

Maximizing Port and Transportation System Productivity by Exploring Alternative Port Operation Strategies

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16. Abstract

Seaports are a critical transportation component that supports the nation's economy. Many U.S. ports are now experiencing significant truck congestion at the gate, which decreases the productivity of ports and truck fleets (e.g. truck wait times) and increases vehicle exhaust emissions, which contributes to air pollution. Actual truck traffic data at the gate, including arrival time, service/processing time, and wait/queue time, is essential for studying truck congestion, but such data has been difficult to obtain with existing manual data collection methods. This research proposes a service time extraction algorithm using video log images taken by surveillance cameras at the gate to effectively acquire this much-needed data.

A service time extraction algorithm consisting of three unique components, 1) a design of two lane-based regions of interest (ROIs) to represent truck trajectories, 2) a frame-differencing change detection algorithm addressing low frame-rate and cast shadow issues, and 3) a unique transition model with a set of decision rules that considers perspective occlusion and other potential sources of false positive detections, was developed to reliably detect truck departures. The performance of the proposed algorithm was evaluated using 6,567 actual images captured via internet at a low frame-rate from a live video feed from a gate surveillance camera in the U.S. Preliminary results demonstrate the robustness of the proposed algorithm by successfully detecting truck departures under various challenging conditions, including day-and-night lighting conditions, perspective occlusion, cast shadows, multi-lane departures, and non-truck movements. The algorithm achieved a correct detection rate of 98.1% for all the images, which can sufficiently represent truck service times at a gate. To further extend the use of this vision-based technology, a vision-based, multi-view gate data acquisition module is proposed to collect the images at the Port of Savannah for wait time extraction validation. In addition, the Georgia Institute of Technology, the Center of Innovation for Logistics, and private sector corporations have initiated a project to extend the proposed algorithm for monitoring and optimizing the flow of truck traffic in the roadway network near the Port of Savannah.

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LIST OF ABBREVIATIONS

ATAMS	Automated terminal asset management system
EIR	Equipment Interchange Receipt
EXPRESS	Application used to capture transport information including Pre-Advise
FY	Fiscal Year
GPA	Georgia Ports Authority
ID	Identification
ILA	International Longshoremen Association
OCR	Optical Character Recognition
PIN	Personal Identification Number
Reefer	Refrigerated container
RDT	Radio data terminal
RFID	Radio-frequency identification
RTG	Rubber tired gantry
TEU	Twenty-foot equivalent unit
WebAccess	Express Web-based application through which transport companies enter information, such as Pre-Advice
ac.	Acre
ft.	Foot
lb.	Pound
lt.	Long ton

SUMMARY

Seaports are a critical transportation component that supports the nation's economy. Many U.S. ports are now experiencing significant truck congestion at the gate, which decreases the productivity of ports and truck fleets (e.g. truck wait times) and increases vehicle exhaust emissions, which contributes to air pollution. Actual truck traffic data at the gate, including arrival time, service/processing time, and wait/queue time, is essential for studying truck congestion, but such data has been difficult to obtain with existing manual data collection methods. This research proposes a service time extraction algorithm using video log images taken by surveillance cameras at the gate to effectively acquire this much-needed data.

A service time extraction algorithm consisting of three unique components, 1) a design of two lane-based regions of interest (ROIs) to represent truck trajectories, 2) a frame-differencing change detection algorithm addressing low frame-rate and cast shadow issues, and 3) a unique transition model with a set of decision rules that considers perspective occlusion and other potential sources of false positive detections, was developed to reliably detect truck departures. The performance of the proposed algorithm was evaluated using 6,567 actual images captured via internet at a low frame-rate from a live video feed from a gate surveillance camera in the U.S. Preliminary results demonstrate the robustness of the proposed algorithm by successfully detecting truck departures under various challenging conditions, including day-and-night lighting conditions, perspective occlusion, cast shadows, multi-lane departures, and non-truck movements. The algorithm achieved a correct detection rate of 98.1% for all the images, which can sufficiently represent truck service times at a gate. To further extend the use of this vision-based technology, a vision-based, multi-view gate data acquisition module is proposed to collect the images at the Port of Savannah for wait time extraction validation. In addition, the Georgia Institute of Technology, the Center of Innovation for Logistics, and private sector corporations have initiated a project to extend the proposed algorithm for monitoring and optimizing the flow of truck traffic in the roadway network near the Port of Savannah.

CHAPTER 1:
INTRODUCTION

Seaports serve as a critical transportation component that support the nation's economy. The ports carry 95% of U.S. foreign trade and contribute 700 billion dollars annually to the U.S. gross domestic product (*1*). With continuous growth in international trade, many U.S. ports are now experiencing significant truck congestion at the gate. Truck congestion is a great concern to port authorities, trucking companies, and the public because it decreases the productivity of ports and truck fleets (e.g. truck wait/queue times) (*2*) and increases truck exhaust emissions and local traffic congestion (*3, 4*). Truck wait times were estimated to be more than 3.7 million hours annually at the Los Angeles and Long Beach ports (*5*), and truck wait costs were estimated at more than two million dollars annually at the Maersk terminal at the Port of New York and New Jersey (*6*). Because of the magnitude and negative impacts of truck congestion, studies on truck traffic at the gate are needed for exploring different solutions to mitigate truck congestion. For example, a terminal gate appointment system was adopted at the Los Angeles and Long Beach ports as a means of reducing truck queues at gates (*7, 8*).

Actual truck traffic data at the gate, including arrival time, service/processing time, and wait/queue time, is essential for better understanding truck behavior at the gate, identifying bottlenecks, and quantitatively evaluating different solutions. Unfortunately, there is limited data available due to the existing data collection methods. Previous studies of truck congestion at the gate were often based on limited data collected through field observation (*8*). In recent years, several studies have reviewed video log images taken by the gate surveillance cameras (*9, 10, 11, 12*) to gather truck traffic data at the gate. However, the data collected has been limited to short periods of time (e.g. hours) because existing manual review methods are tedious and time-consuming. The difficulties in obtaining the data have limited the study of truck congestion at the gate.

