



# Counting Empty Parking Spots at Truck Stops Using Computer Vision

## Final Report

*Prepared by:*

Pushkar Modi  
Vassilios Morellas  
Nikolaos P. Papanikolopoulos

Department of Computer Science and Engineering  
University of Minnesota

CTS 11-08

## Technical Report Documentation Page

1. Report No. <b>CTS 11-08</b>	2.	3. Recipients Accession No.	
4. Title and Subtitle <b>Counting Empty Parking Spots at Truck Stops Using Computer Vision</b>		5. Report Date <b>May 2011</b>	
		6.	
7. Author(s) <b>Pushkar Modi, Vassilios Morellas, Nikolaos P. Papanikolopoulos</b>		8. Performing Organization Report No.	
9. Performing Organization Name and Address <b>Department of Computer Science and Engineering University of Minnesota 200 Union Street SE Minneapolis, MN 55455</b>		10. Project/Task/Work Unit No. <b>CTS Project #2008076</b>	
		11. Contract (C) or Grant (G) No.	
12. Sponsoring Organization Name and Address <b>Intelligent Transportation Systems Institute Center for Transportation Studies University of Minnesota 200 Transportation and Safety Building 511 Washington Ave. SE Minneapolis, MN 55455</b>		13. Type of Report and Period Covered <b>Final Report</b>	
		14. Sponsoring Agency Code	
15. Supplementary Notes <a href="http://www.its.umn.edu/Publications/ResearchReports/">http://www.its.umn.edu/Publications/ResearchReports/</a>			
16. Abstract (Limit: 250 words)  <p>For at least the past decade, truck driver fatigue has been thought to be a contributing factor in a number of heavy truck accidents. For better utilization of truck stops and to provide truck drivers with safe rest options, we are designing an automated truck stop management system that can compute occupancy rates at stops and notify drivers about the availability of parking spots using variable message displays located about 30 or 40 miles before the stop. Our system detects, classifies and localizes vehicles on the truck stop's grounds by using a set of video cameras, from which video frames are analyzed in real-time.</p>			
17. Document Analysis/Descriptors <b>Computer vision, Truck stops, Variable message signs, Vehicle detection, Automatic vehicle classification</b>		18. Availability Statement <b>No restrictions. Document available from: National Technical Information Services, Alexandria, Virginia 22312</b>	
19. Security Class (this report) <b>Unclassified</b>	20. Security Class (this page) <b>Unclassified</b>	21. No. of Pages <b>31</b>	22. Price

# Counting Empty Parking Spots at Truck Stops Using Computer Vision

## Final Report

*Prepared by:*

Pushkar Modi  
Vassilios Morellas  
Nikolaos P. Papanikolopoulos

Department of Computer Science and Engineering  
University of Minnesota

**May 2011**

*Published by:*

Intelligent Transportation Systems Institute  
Center for Transportation Studies  
University of Minnesota  
200 Transportation and Safety Building  
511 Washington Avenue SE  
Minneapolis, Minnesota 55455

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the Department of Transportation University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof. This report does not necessarily reflect the official views or policies of the University of Minnesota.

The authors, the University of Minnesota, and the U.S. Government do not endorse products or manufacturers. Any trade or manufacturers' names that may appear herein do so solely because they are considered essential to this report.

## **ACKNOWLEDGMENTS**

The authors wish to acknowledge those who made this research possible. The study was funded by the Intelligent Transportation Systems (ITS) Institute, a program of the University of Minnesota's Center for Transportation Studies (CTS). Financial support was provided by the United States Department of Transportation's Research and Innovative Technologies Administration (RITA).

# TABLE OF CONTENTS

CHAPTER 1. INTRODUCTION .....	1
A. Problem Description .....	1
B. Summary of Existing Methods .....	1
C. Advantages of a Computer Vision Based System .....	4
CHAPTER 2. FRAMEWORK FOR MEASURING OCCUPANCY .....	7
A. Approach.....	7
i. Physical Layout .....	7
ii. Calibration .....	7
iii. Seamless Installation .....	7
iv. Greater Accuracy.....	8
v. Extensibility.....	8
vi. Foreground Detection.....	8
vii. Detection and Classification of Vehicles .....	8
viii. Bad Light and Weather.....	8
ix. Manual Over-ride .....	9
B. Methods Evaluated for Foreground Detection.....	9
i. Layering.....	9
ii. Mixture of Gaussians.....	11
CHAPTER 3. IMPLEMENTATION.....	13
A. Data Collection .....	13
B. Algorithm for Determining Occupancy of a Parking Spot .....	14
C. Implementation .....	15
i. Calibration Tool .....	15
ii. Analysis Tool .....	16
D. Challenges.....	17
i. Sudden Changes in Illumination .....	17
ii. Occlusions Due to Vehicles and People.....	18
CHAPTER 4. CONCLUSIONS.....	19
A. Results.....	19
B. Future Work .....	20
i. Trajectory Tracking.....	20

ii.	Voting from Multiple Cameras .....	20
iii.	Gathering Empirical Results under Different Conditions .....	20
	REFERENCES .....	21

## LIST OF FIGURES

Figure 1 – Aerial view of a truck stop, next to a highway.....	ES1
Figure 2 – A sample Variable Message System with live information. ....	ES2
Figure 3 – An illustration of a truck stop with an inductive loop at the entry/exit. ....	3
Figure 4 – Possible camera placement for 9 cameras (C1 through C9) on 5 extended poles [2]. ....	7
Figure 5 – Results from sample runs of Layering.....	10
Figure 6 – Sample of how foreground objects are detected in a sequence of images [6, 11]. ....	10
Figure 7 – A Mixture of Gaussians.....	11
Figure 8 – False positive detected due to a shadow.....	12
Figure 9 – Foreground detected before [center] and after [right] shadow removal based on [7]. ....	12
Figure 10 – A picture of TIM in the non-functional state.....	13
Figure 11 – TIM (on the left) in action in the University of Minnesota – Twin Cities parking lot. ....	14
Figure 12 – Calibration tool used for identifying individual parking spots visible through a camera. ....	16
Figure 13 – Implementation of the algorithm. ....	17
Figure 14 – False positives detected due to lens flare caused by reflection of the sun from the surface of a moving vehicle. ....	18
Figure 15 – False positives detected due to occlusion of a parking spot caused due to a camera’s perspective. ....	18
Figure 16 – Visualization of results to show improvement due to blob tracking. ....	19

## LIST OF TABLES

Table 1 – Driver Preferences for Overnight Stops and Short Naps [1] .....	1
Table 2 – Comparison of Vehicle Detection Technologies [8] .....	2
Table 3 – Results of Simple Grading System for Disseminating Live Information Related to Truck Stops.....	4
Table 4 – Tabulation of Results to Show Improvement Due to Blob Tracking .....	20

## EXECUTIVE SUMMARY

For at least the past decade, truck driver fatigue has been thought to be a contributing factor in a number of heavy truck accidents. It is estimated that driver fatigue leads to about 40% of all truck accidents and 90% of drivers perceive a shortage of parking. Contrary to this, only 53% of truck stops are occupied on any given night [1].



