ST-map count		687	827
Error rate	9.	61%	-0.61%

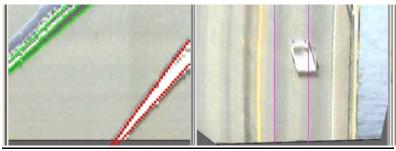
### **Hour-Long Tests Summary**

- Significant errors are usually undercounts
- Conditions did not affect accuracy
- Volume seemed to have an adverse affect
- Latitudinal occlusions (extending from left lane to right lane) did not have big effect

### 10-minute Tests

SR 520 East during 6:30 pm - 6:40 pm, on July 6, 2008



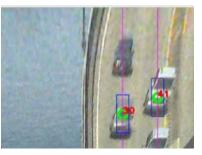


Performance measure	Left lane	Right lane
Under-count	21	12
Over-count	1	3
Lane Changes	1	2
ST-Map Count	191	178
Manual Count	212	189
Overcount Rate	0.47%	1.59%
Missed Rate	9.86%	6.28%

#### 10-minute Tests

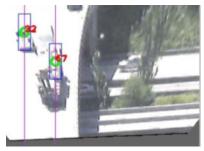
#### SR-520 West during 1:30 pm - 1:40 pm, on July 7, 2008





Performance measure	Left lane	Right lane
Under-count	17	34
Over-count	7	3
Lane Changes	1	1
ST-Map Count	222	234
Manual Count	233	266
Overcount Rate	3.00%	1.13%
Missed Rate	7.26%	12.73%

#### **I5 Southcenter during 2:00pm - 2:10pm, July 7, 2008**





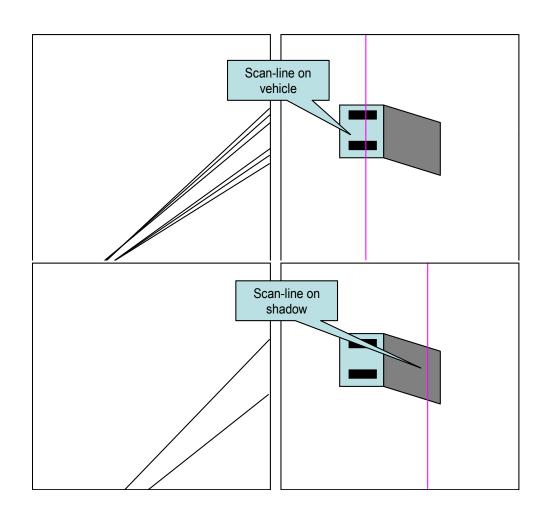
Performance measure	Left	Right
Under-count	9	13
Over-count	11	19
Lane Changes	0	1
ST-Map Count	147	280
Manual Count	145	275
Overcount Rate	7.59%	6.91%
Missed Rate	6.21%	4.71%

#### **Findings: Occlusions**

- Occlusions
  - Lateral occlusions are mitigated
    - Scan-line placement can be manipulated
  - Longitudinal occlusions are more difficult
    - Hard to distinguish where one vehicle begins and another ends
  - Need additional information to reason through occlusions

## Findings: Environmental Effects

- Shadows
- Headlights
- Vibration
- Lighting
- Water trails



#### **VVDC2** Conclusions

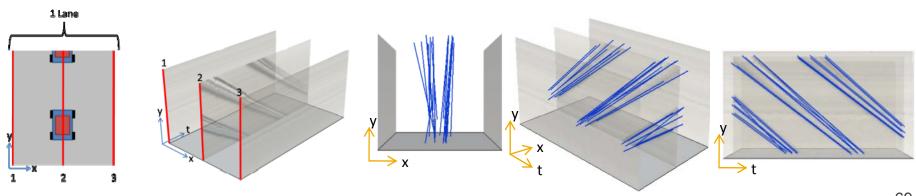
- ST-maps provide a standardized way to view vehicle movement.
- Interpreting ST-maps is simpler than entire frames.
- Relying on Hough transforms to interpret STmaps results prevents many common errors.
- Interpretation of ST-maps through Hough line intersection graphs is a novel concept.
- A variety of conditions were tested, with resulting in error rates from 1 to 15%.

### Applicability to Rural Settings

- Major strength of approach is robustness to environmental factors.
- Works best in low-volume situations.
- Ideal for rural applications.

## Further Work – VVDC3

- Accuracy loss in high volumes
- Stop and go traffic
- Information redundancy for occlusions
  - Texture Model
  - Combine feature points with ST-maps
  - Add third dimension



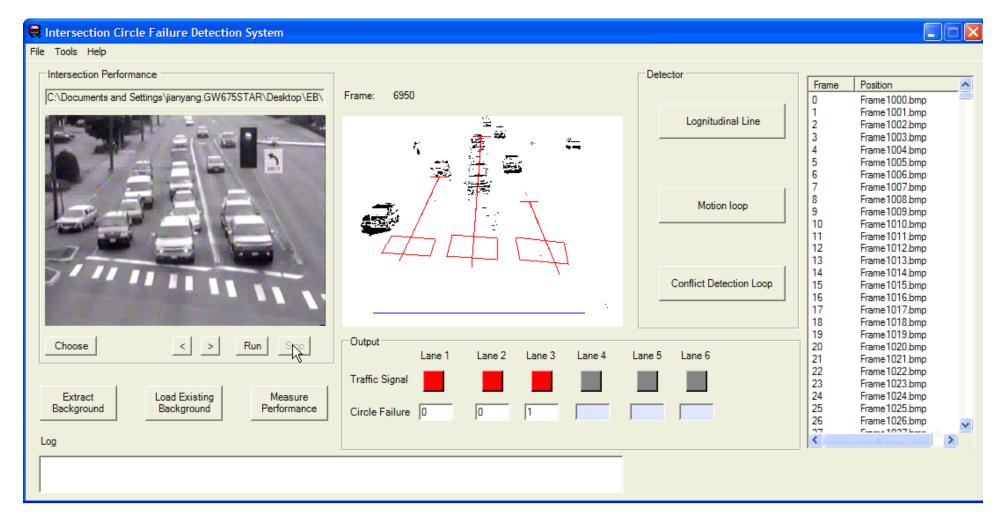
#### **Potential Applications at WSDOT**



### **Additional Directions**

- Cycle Failure
  - Determine potential cycle failures
- PBTrack
  - Track pedestrians and cyclists
  - Determine waiting and crossing times

## **Cycle Failures**



#### **PBTrack**





#### Summary

- VVDC1
  - Accurate
  - Speed and classification info
  - Sensitive to environmental effects
- VVDC2
  - Robust to environmental factors
  - Reasonable accuracy
- Video Detection
  - Many applications, great potential