This research proposes a service time extraction algorithm to automatically extract service times from video log images taken by the gate surveillance cameras. The unique challenges, such as low frame-rate, day-and-night lighting conditions, and perspective occlusion, in developing a robust service time extraction were first identified, and a literature review of classical image processing techniques for traffic monitoring applications was conducted. A service time extraction algorithm integrating three unique components: 1) a design of two lane-based regions of interest (ROIs) to represent truck trajectories, 2) a frame-differencing change-detection algorithm addressing the low frame-rate and cast shadow issues, and 3) a unique transition model comprising of a set of decision rules for determining truck movement, was developed to automatically extract service time data under various challenging conditions. An experimental test was conducted using actual images captured via the internet from a live video from a single gate surveillance camera to evaluate the performance of the proposed algorithm. To extend the application of the vision-based technology, a vision-based, multi-view gate data acquisition module is proposed to collect the images at the Port of Savannah for automatic truck wait time extraction validation.

The remainder of this report is organized into the following chapters. Chapter 2 summarizes the literature regarding traffic monitoring using image processing techniques.

Chapter 3 presents the development and validation of the service time extraction algorithm. This chapter presents the flow charts and detailed designs for the three important components in the proposed algorithm and the algorithm's test. Chapter 4 proposes a vision-based, multi-view gate data acquisition module to collect the images at the Port of Savannah for validating automatically extracted wait time. This chapter also reviews the business and logistic processes at the Port of Savannah. Chapter 5 concludes the findings of this study and discusses future research.

CHAPTER 2:
LITERATURE REVIEW

This chapter reviews the image processing techniques for traffic monitoring and vehicle detection, focusing on the challenges of developing a robust service time extraction algorithm. The challenges, including low frame-rate, perspective occlusion, and cast shadows, are first reviewed. A literature review was conducted and shows that current vehicle tracking techniques are not suitable for the low frame-rate sequences. A unique approach that integrates the knowledge of the geometry of the scene and expected truck trajectories is proposed to detect truck departures in this study. In addition, the approaches for addressing perspective occlusion and cast shadows are presented.

2.1 Unique Challenges in Extracting Service Time

The images used in this study were captured via the internet from a live video feed from a gate surveillance camera in the U.S. Due to the limitation on the refresh rate, the images were captured at a low frame-rate (e.g. 0.2 frames per second (fps), which equates to one full frame for every five seconds). The use of low frame-rate images poses challenges to the proposed algorithm because the change in illumination between consecutive images can be large. In addition, the unique characteristics posed by the gate layout and operation, including day-and-night lighting conditions, multi-lane departures, perspective occlusions, non-truck movements (e.g. operations crews and vehicles), cast shadows, and weather conditions, can also affect the detection of truck departures. Because the image covers multiple lanes, there might be several trucks departing at the same time in different lanes, which is called multi-lane departures. In addition, there are different degrees of perspective occlusion associated with each lane. This issue is further complicated by multi-lane departures. Some trucks may be occluded and cannot be seen in the images. Non-truck movements by operations crews and/or vehicles can also trigger false detections. Figure 2.1 shows an example of perspective occlusion, multi-lane departures in occluded adjacent lanes, and non-truck movement (e.g. an operations crew) that can trigger false detections.

(a) Perspective occlusion (b) Multi-lane departures (c) An operation crew

Figure 2.1 Unique challenges in developing a robust service time extraction algorithm.

2.2 Literature Review of Traffic Monitoring Applications

A large amount of research has been conducted for traffic monitoring applications with fixed cameras (*13, 14, 15*). The most frequently used approach integrates two algorithms referred to as "core technologies," which were used in a recent survey on behavior analysis (*16*): a motion detection algorithm that aims at detecting moving objects in the images and a tracking algorithm that establishes object temporal correspondences between successive frames.

Motion detection in the context of a static camera is a hot topic in computer vision, and many different solutions have been proposed using algorithms that can be categorized into three main types: frame differencing, optical flow, and background subtraction. The first category, frame differencing, is the simplest method, which consists of subtracting a previous frame from the current frame and thresholding the difference between the pixels in two images (*17, 18*). Textured objects are needed to obtain precise foreground masks (*18*). Two challenges are associated with this method. First, there are some artifacts in the foreground masks. In particular, "ghost objects" can be observed if the current frame does not contain the moving objects of the previous frame. This challenge can be partially addressed by combining results from different frame differences or by using the gradient information (a ghost is not associated with any edge). For example, a double-difference operator (also called three-frame differences) could be combined with an edge-detection step (*19, 20*). Second, temporarily stopped objects are not detected. However, the main advantages of this method lie in its simplicity and its ability to take into account illumination variations without any update process. The second category consists of estimating the motion vector field between two frames (i.e. the optical flow) (*21*). It is based on the assumption of color/intensity consistency between frames. The algorithm works with a moving camera, which is a real advantage for some applications. However, it is an iterative method, which minimizes an energy function and, therefore, is computationally expensive. The second category, optical flow, requires special hardware for the real-time implementation; therefore, it is not included in our review. The third category is the background subtraction method that is often preferred to frame differencing and optical flow (1*3, 14, 15, 22*). This method obtains good detection results while limiting the computational cost. The principle of the method is to model the background. Then, the current frame can be compared with the background model in order to extract the moving objects. The background model is to grasp the statistics of each background pixel. Adaptive models have been proposed in order to deal with changes in illumination. Recursive techniques, which update the background model based on the information contained in the last frame, are often employed for their simplicity (*13*). In particular, one popular solution that addresses the multi-modal background is the Gaussian Mixture Model proposed by Stauffer and Grimson (*23*). This model has been used in several transportation applications (*14, 24, 25*).

Tracking consists of establishing temporal correspondence between successive frames. In other words, a tracker associates a consistent ID with the objects of interest present in different frames. Therefore, it is a crucial step for deriving the vehicle trajectories. The main challenges of tracking are occlusion, unpredictable and abrupt motion patterns, changes in appearance, and deformed objects. Occlusion is still an open problem (*26*). Occlusion situations are caused by the perspective effect: two objects (for example, two vehicles in adjacent lanes or one vehicle in a part of the scene) are overlapping in the image plane due to the camera position. A bird's-eye view (i.e. aerial images), theoretically, prevents such a situation. Unpredictable movements are related to maneuvering targets, pedestrians (a person can suddenly turn direction), and other situations. In particular, camera panning makes the tracking more challenging (*27*). A low frame-rate makes the prediction of the movement difficult, too, since observations are far away in time (abrupt variations). The tracked object can also change in appearance between frames and make the tracking more challenging. This issue occurs particularly in approaching vehicles, maneuvering/turning vehicles, and camera zooming. The perspective effect is related to the camera position and is responsible for the changes in appearance (aerial images are not subject to changes in appearance). The tracking algorithms can be divided into several groups: region-based methods, model-based methods, feature-based trackers (*28*), and contour-based trackers. Recent reviews on tracking algorithms can be found in several articles (*29, 30*).