Figure 1 – Aerial view of a truck stop, next to a highway.

For better utilization of truck stops and to provide truck drivers with safe rest options, we envision an automated truck stop management system that can compute occupancy rates at stops and notify drivers about the availability of parking spots using variable message displays (Figure 2) located about 30 or 40 miles before the stop. The proposed system will detect, classify and localize vehicles on the truck stop's grounds by using a set of video cameras, from which video frames will be analyzed in real-time. Since exact knowledge of which stops are occupied will be available, variable message displays at the site of the stop itself will be able to direct drivers to free spots.



Figure 2 – A sample Variable Message System with live information.

There have been other attempts to develop such truck stop management systems in the past but there have been some challenges from the point of view of accuracy [1]. Over the last few years, as camera and processors have advanced while lowering costs, vision has become a tempting option as the primary sensor for detecting the occupancy of individual spots. There are a number of advantages a Computer Vision based system offers over some of the other options, as we shall see in Chapter 1, Section C.

We developed a novel Computer Vision based framework and algorithm for getting a reliable state of individual parking spots. We have also tested an intuitive calibration system, with which a new parking area can be setup in a matter of minutes. We tested our approach on sample videos and the preliminary results have been very convincing. We have identified and overcome some practical challenges in using such a system outdoors, and finally, we have identified future steps to make the system deployable and trustworthy.

# CHAPTER 1. INTRODUCTION

## A. Problem Description

For at least the past decade, truck driver fatigue has been thought to be a contributing factor in a number of heavy truck accidents. There have been a number of studies around the availability of truck stops, driver habits towards parking and the implementation of automatic truck stop management systems [1], [8], [9], [10]. It is estimated that driver fatigue leads to about 40% of all truck accidents and 90% of drivers perceive a shortage of parking. Contrary to this only 53% of truck stops are occupied on any given night [1].

One issue contributing to commercial motor vehicle fatigue may be the lack of safe, available truck parking on or near interstate highways. Even if a parking area is available nearby, a driver may not know about it due to lack of information. According to a recent survey (Table 1), for overnight rests, most drivers preferred truck stops. Even if a driver is not too far from a truck stop, while remaining legal under the hours-of-service rules, he or she may run out of available driving hours with no legal parking available nearby. As a result, drivers sometimes park on the shoulder of a highway or ramp, creating a safety hazard.

Table 1 – Driver Preferences for Overnight Stops and Short Naps [1]

	Overnight Stops	Short Nap
Truck stop	78%	19%
Rest area	6%	45%
No preference	16%	36%

Although existing truck stop directories provide helpful information, an enhancement would be to inform the driver which stops are likely to have parking spaces available. Thus, a system that can assess live parking occupancy would help. They would also contribute towards optimizing the usage of truck stops thus partially alleviating the shortage.

Finally, using such a system, a historical record of parking availability can also be constructed which would also indicate seasonal peaks [1]. This type of information will undoubtedly give us vital insights in the areas of usage, planning and safety.

## B. Summary of Existing Methods

Based on literature reviews highlighted in [8], a wide range of technologies have been successfully introduced or proposed in practice to obtain the basic input data for parking systems. They mainly include: (1) inductive loop detector, (2) ultrasonic sensor, (3) infrared

sensor, (3) Computer Vision (video image processor), (4) microwave radar sensor, (5) laser sensor, and (6) magnetic sensor.

In summary, four technologies' weaknesses and strengths were evaluated and compared across a number of key performance criteria:

1 – Very poor, 2 – Poor, 3 – Adequate, 4 – Good, 5 – Very good, 6 – Excellent

Table 2 – Comparison of Vehicle Detection Technologies [8]

Performance Criteria	Methods of Vehicle Detection			
	Inductive Loop	Ultrasonic Sensor	Infrared Sensor	Computer Vision
Accuracy	2	6	6	6
Cost	5	2	4	2
Installation	2	1	5	3
Reliability	2	4	5	4
Lifespan	3	5	5	4
Effectiveness	2	6	5	6
Total	16	24	30	25

The State of Illinois has implemented a pilot system at two rest stops along I-80 using inductive loops. The observed error of approximately 1 vehicle per hour can add up significantly over the course of several days [1] making the system non-reliable.



Figure 3 – An illustration of a truck stop with an inductive loop at the entry/exit.

It will not be enough to simply broadcast the current space availability via a VMS, when that space availability is likely to change by the time the driver arrives. For example, if a truck stop has 5 spaces left, and 30 drivers converge on the truck stop based on a broadcast of that information, 25 of those drivers will be left unsatisfied [1].

Comprehensive studies have been done in the past [1] where various technologies were considered for disseminating live information from a parking spot. The technologies were broadly classified into pre-trip and en-route information systems and were evaluated for criteria such as Readability, Information Capacity, Currency, Accessibility, Acceptability, Interactivity, Usability, Maintainability, Users' Cost and System Cost. The tools in question were then graded. The results indicated that Variable Message Systems that disseminate live information en-route are the most preferred:

Table 3 – Results of Simple Grading System for Disseminating Live Information Related to Truck Stops

Measures Alternatives	1. Readability	2. Capacity	3. Currency	4. Accessibility	5. Acceptability	6. Interactivity	7. Usability	8. Maintainability	9. User Cost	10. System Cost	Sum	Rank
	Variable Message Sign	4	3	4	5	5	1	5	3	5	3	38
Static Sign	3	1	1	5	5	1	5	5	5	4	35	<b>4</b>
Internet	5	5	5	2	4	5	3	3	2	2	36	<b>2</b>
Radio Broadcasting	3	3	3	4	3	1	4	4	4	2	31	<b>5</b>
Information Kiosk	5	5	5	2	2	4	3	4	4	2	36	<b>2</b>
Telephone Service	2	2	4	3	2	3	3	4	3	3	29	<b>6</b>
Pager Information Service	3	3	3	3	2	2	3	3	3	3	28	<b>8</b>
In-vehicle Navigation Systems	4	4	5	2	3	4	2	2	1	2	29	<b>6</b>
Television Broadcasting	5	3	2	2	2	1	2	4	3	2	26	<b>9</b>

### C. Advantages of a Computer Vision Based System

Although computer vision based truck stop management systems have been considered in the past, one hasn't been implemented till now. With the current state of the world, where high performance cameras and computing power are available at reasonable prices, we are convinced that a computer vision based implementation will have many key advantages:

- Convenient – Cameras can be installed or maintained without interfering with the day-to-day activities at a truck stop, unlike inductive loops, which require pavement cuts and lane closures.
- Non-intrusive – Cameras can be deployed on poles or rooftops where there is a smaller risk of tampering or accidents.
- Practical – A computer vision based system can handle parking areas with multiple entry / exit points and can be easily re-calibrated if the layout of the parking spots change for any reason.
- Economical – Due to the availability of cheap hardware, such a system can be deployed for a fraction of the cost, as compared to systems that rely on inductive loops or infrared sensors. A truck stop already equipped with camera based surveillance systems would need an even smaller investment by extending their existing setup for such a solution.

- Accurate – Computer Vision based systems can offer richer data by identifying the occupancy of every parking spot. Additionally, the margin of error is localized to individual parking spots vs. the entire truck stop.
- Intelligent – Computer vision based systems can offer more than just occupancy related information. With rapid advancements in the field, there are endless possibilities once the basic system is in place. By using advanced classification techniques we would be able to classify vehicles into types and gather historical information for better planning and to identify seasonal peaks and trends. The algorithms could also be optimized to let two smaller trucks share a single large spot or identify parking spots that have not been vacated for certain durations of time.



## CHAPTER 2. FRAMEWORK FOR MEASURING OCCUPANCY

### A. Approach

#### i. Physical Layout

We will design this system to monitor a central parking area with a set of cameras suspended at an elevation of 30-60 feet (on poles, roof-tops, etc.). Depending on the layout of the parking area and the placement of cameras (Figure 3), the administrator may have more than one camera overlook a parking spot.

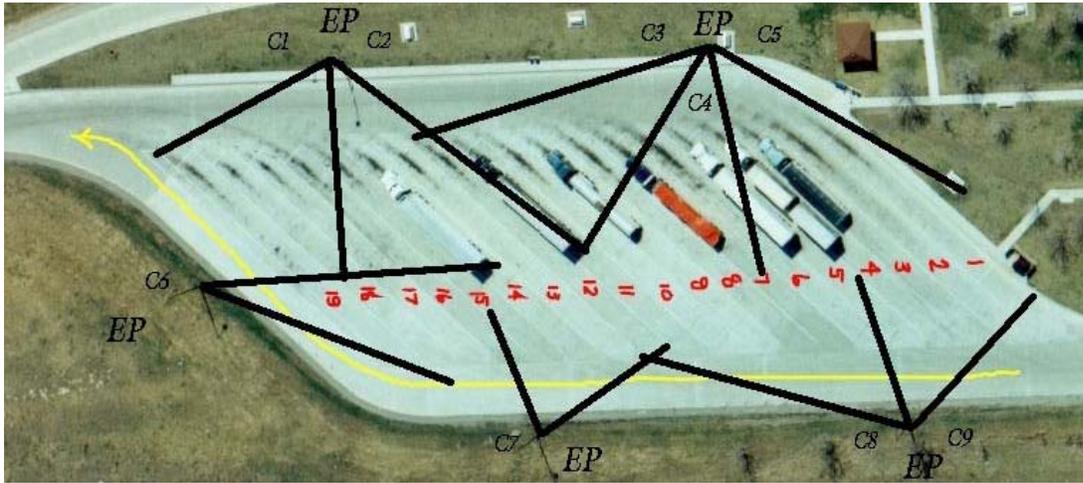


Figure 4 – Possible camera placement for 9 cameras (C1 through C9) on 5 extended poles [2].

#### ii. Calibration

On initial install, the system will need configuration and calibration for modeling the parking area per camera view. During this phase, we will have an administrator point out the parking spots to be monitored using an easy to use Graphical User Interface (GUI), similar to what has been described in [5]. We assume that a parking spot is a rectangular plane. Thus, by accurately marking the four corners of the rectangular region that defines a parking spot, the administrator will help identify the parking spots a camera needs to monitor.

A unique label will be assigned to every parking spot and we will rely on the administrator to help apply an existing label to the same parking spot in a different camera view. At the end of the calibration phase, the total number of labels created will indicate the number of parking spots the truck stop offers. Additionally, we will also have a count of how many cameras monitor a given parking spot.

#### iii. Seamless Installation

We assume that a truck stop will not be vacant during the installation phase. This will avoid any discomfort the drivers and operators would otherwise face and will allow the system to be installed seamlessly, without affecting the existing operations. We should be able to achieve this

by providing a way for the administrator to manually point out if a parking spot is occupied just before the system is activated.

#### **iv. Greater Accuracy**

This implementation will significantly improve accuracy as compared to inductive loop systems by moving the margin-of-error from the overall truck stop to individual parking spots. By employing the vigilance of more than one camera for a given parking spot, we will have greater confidence in deciding whether a parking spot is occupied or not. At the same time, to avoid computationally intensive cross-camera associability, we will let them function independently and let them vote their opinion to the central server. Finally, we hope to extend the system such that the central server can query each camera about the current status of a particular spot.

#### **v. Extensibility**

Unlike inductive loop systems, which are rigid in terms of installation, our system will be easily extensible. If the administrator wishes to improve the accuracy of the overall system by introducing more cameras or if the truck stop requires a change in the layout of the parking spots, the system can simply be recalibrated.

#### **vi. Foreground Detection**

We will mark a parking spot as “occupied” if more than a certain percentage of the background (rectangular plane that defines a parking spot) is occluded by a foreground object (eg: truck). We will determine this threshold on empirical results, as it will change significantly depending on the angle and elevation of the camera. By using a percentage factor, we will not have to worry about the placement of the camera with respect to the parking spots or with respect to each other as both the foreground and background regions will change their size proportionally.

We will not have to employ a sophisticated, computationally intensive segmentation technique in this case as we do not require a high-quality representation of the foreground object. As a fallback, if we need a quick and powerful segmentation technique, we have identified a good probable approach as proposed by X. Bai et. al. in [3].

#### **vii. Detection and Classification of Vehicles**

In order to gather historical data about the usage of parking spots, it will be important to classify the vehicles into various categories. Gupte et. al. illustrates in [5] how they measure the length, height and regions of a vehicle to classify it into a group. They explain that since we have little control over the placement of the camera with respect to the vehicle, we can use known facts of constant features in the view to approximate the measurements of the vehicles. It will be easier to capture the length of a vehicle, when the camera can face the side of the vehicle. Thus, we may use a task-specific camera, placed strategically for detecting and classifying vehicles.

#### **viii. Bad Light and Weather**

Nayar and Narasimhan explain in [4] that virtually all work in vision is based on the premise that the observer is immersed in a transparent medium (air). They illustrate that vision systems must

include mechanisms that enable them to function (even if somewhat less reliably) in the presence of haze, fog, rain, snow and hail. It is not clear to us if adverse weather conditions significantly hamper the performance of the layering tool. We will approach the problem, keeping in mind an interesting technique employed in [5]. Here, the background is modeled as a slow, time-varying image sequence, which allows it to adapt to changes in lighting and weather conditions. Since we do not necessarily compare the cameras view to a model image, we hope the effects of adverse weather will be minimized.