A large majority of the proposed algorithms make use of images taken from a static camera at a normal frame rate (10 - 30 fps). However, in this application, the images are taken from the web at a frame rate of 0.2 fps. Only a few studies have been conducted to address the challenges of the low frame-rate sequences of images (*31, 32, 33, 34*). The first two studies deal with frame-rates of 1-2 fps, which is much larger than the frame-rate used in our study. Santini uses low-resolution images at a frame rate between 10 sec/image and 30 min/image to analyze the traffic flow in urban areas. However, the work aims at providing a global, rough measurement of the traffic flow, whereas, in our study, local and precise information must be derived (for each lane). The main challenges associated with the very low frame-rate camera are well highlighted in Santini's papers; due to the low frame-rate, the assumption that the background is smoothly changing cannot be made. Significant changes in image appearance can be observed because of illumination changes, camera adaptive gain control, and poor color consistency. In addition, as the frequency of observation is very low, it is difficult to build a representative model of the background and to maintain it. Consequently, an algorithm based on the update of a background model does not seem adaptable to this problem. An algorithm based on frame differencing has been chosen because it is highly adaptive to changes in illumination and does not require the update process. In addition, the proposed algorithm is based on changes detected inside manually designed ROIs (as explained in next paragraph). A precise foreground mask is not required, and the "ghost" detection associated with the frame differencing technique is not problematic.

The low frame-rate in this study also makes finding object correspondences between consecutive images (i.e. the tracking) very difficult due to poor motion continuity, increased search space, and larger appearance variations. Even if some solution has been proposed to address this challenge (*32, 35*), the frame-rate considered is still larger than in this application. Furthermore, the camera position at the port gate introduces large perspective occlusion between lanes. For all of these reasons, two ROIs for each lane are defined based on the knowledge of the geometry of the scene and expected truck trajectories to detect truck departures. This injection of prior knowledge allows replacing the tracking by a trajectory validation process: a truck departure is validated by checking the motion information in pre-defined areas matching the known trajectory. There are two advantages of employing this strategy. First, the algorithm is simplified. Second, false positive/false negative detections caused by tracking error can be eliminated.

Cast shadows are also an issue. The areas corresponding to the shadows of moving vehicles are associated with large changes in illumination and can lead to false positive truck departures. In classical traffic monitoring algorithms, researchers add a shadow detection step inside the motion detection module to separate different vehicles and improve the accuracy of the foreground mask. The color information allows detection of foreground pixels corresponding to a darkening background. The HSV color space can be used to detect pixels having the same hue as the background but with a lower saturation and value (*14, 25, 36, 37*). Some studies consider the brightness and color distortion derived from the RGB components (*38, 39*). Other researchers make use of texture information, since the shadow regions are quite uniform (*15, 40, 41*). Algorithms working with grayscale images are also proposed (*26, 42*). A review of shadow suppression algorithms has been published (*43*). In this application, precise foreground segmentation is not needed. The system aims at analyzing global statistics inside the ROIs in each lane to discriminate cast shadows from a truck inside the ROI. Therefore, the brightness distortion has been selected for its simplicity.

CHAPTER 3:
PROPOSED SERVICE TME EXTRATION ALGORITHM

To effectively extract the service time data from the video log images taken by the surveillance cameras at the gate, a service time extraction algorithm using image processing techniques was developed. This chapter presents the development and validation of the proposed algorithm. The procedure for measuring the service time using the image was first defined. The flow chart and detailed design of the proposed algorithm are presented. The proposed algorithm integrates three components: 1) a design of two lane-based ROIs to represent truck trajectories, 2) a frame-differencing change-detection algorithm addressing the low frame-rate and cast shadow issues, and 3) a unique transition model comprised of a set of decision rules for determining truck movements and providing reliable truck departure detection. The performance of the proposed algorithm was then evaluated using the actual video log images captured via the internet from a live video from a gate surveillance camera. Finally, analyses at a detailed level were performed to explore the value of utilizing the service time data extracted.

3.1 Service Time Measurement

To measure service time, the truck movement at the gate was first identified through a review of a series of images/actions. A truck arrives at the port and joins the end of the waiting line in a particular lane that the driver chooses. The truck stays in the same lane and gradually moves to the waiting line. The truck stops at the waiting line and proceeds to a station when available, as shown in Figure 3.1. A truck often stays in the same lane after reaching the waiting line, rarely changing lanes. As service time is the time a truck is being processed or served at the terminal gate, it can be measured as the difference in time between two consecutive truck departures at the waiting line in the same lane, assuming the travel time between the waiting line and the station is short. A truck departure is referred to as the earliest movement that a truck makes when leaving from the waiting line and moving toward the station. A truck stopping at the waiting line or continuing to move toward the station after leaving the waiting line is not considered as a truck departure. Note that with this measurement method, the service time will include the idle time (i.e. no truck at the waiting line) when there is no queue.

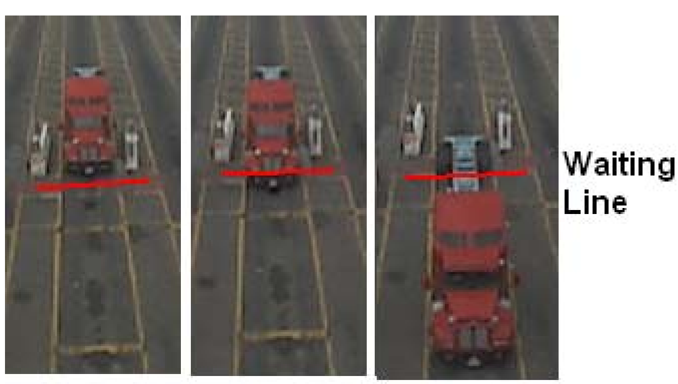


Figure 3.1 Example of the truck movement at the waiting line.