Also, truck stops tend to be in either hilly or open areas and hence we must handle the influence of the wind on the cameras that will be mounted at a height of 30-60 feet. While the layering approach (explained in F) can handle minimal movements of the camera, we feel that the presence of more than one camera will help compensate for the lack of reliability in windy conditions.

#### **ix. Manual Over-ride**

While our system is being tested and bugs are being ironed out, it may be necessary to employ the vigilance of a human operator to manually over-ride obvious mistakes made by our system. We will provide an easy to use GUI to manually over-ride the overall vacancy or the decisions of our algorithms on a spot-by-spot basis. This functionality will play a critical role in letting the system go live while we work to make it more reliable.

Additionally, this functionality may also prove to be useful in extreme conditions of bad weather or light, other unforeseen circumstances or during calibration. We will capture live screen-shots, data and comments from the operator on every instance of an over-ride for debugging purposes.

### **B. Methods Evaluated for Foreground Detection**

#### **i. Layering**

A layering-based technique for detecting a foreground is described in [6] and [11]. In this paper, Patwardhan et. al. model a scene as a group of layers in order to detect a foreground under static or dynamic background and in the presence of nominal camera motion. The system first clusters a scene into “layers” based on statistical similarity between pixels. An in-coming pixel is detected as foreground if it does not adhere to these adaptive models of the background. The authors describe that the technique is fairly efficient and can compute up to 10 frames a second on a standard laptop for a frame size of about 180 x 120 pixels.

From our test runs, we saw that if vehicles with similar colors are parked next to each other [Fig. 5] the layering tool does not do an accurate job of determining new pixels if there is an overlap of pixel with the same color. Additionally, the technique is fairly expensive in terms of computational needs with a time consuming learning cycle that needs to take place before the processing. In order to make this system work for our application, we would need to learn the background every time the status of a parking spot changes making it less desirable.

Here are results from three sample runs:

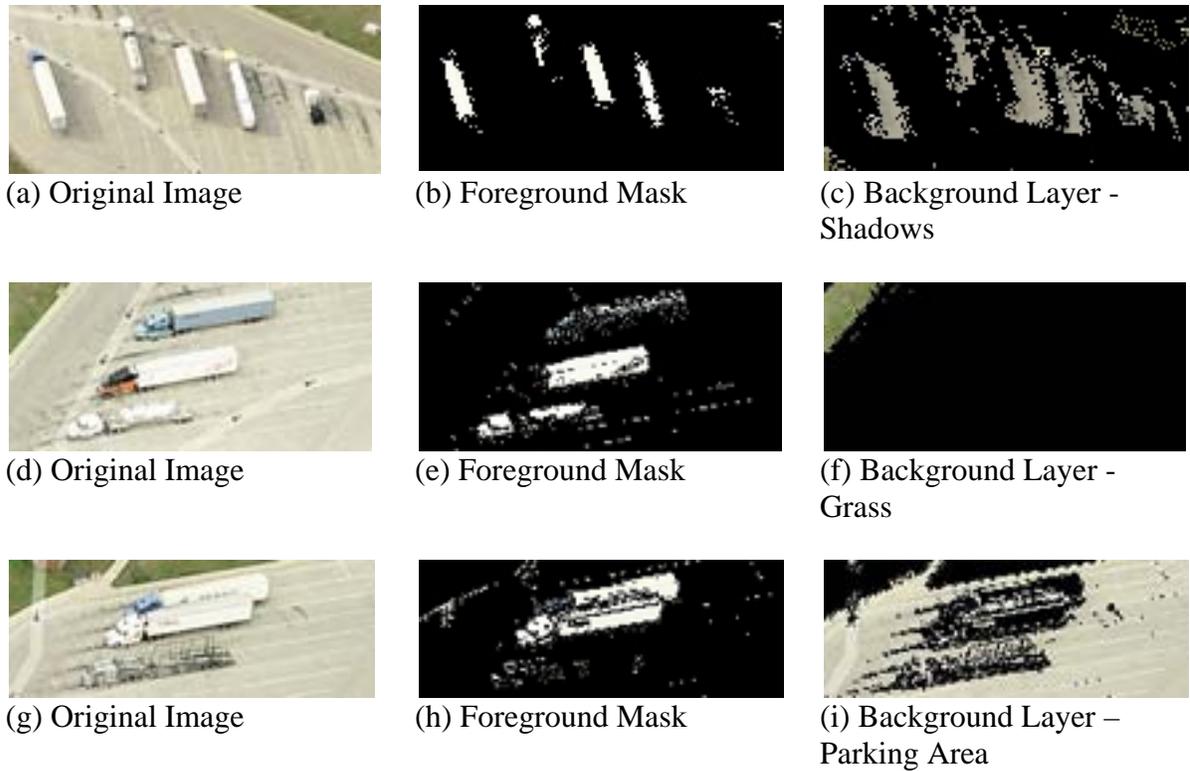


Figure 5 – Results from sample runs of Layering.

We noticed in our segmentation efforts that some trucks have hollow frames and they introduce an additional challenge for the tasks of vehicle identification and classification [Fig. 4(g) and 4(h)].

Foreground Detection using the layering tool:

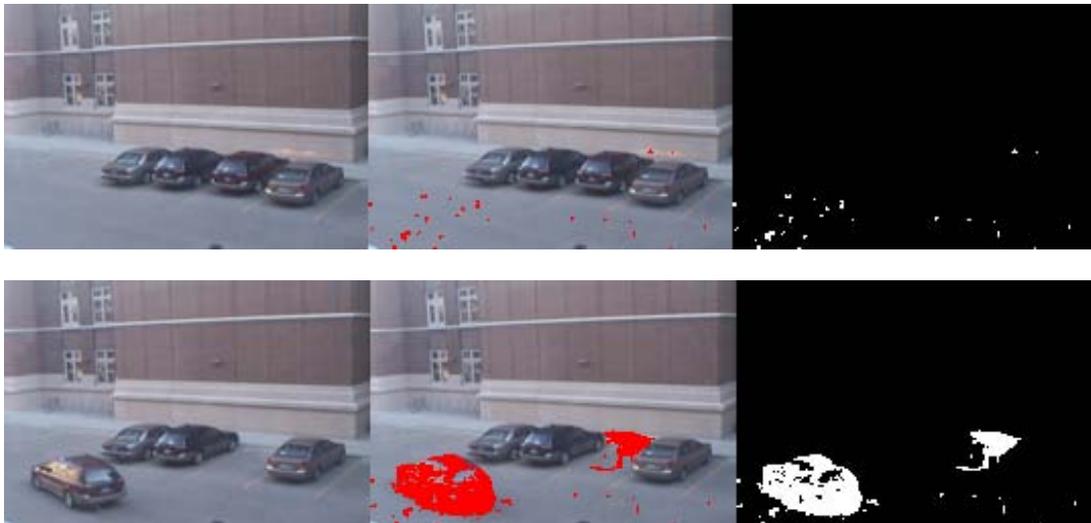


Figure 6 – Sample of how foreground objects are detected in a sequence of images [6, 11].

## ii. Mixture of Gaussians

The second approach we looked at, proposed by Stauffer et. al. [12], describes an approach where each pixel is modeled as a Mixture of Gaussians and is thereafter updated using on-line approximation. Based on the persistence and the variance of each of the Gaussians of the mixture, it is determined which Gaussians correspond to background colors. Pixel values that do not fit the background distributions are considered foreground until there is a Gaussian that includes them with sufficient, consistent evidence supporting it.

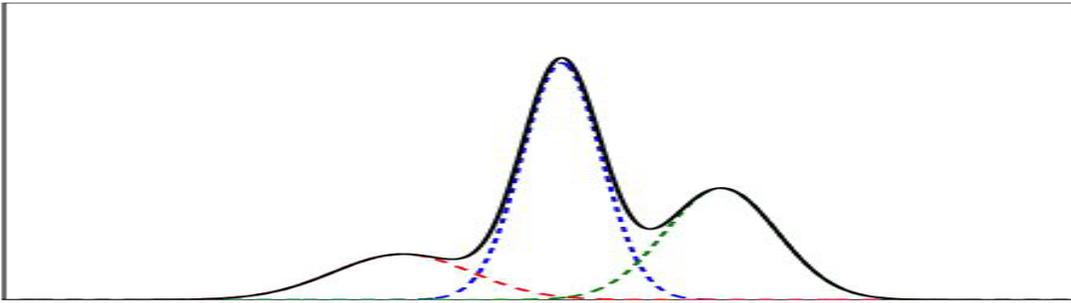


Figure 7 – A Mixture of Gaussians.

An advantage of this technique is that it adapts quite well to lighting changes and slow moving objects (eg: shadow of a pole that would change with respect to the sun's position in the sky). Such a scenario is highly likely in an open environment such as a truck stop and we would prefer that a technique inherently ignore such changes. Another advantage of this technique is that it is relatively less computationally expensive than the layering approach. We could achieve close to real-time performance of frames up to 360 x 240 pixels on a standard laptop. For the approach we have in mind, enhanced image quality will lead to enhanced accuracy. Additionally, it leaves much more room for us to include additional computational cycles for introducing new features as we go ahead.

Unfortunately, for our application the Mixture of Gaussian detects more foreground than we need by detecting a vehicle's shadow as well. Towards the beginning or end of the day when the rays of the sun come at a steep angle, we noticed that the shadow of a vehicle could completely overlap a neighboring parking spot and lead to errors.

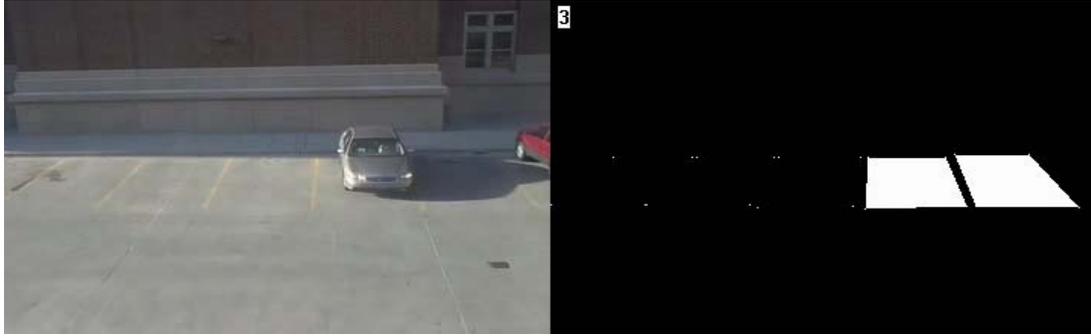


Figure 8 – False positive detected due to a shadow. Note that although only one of the 5 parking spots calibrated has been occupied at position 4, position 5 is also marked as occupied due to the shadow.

Hence, we incorporated a shadow removal technique, as described in [7] that suits our application well. This technique, simple yet effective, is based on the principal that the ratio of RGB values of a pixel will not change in spite of changes in intensity.

Results of foreground detection using Mixture of Gaussians, before and after removing shadows:

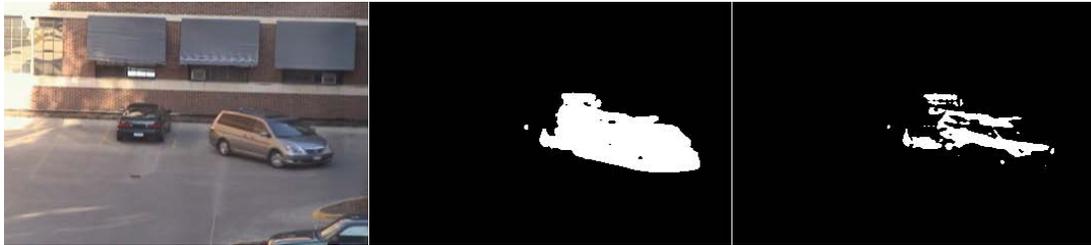


Figure 9 – Foreground detected before [center] and after [right] shadow removal based on [7].

## CHAPTER 3. IMPLEMENTATION

### A. Data Collection

An ideal data-set for this task would involve video feeds of one or more truck-stops, with coverage of the same regions from more than one angle (Figure 4), in different light and weather conditions. We tried (to no avail) obtaining such feeds from the Minnesota Department of Transportation and online webcams. One option is to hire a bucket-truck and record such video from actual sites but that involves some logistical planning given the harsh winters. Carrying this out was an especially difficult option as the closest truck stop from the University of Minnesota – Twin Cities is about 80 miles away.

We started our experimentation with high-resolution, static images (Figure 1) from a website that offers aerial views ([www.maps.live.com](http://www.maps.live.com)). Eventually, we collected some data from car parks on campus behind the Mechanical Engineering building at the University of Minnesota – Twin Cities. A total of 20 hours of video was collected over a span of three days from three different angles and heights using standard tripods, camcorders and a specially made recording device called TIM.



Figure 10 – A picture of TIM in the non-functional state.



Figure 11 – TIM (on the left) in action in the University of Minnesota – Twin Cities parking lot.

TIM, which stands for Traffic and Intersection Monitoring device, is a special trolley-based, camera deployment system designed specifically for such tasks. It has an extensible pole with a high-resolution camera and an on-board computer with many gigabytes of storage available for recording the video feed. Standard 12V car batteries power all this, which allows us to deploy the device for a couple of days. We would like to thank Ted Morris from the Minnesota Traffic Observatory at the University of Minnesota – Twin Cities for letting us borrow TIM.

Data was collected between 7am and 6pm, since that is the time students, faculty members and staff commute to and from campus. In all, we collected over 5 hours of data with some activity with a number of instances of parking lots being occupied or vacated. Our videos do not include changing weather conditions but do include changes in the intensity and angle of sunlight, depending on time of day or cloud cover. The data captured was applied to our simulations for foreground detection techniques (Figure 6, 8).