3.2 Development of a Service Time Extraction Algorithm

The service time is the difference in time between two consecutive truck departures at the waiting line in the same lane; therefore, detecting a truck's departure movement is essential for deriving service time data. This section presents a service time extraction algorithm that aims at reliably detecting a truck's departure movement in each lane under various challenging conditions (e.g. low frame-rate, day-and-night lighting conditions, perspective occlusion, cast shadows, multi-lane departures, and non-truck movements). To address the challenges of low frame-rate sequences, a trajectory validation process is proposed for detecting a truck departure. The validation process checks a truck proceeding through expected locations within a sequence of images (times). This design incorporates prior-knowledge about a truck's trajectory and enhances the robustness of false positive detections while simplifying the algorithm. The flow chart of the proposed algorithm is shown in Figure 3.2. First, ROIs were pre-defined to capture two critical movements in the expected truck's trajectory to correctly detect truck departure movements. F_t, F_{t-1} and F_{t-k} are the current frame, the previous frame, and the k^{th} previous frame, respectively. The color frame difference is computed from F_t and F_{t-1} to be robust to changes in illumination. The brightness distortion is calculated using F_t and a further-delayed frame, F_{t-k}, in order to have access to a reference frame without any cast shadow. The change detection conditions that describe the motion and the truck texture make use of the aforementioned features: color frame difference and brightness distortion. Finally, a unique state transition model that includes a set of complex rules enables the reliable detection of the truck departures while considering perspective occlusion and other sources of potential false positive detections. The three major steps, including the ROI design, a change detection using the color frame difference and the brightness distortion, and a state transition model, are presented below.

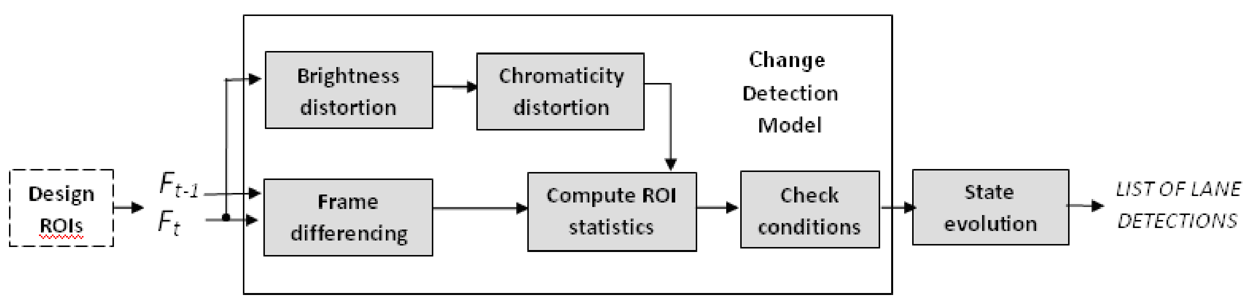


Figure 3.2 Flow chart of the proposed algorithm.

3.2.1 ROI Determination

Two ROIs per lane were designed to match a truck's trajectory by capturing two critical movements along the expected trajectory (departing from the waiting line and moving toward the station). Validating a truck departure requires a truck proceeding through two ROIs in order within a sequence of images (times); the detailed rules are to be further discussed in the state transition model. Figure 3.3 shows the two ROIs in each lane. The first ROI, located before the waiting line (BWL ROI), was designed to detect a truck departing/crossing the waiting line and was carefully sized to avoid a perspective occlusion effect. As the ROIs were designed to capture the expected lane geometries inside the image, the ROIs' size varies. The second ROI, located after the waiting line (AWL ROI) was designed to verify a truck is moving to the station. The texture of the trucks was considered when determining the position of the ROIs. These designed ROIs partially address perspective occlusion and eliminate the requirement for a tracking module (challenging for low frame-rate sequences) by incorporating prior knowledge of the truck trajectory within the scene geometry.

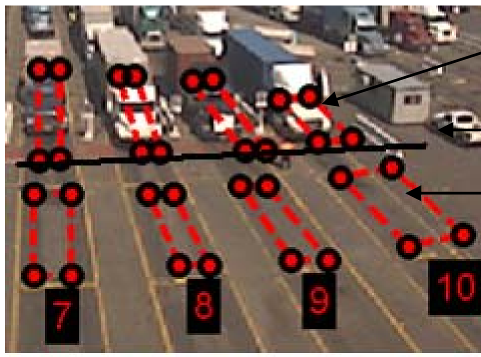


Figure 3.3 Two ROIs (BWL ROI and AWL ROI) for each lane.

3.2.2 Change Detection using Frame Differencing & Brightness Distortion

A change detection algorithm based on color frame difference and brightness distortion was developed to detect the presence of a truck in the ROIs. The low frame-rate makes the use of an adaptive background model very difficult. Therefore, a model based on frame difference, which does not require the background update process, is employed. The drawbacks associated with this technique, such as poor foreground mask and "ghost" detections, can be resolved because of the use of ROIs for change detection. The color frame difference and the brightness distortion used to describe a textured moving object in the ROIs are described below, and the conditions for detecting a truck in the ROIs are presented.

<u>*Computation of Color Frame Difference and Brightness Distortion*</u>

The color frame difference value is computed by summing the absolute difference between the current and the previous frame's intensity for each channel in color space (Equation 1).

$$CFD_t(x) = \sum_{c=1}^{3} |I_t^c(x) - I_{t-1}^c(x)| \qquad \text{(Equation 1)}$$

CFD stands for the color frame difference; I^c_t refers to the intensity of the channel c (red, blue, or green) of the color image at time t; x is the pixel position. The mean color frame difference allows computing a global statistic inside the ROI. However, the mean can be affected by the outliers and noisy values. Therefore, a confidence measure is associated with the color frame difference values through a fuzzy membership function (Figure 3.4). This function introduces the use of saturation in order to reduce the impact of the outlier values. The influence of noisy values is also reduced by using a minimum threshold. This membership function has been designed by analyzing the CFD in calibration images with different weather conditions; it can be modified by statically analyzing the values of the CFD obtained from reference frames when applying it to different sites.