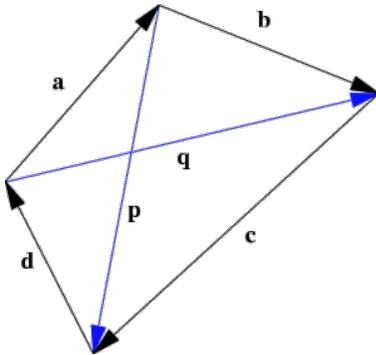
### **B. Algorithm for Determining Occupancy of a Parking Spot**

We determine the occupancy of a parking spot using simple heuristics of how much area a vehicle occludes or uncovers while parking or un-parking respectively. Based on calibration, the operator indicates the image co-ordinates of each parking spot that needs to be monitored.

First, we calculate the lengths of the sides of the quadrilateral that marks the parking spot. Then, using Bretschneider's Formula [14], we calculate the area  $K$ , where

$$K = \frac{1}{4} \sqrt{4 p^2 q^2 - (b^2 + d^2 - a^2 - c^2)^2}$$

and sides  $a$ ,  $b$ ,  $c$ ,  $d$  and diagonals  $p$ ,  $q$  are given as follows:



A pixel that has been marked as a foreground pixel after shadow removal [as explained in Fig. 6] is then checked to see if it falls within any of the parking spots. Based on a threshold, we can then determine if a sufficient percentage of the parking spot has been covered to label it as “vacant” or “occupied”.

### C. Implementation

#### i. Calibration Tool

We developed a special tool for calibrating the system at the time of initial deployment. The tool is designed for a rich user interface for maximum ease of use and is written in XAML and C# on .NET 3.0 using Visual Studio 2005.

The purpose of the tool is to allow an administrator to point out the regions to be monitored as parking spots. With an intuitive user interface, an administrator would be able to hop through live camera views (depending on how many cameras have been deployed) and quickly point out visible parking spots by marking the corners of the respective quadrilaterals.

A parking spot is denoted by a purple overlay once calibrated successfully. The tool is flexible enough to allow calibration regardless of the height, angle or distance the camera is placed at from the parking spots, yet accurate enough to identify one parking spot from another.

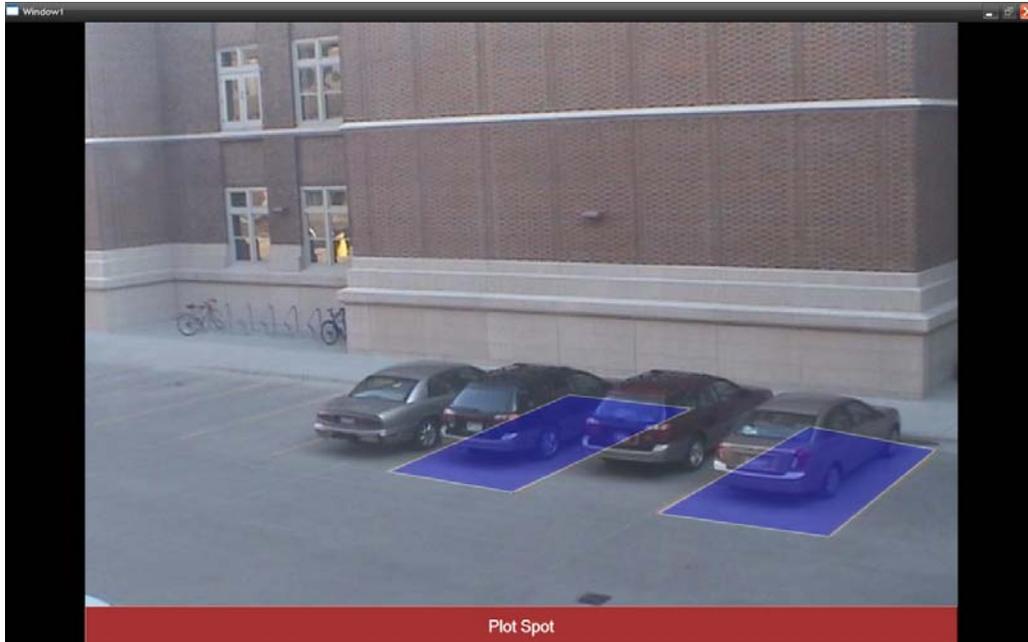


Figure 12 – Calibration tool used for identifying individual parking spots visible through a camera.

As we discussed earlier, we do not expect a parking lot to be vacated when the system is being configured. To allow for this tool provides the option to mark a parking spot as vacant or occupied at the time of calibration. As long as the administrator ensures that every parking spot is set to the correct initial value at the end of calibration, the system will take care of future changes.

This tool allows for re-calibrating the complete system with very little effort. Even if all the parking spots at a given truck stop are re-positioned an administrator should be able to re-calibrate the system in a matter of minutes. As long as the same label is applied to a parking spot, its historical data is not lost. For additional flexibility, the tool allows only a selected set of parking spots to be monitored. Thus, if only two parking spots have been calibrated (as shown in Figure 11) then only those will be tracked for occupancy leading to better overall performance.

## ii. Analysis Tool

Co-ordinates of parking spots from the calibration tool are fed into a proprietary tool where a combination of the Mixture of Gaussians and the shadow removal techniques are implemented in addition to the algorithm for detecting whether an individual parking spot of occupied or not. The implementation was carried out in C++ for Windows using third-party libraries like OpenCV and VXL. Here, each frame, of every deployed camera, is analyzed at close to real-time for activity and overall occupancy for a given camera is displayed on the top-left of the mask frame.