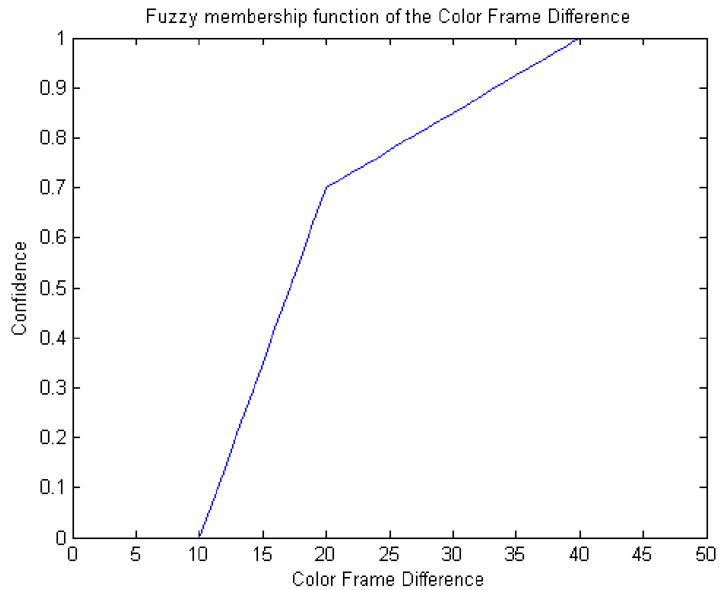


Figure 3.4 Fuzzy membership function for the color frame difference.

The color frame difference alone cannot differentiate between a textured moving object and cast shadows. Indeed, the cast shadows may be associated with large changes in color intensity and result in a false detection of a truck departure if the lane has been pre-detected (e.g. large changes in illumination). To address this issue, the global color distortion is separated into the brightness distortion and the chromaticity distortion (*38, 39*). This separation enables differentiation of the changes in color from the changes in illumination. Figure 3.5 shows the brightness distortion (α_i) and the chromaticity distortion (CD_i) between the current RGB values I_i and the reference value E_i in the RGB color space. In these notations, the index i refers to the pixel position.

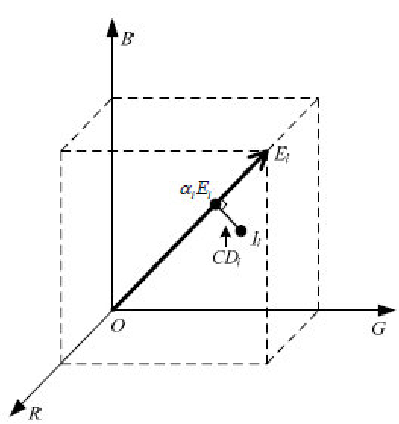


Figure 3.5 RGB color space with the brightness and chromaticity distortion.

The brightness distortion (BD_i) is defined as the scalar value such that BD_iE_i is the projection of OIi on OEi. It is obtained by minimizing the function Φ (Equation 2).

$$\Phi(BD_i) = (I_i - BD_iE_i)^2 \qquad \text{(Equation 2)}$$

BD_i is 1 if the brightness of the pixel in the current image is the same as in the reference image. It is less than 1 if it is darker and greater than 1 if it is brighter. Cameras may have unequal sensitivity among color bands. Therefore, the pixel values are normalized by the standard deviations of each band. It leads to the following formula (Equation 3) for the brightness and the chromaticity distortion (*38*):

$$BD_i = \frac{\left(\frac{I_R(i)E_R(i)}{\sigma_R(i)}\right) + \left(\frac{I_G(i)E_G(i)}{\sigma_G(i)}\right) + \left(\frac{I_B(i)E_B(i)}{\sigma_B(i)}\right)}{\left(\frac{E_R(i)}{\sigma_R(i)}\right)^2 + \left(\frac{E_G(i)}{\sigma_G(i)}\right)^2 + \left(\frac{E_B(i)}{\sigma_B(i)}\right)^2} \qquad \text{(Equation 3)}$$

The index i refers to the pixel position. The standard deviations are noted σ. The cast shadows are discarded by considering the brightness distortion information. Indeed, cast shadows correspond to a global darkening of the ROIs (i.e. BDi <1). On the contrary, trucks are textured objects containing both lightened and darkened pixels. Shadow in the reference image forces some pixels in the areas to be considered as darkened (those which are shadowed in the current frame) and some others brightened (those which were shadowed in the reference frame), as shown in Figure 3.6. In order to reduce the probability of having shadow in the reference frame, this one is not the direct previous frame but the k^{th} previous frame. Thus, we avoid the shadow created by the truck itself. The value of k is set to 3 in this study, corresponding to 15s, because it is sufficient to avoid the shadow of the truck and limit the effects of condition changes between the reference frame and the current frame. The Color Frame Difference is calculated using the direct previous frame to be less sensitive to changes in illumination and “ghost” trucks.

Figure 3.6 Darkened and lightened pixels due to moving shadow.

Conditions for ROI Detection

The conditions that describe the textured moving object (e.g. truck) in the BWL ROI and the AWL ROI are presented below:

- C_1: mean^1(CFD, CFD_{max}) > CFD_1 AND
[(min^1(BD) < BD_{m1} **AND** max^1(BD) >BD_{M1}) **OR** (min^1(BD) < BD_{m2} **AND** max^1(BD) > BD_{M2})]

C1 represents the condition for the BWL ROI. CFD and BD refer to Color Frame Difference and Brightness Distortion, respectively. Mean, min, max stand, respectively, for average, minimum value, and maximum value inside the ROI. μ is the membership function. μ_{min}, CFDmax, CFD1, BD_{m1}, BD_{M1}, BD_{m2}, BD_{M2} are several thresholds. This condition (C1) ensures that intensity changes are present in the whole ROI and that the changes are not uniform. The non-uniformity is translated in terms of brightness distortion. A shadow produces a uniform darkening (i.e. BD < 1). The brightness distortion term of the criterion ensures that a detected region includes both dark (min^1(BD) < BD_{m1}, BD_{m2}) and light (max^1(BD) > BD_{M1}, BD_{M2}) changes. In other words, the condition C1 corresponds to a textured object passing through the whole ROI.

- C_2: [mean2(μ(CFD)) > μ_{min} AND
[(min^2(BD) < BD_{m3} AND max^2(BD) > BD_{M1}) OR (min^2(BD) < BD_{m4} AND max^2(BD) > BD_{M4})]

C_2 represents the condition for the AWL ROI. The notations are the same as the ones introduced in C_1. The criterion of the BD minimum and maximum value is more restrictive. The use of more restraining BD thresholds is possible, since the validation ROIs are wider and include more truck texture. The purpose of a validation ROI is to validate true truck departure and to remove false positives using truck trajectory; large BD thresholds allow for eliminating more false positive detections due to cast shadows.

The aforementioned conditions are complex and require many parameters. A calibration of these parameters is necessary to take into account the statistical variability due to the changes in lighting conditions, image contrast, and truck appearance in order to achieve a robust detection. Thresholds, μ_{min}, BD_{m1}, BD_{M1}, BD_{m2}, BD_{M2}, BD_{m3}, BD_{M3}, BD_{m4}, BD_{M4}, are obtained by statistical analysis of values taken by the CFD and the BD for positive and negative frames from several sets of one day's data (7000 frames per day) with a comprehensive range of conditions. Table 3.1 summaries these values.

Table 3.1 Threshold values used in the proposed algorithm

μ(CFD)	0,5	BD_{m2}	0,85	BD_{M3}	0,8
BD_{m1}	0,6	BD_{M2}	1,4	BD_{m4}	1,25
BD_{M1}	1,15	BD_{m3}	0,4	BD_{M4}	1,3

3.2.3 State Transition Model

A unique state transition model, including a set of complex rules, was developed to reliably detect truck departures. It is one of the major components that constitute the uniqueness of this algorithm, since it allows addressing the perspective occlusion and other potential sources of false positive detections. Each lane is associated with one of five states ("No departure," "Validating departure," "Checking occlusion," "Departure detected," and "Detection disabled") and initialized as "No departure." Figure 3.7 shows a state transition model. When the BWL ROI is triggered (C_1), the lane's state is changed into "Validating departure." If the lane is not affected by the perspective effect (C_5), a truck departure is validated if the AWL ROI is detected (C_2) within a few frames. The lane state in this case is defined as "Departure detected." In the contrary case (affected by the perfective effect), the state of the adjacent lane (which may produce the perspective occlusion) is considered. If this state is “Departure detected,” “Validating departure,” or “Detection disabled,” a check for perspective occlusion is required to validate a detection. The perspective occlusion is checked using the color frame difference inside the AWL ROI of the adjacent lane (C_5 and C_6). If the considered lane can be affected by perspective occlusion, its departure will also affect the following lane (Domino effect). If this checking is not validated, the lane state is changed into “Checking occlusion.” This state allows certain flexibility: the perspective validation can be done in a few frames. If this check is not satisfied, the detection is not validated. After a validated detection, the state is directly (no condition) modified to “Detection disabled” in the next frame. This “Detection disabled” state corresponds to a transitional state in which the lane cannot be detected again during a certain number of frames (C_4). In a way, a minimum duration between two truck departures in the same lane (i.e., a minimum processing time) is ensured. The “Detection disabled” state also prevents the departure caused by the truck arriving in the few frames following a detection. The conditions for the state transitions are noted as C_i in Figure 3.7 and explicitly defined in the following:

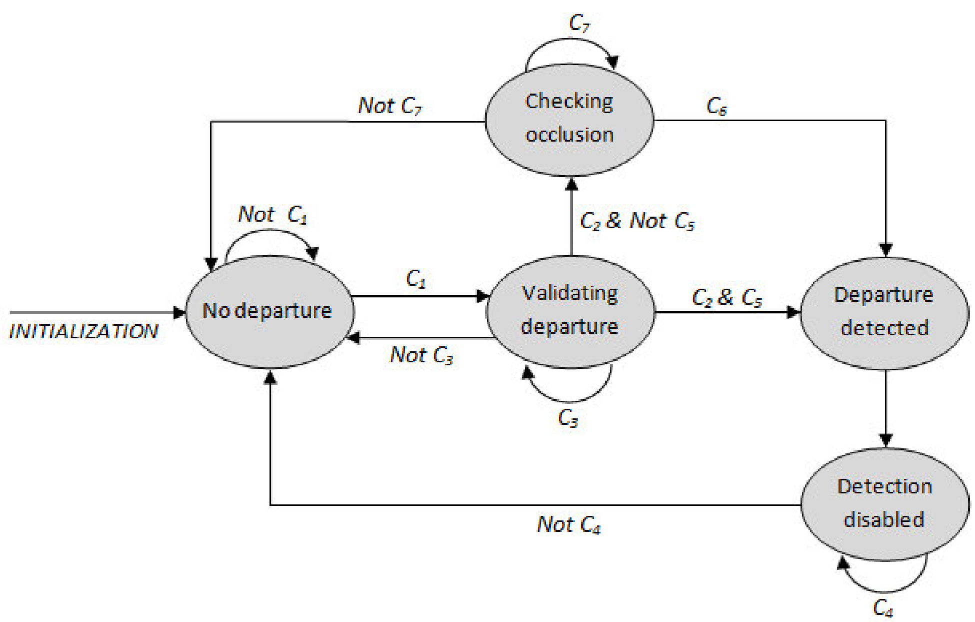


Figure 3.7 State transition model.

- C_1: Motion detected in the BWL ROI
- C_2: Motion detected in the AWL ROI
- C_3: Not C2 but there are validation frames remaining

A maximum number of frames for the validation is fixed at 4 (20 seconds). This number is justified by the fact that it covers cases in which the departure of the truck is too slow when it leaves the waiting line. If no frame remains for the validation, the condition C_1 is checked again. This last criterion increases the “Validating departure” period for a truck with very slow motion or stop-and-go behavior.

- C4: Detection of remaining disabled blocking frames

The lane stays in the Disabled Detection state until 6 frames (30 seconds) are used to have the time needed for a slow truck to leave the AWL ROI and less than the service time.