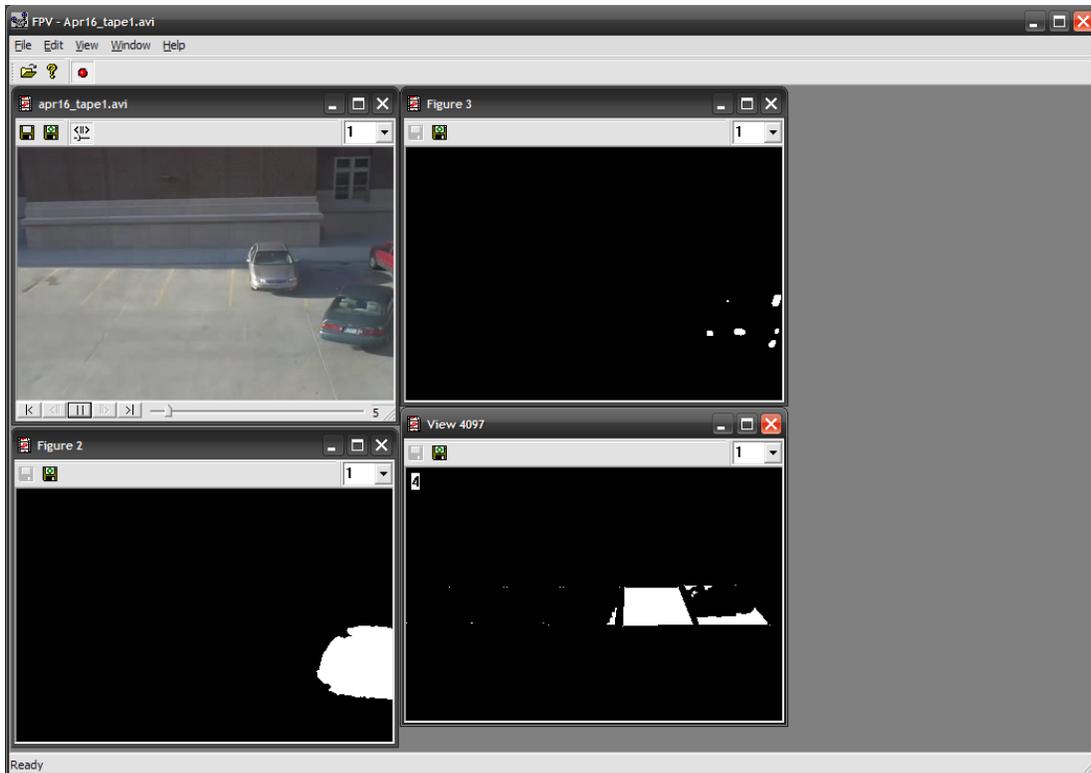


Figure 13 – Implementation of the algorithm. Top-left shows the original implementation. Bottom-left shows the output from the Mixture of Gaussians. Top-Right shows the Region of Interest after shadow-removal. Bottom-Right shows the status of individual parking spots with a counter on the left side.

## D. Challenges

In addition to false positives due to moving shadows, we faced a couple of interesting challenges as we carried out our experimentation. Each of the problems required a custom solution.

### i. Sudden Changes in Illumination

An inherent problem of the Mixture of Gaussians technique is that it fails in conditions where there are sudden changes in illumination. Example: lens-flare, lightning, fast-moving clouds, solar-eclipse, etc. leading to a whiteout in the resultant output. We got a sample of this when the side-view mirror of a truck reflected the rays of the sun for a fraction of a second into one of our cameras.

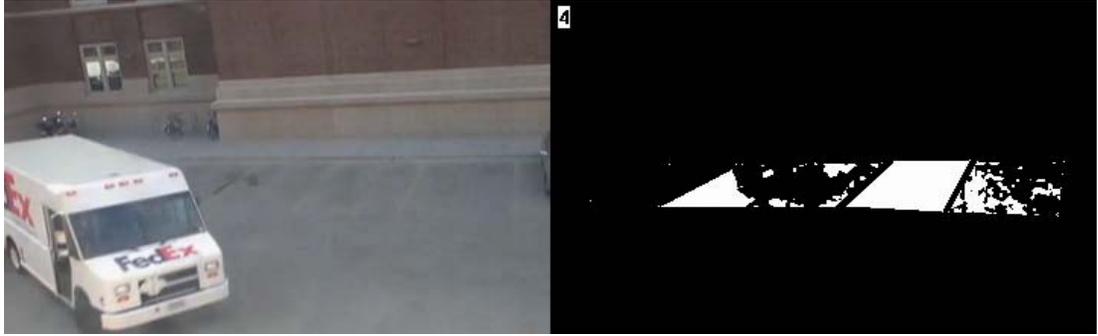


Figure 14 – False positives detected due to lens flare caused by reflection of the sun from the surface of a moving vehicle.

We solved this problem to a great extent by tracking the changes in the mask over a second or two. Given that we can process up to 30 frames per second, our experiments showed that if a change persisted for over 60 frames then there was a high probability that it is not caused due to one of the aforementioned phenomenon.

We also took this opportunity to explore the possibility of comparing data from different camera angles for the same parking spot in case there is an overlap. This theory is based on the assumption that a lens-flare is restricted by the angle of stray light and the probability that it affects more than one camera with different perspectives is small. Finally, there are a number of hardware solutions also available such as special lens coatings, hoods, filters, etc. that can minimize such effects.

**ii. Occlusions Due to Vehicles and People**

If a vehicle occludes more than one parking spot enroute to a parking area, it can lead to erroneous results. We expect the cameras to be deployed at a reasonable height where such issues do not arise. However, if a driver deliberately drives over a number of parking areas before stopping we could still have problems. We aim to resolve this issue by calculating the trajectory of the vehicle and taking it into account with the expected trajectory aligned with the parking spot.

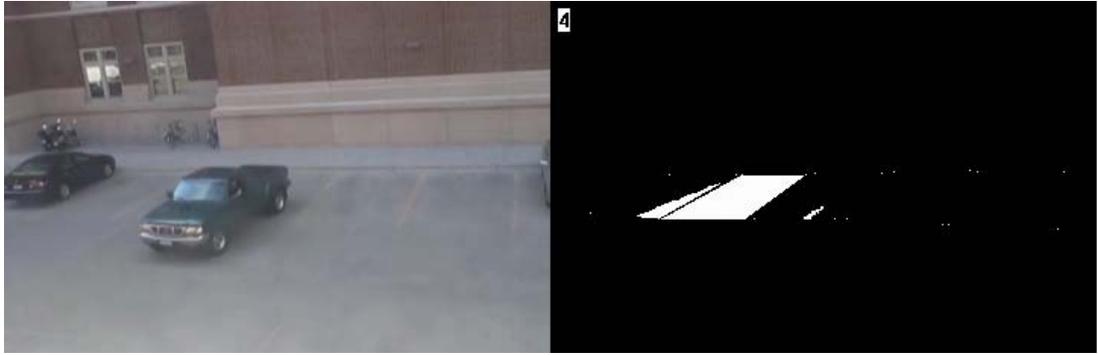


Figure 15 – False positives detected due to occlusion of a parking spot caused due to a camera’s perspective.

## CHAPTER 4. CONCLUSIONS

### A. Results

In all, over twenty hours of video was captured over three days out of which approximately five hours worth of video was useful [13]. We looked for long segments of video where a lot of activity (parking and leaving) happened in quick succession.

We noticed some errors when a person or a group of people walked over a parking spot. Such problems can be solved by tracking a blob through the scene from point of entry to rest or from rest to point of exit. A number of false states were computed before the implementation of blob tracking. The results improved significantly after blob tracking was introduced, where blobs below a certain threshold were ignored. The threshold was calculated based on average number of pixels influenced by sedans.