- C_5: No recent activity in the lane OR the truck in the lane is moving and occludes the adjacent lane or mathematically [NOT Active (Occlusion lane) OR (Active (Occlusion lane) AND $mean^2(\mu(CFD(Occluded\ lane))) > \mu_{min})$]

This condition is introduced to eliminate the false detections caused by perspective occlusion. A "Considered lane" is a lane being detected. A lane could occlude an adjacent lane on one side and be occluded by another adjacent lane on the other side. An "Occlusion lane" refers to the lane occluding the considered lane, and an "Occluded lane" is the lane being occluded by the considered lane. These three terms can be illustrated in Figure 3.8. If lane 2 is the "Considered lane," lane 1 is the "Occluded lane" and lane 3 is the "Occlusion lane." An AWL ROI can only be validated if the occluded lane satisfies the motion change condition (i.e. if parts of the truck pass through this zone). Otherwise, the changes in the considered lane must be caused by a truck in the "Occlusion lane." Active (Occlusion lane) means that occlusion lane is associated with a state "Validating departure," "Departure detected," or "Detection disabled" in the previous frame. The remaining condition checks if the AWL ROI confidence in the "Occluded lane" is large enough. It corresponds to an occlusion of the occluded lane by a truck in the considered lane. In Figure 3.8, the truck in lane 3 can't validate lane 2 since lane 1 is not triggered.

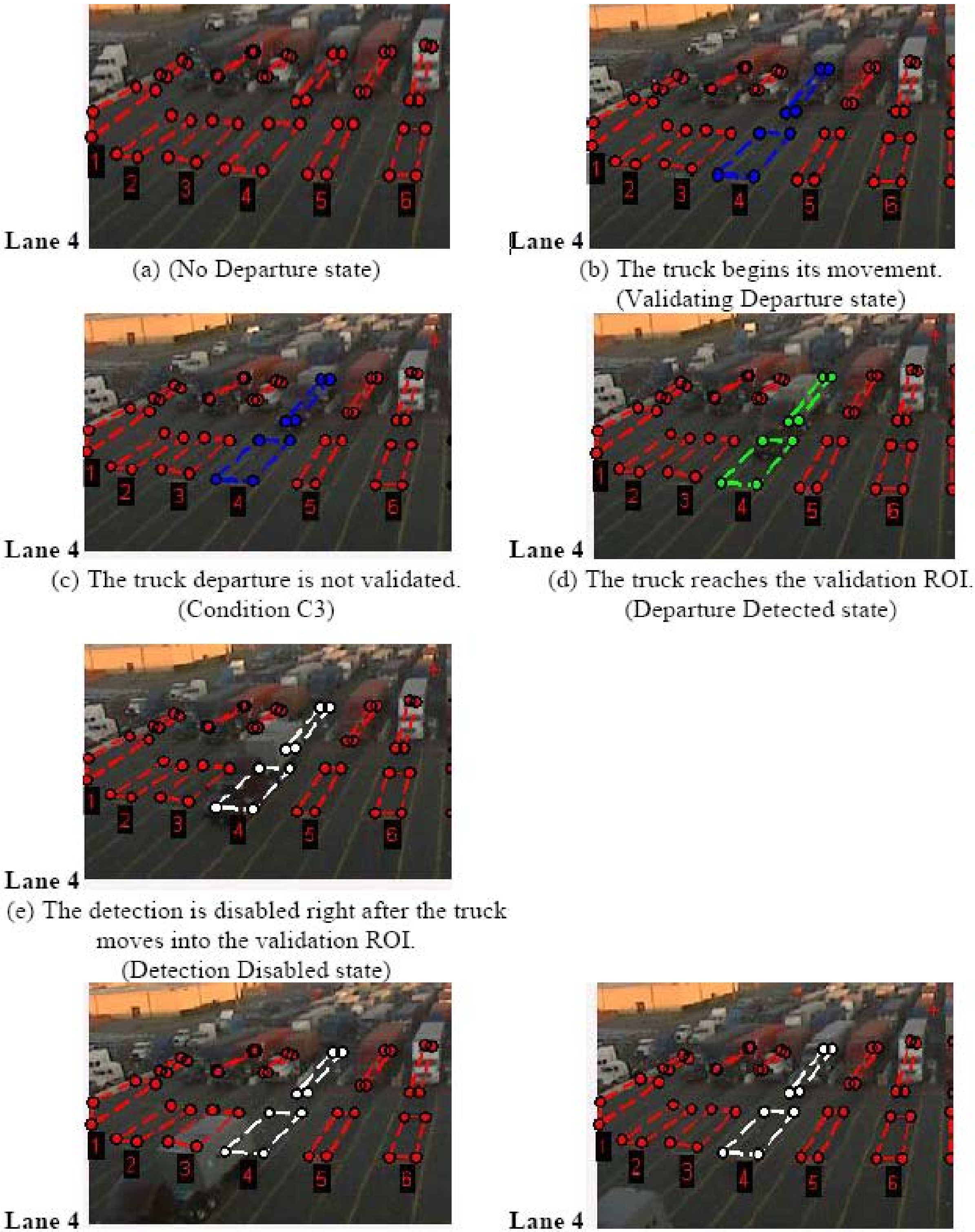
Figure 3.8 Perspective occlusion effect.

- C_6: The adjacent lane is occluded [$mean^2(\mu(CFD(Occluded\ lane))) > \mu_{min})$]

  C_6 corresponds to the perspective validation using the "Occluded lane" confidence statistic. The same notations as C_5 are used.
- C_7: Not C_6 AND Perspective validation frames remaining

Two frames of validation are set to confirm the perspective occlusion because it represents the maximum number of frames for the occlusion to occur in the "Occluded lane."

Figures 3.9, 3.10, and 3.11 give three examples of paths taken in the following cases: a simple detection (Figure 3.9), the avoidance of a false positive with a departure not validated (Figure 3.10), and a multi-lane departure with a perspective occlusion (Figure 3.11).