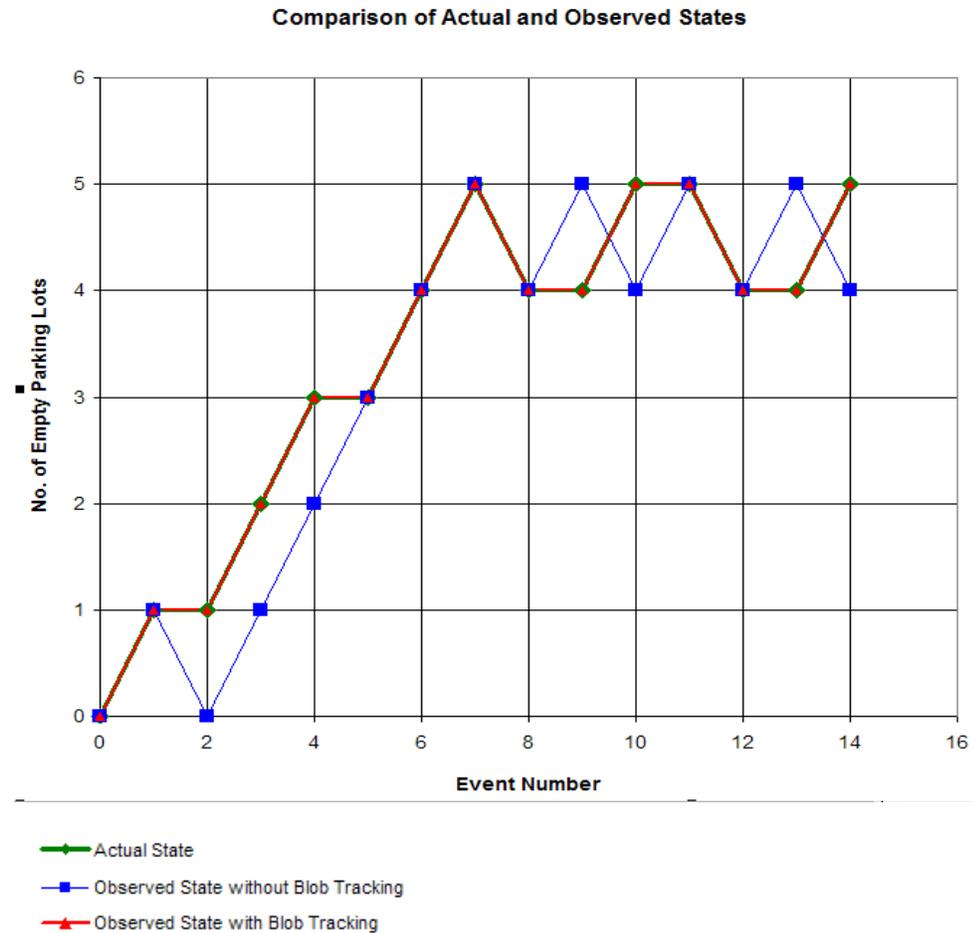


Figure 16 – Visualization of results to show improvement due to blob tracking.

Table 4 – Tabulation of Results to Show Improvement Due to Blob Tracking

Mixture of Gaussians	Events	Detected	False Positives	False Negatives	Accuracy
Without blob tracking	9	9	4	3	44%
With blob tracking	9	9	0	0	100%

**B. Future Work**

**i. Trajectory Tracking**

We aim to calculate the trajectory of the regions of interest to avoid noise and occlusion related problems.

**ii. Voting from Multiple Cameras**

If more than one camera overlooks a given parking area, we could implement a voting based mechanism to improve the overall confidence in the system’s decision-making process. Based on the accuracy record of a camera and its vantage point, we would be able to know which camera should have higher precedence.

**iii. Gathering Empirical Results under Different Conditions**

Capturing data for this project has been a challenge from the onset and it will be essential to exercise and tune these algorithms in different conditions for reliability. Verification in different weather and light conditions is also of the utmost importance. Most truck drivers prefer to use the truck stops at night. Hence, to make this system truly useful, it is essential to test it against a data set, which consists of video in different weather and light conditions.

## REFERENCES

1. S. Smith, W. Baron, K. Gay, G. Ritter, *Intelligent Transportation Systems and Truck Parking*, U.S. Department of Transportation Research and Special Programs Administration, Volpe National Transportation Systems Center, Cambridge, MA, February 2005.
2. N. Papanikolopoulos, Research Project Proposal, Center for Transportation Studies, University of Minnesota, Minneapolis, MN, 2008.
3. X. Bai, G. Sapiro, “A Geodesic Framework for Fast Interactive Image and Video Segmentation and Matting”, *IEEE Int’l Conference on Computer Vision*, Rio de Janeiro, Brazil, 2007.
4. S. Nayar, S. Narasimhan, “Vision in Bad Weather”, *Int’l Conference on Computer Vision*, Vol. 2, pp. 820-827, 1999.
5. S. Gupte, O. Masoud, R. Martin, N. Papanikolopoulos, “Detection and Classification of Vehicles”, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 3, Issue 1, pp. 37-47, 2002.
6. K. Patwardhan, G. Sapiro, V. Morellas, “Robust Foreground Detection in Video Using Pixel Layers”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 30, Issue 4, pp. 746-751, 2008.
7. A.J. Joshi, S. Atev, O. Masoud, N. Papanikolopoulos, “Moving Shadow Detection with Low- and Mid-Level Reasoning”, *Proc. IEEE International Conference on Robotics and Automation*, Rome, Italy, 2007.
8. N. Garber, H. Teng, Y. Lu, “A Proposed Methodology for Implementing and Evaluating a Truck Parking Information System”, CTS, University of Virginia, Charlottesville, VA, May 2004.
9. J. Hall, J. Jammerschmidt, J. Goglia, G. Black, Jr., *Truck Parking Areas, Highway Special Investigation Report*, National Transportation Safety Board, Washington, D.C., May 2000.
10. S. Fleger, R. Haas, J. Trombly, R. Cross, III, J. Noltinius, K. Pécheux, K. Chen, *Study of Adequacy of Commercial Truck Parking*, Federal Highway Administration, Washington, D.C., March 2002.
11. K. Patwardhan, G. Sapiro, V. Morellas, “A Pixel Layering Framework for Robust Foreground Detection in Video”, Dept. of Electrical Engineering & Computer Science, University of Minnesota, Minneapolis, MN.
12. C. Stauffer, W.E.L. Grimson, “Adaptive Background Mixture Models for Real-Time Tracking”, *Proc. Int’l Conf. Computer Vision and Pattern Recognition*, Vol. 2, Ft. Collins, CO, 1999.

13. P. Modi, V. Morellas, N. Papanikolopoulos, "Counting Empty Parking Spots Using Computer Vision", <http://www.youtube.com/watch?v=8Uv-NuXMg7Y>, May 2003. Accessed May 26, 2009.
14. E. Weisstein. "Bretschneider's Formula", MathWorld - A Wolfram Web Resource, <http://mathworld.wolfram.com/BretschneidersFormula.html>. Accessed January 3, 2009.
15. D. Finley, "Point-In-Polygon Algorithm - Determining Whether a Point is Inside a Complex Polygon", <http://alienryderflex.com/polygon>. Accessed January 7, 2009.