(a) (No Departure state)

(b) The truck begins its movement.
(Validating Departure state)

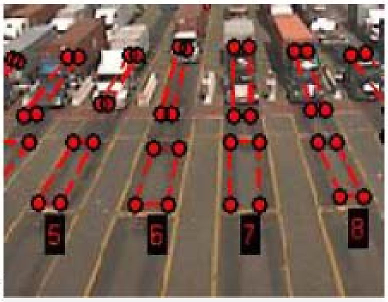
(c) The truck departure is not validated.
(Condition C3)

(d) The truck reaches the validation ROI.
(Departure Detected state)

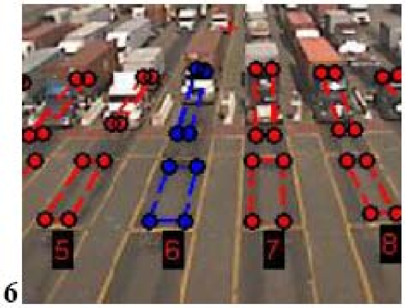
(e) The detection is disabled right after the truck moves into the validation ROI.
(Detection Disabled state)

(f) and (g) The detection is disabled and will resume after the number of disabled frames is reached.
(Condition C4)

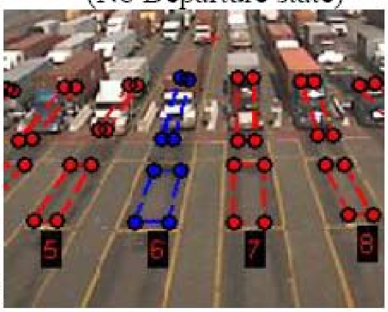
Figure 3.9 Example of the states for lane 4 truck departure.

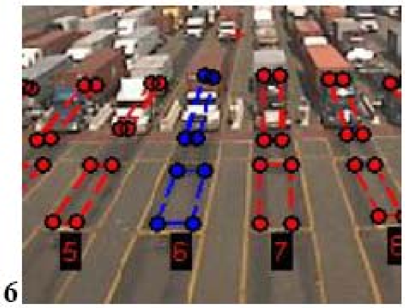
Lane 6


(a) Lane 6: The subsequent truck is late to the waiting line.
(No Departure state)

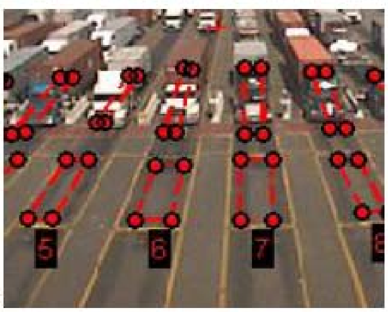
Lane 6


(b) Arriving at the waiting line, C1 is verified.
(Validating Departure state)

Lane 6


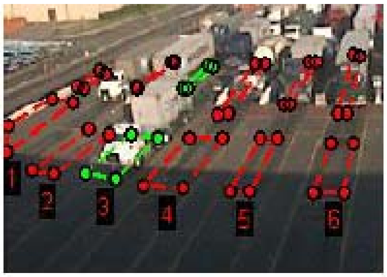
Lane 6


(c) and (d): The truck has not entered the AWL ROI, so the lane remains in the validating departure state.
(Condition C3)

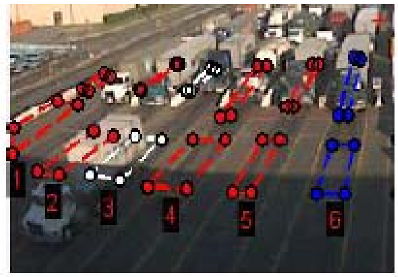
Lane 6


(e) The lane re-entered the No Departure state after 4 frames without validation frames.

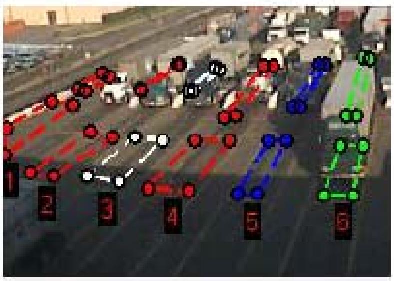
Figure 3.10 Example of using states in lane 6 to successfully handle the case when the subsequent truck is late to the waiting line (a false positive is avoided).



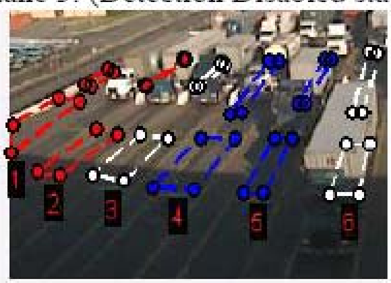
(a) Lane 3: (Departure Detected state)
Lane 4,5,6: (No departure state)



(b) Lane 6: The truck begins its movement.
(Validating Departure state)
Lane 3: (Detection Disabled state)

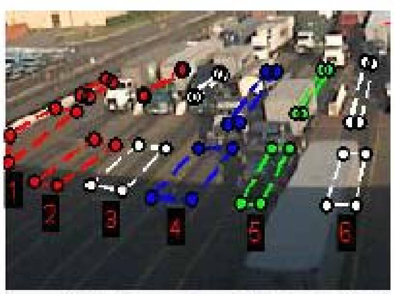


(c) Lane 6: (Departure Detected state)
Lane 5: the movement of the truck is detected.
(Validating Departure state)

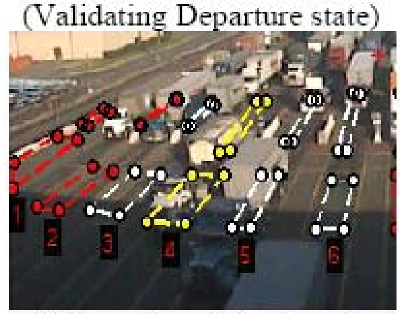


,6

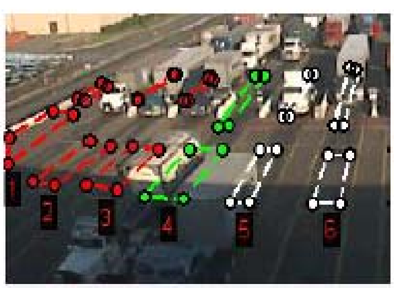
(d) Lane 6 does not occlude lane 5.
Lane 6: (Detection disabled state)
Lane 5: (Validating Departure state)
Lane 4: A movement is detected.
(Validating Departure state)



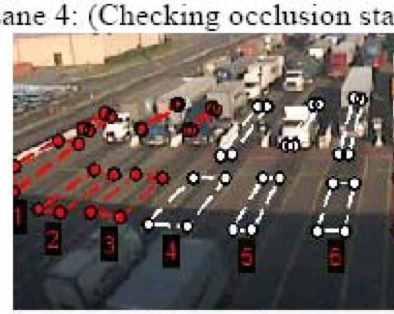
(e) Lane 5: (Departure Detected state)



(f) Lane 5 occludes lane 4.
Lane 5: (Detection disabled state)
Lane 4: (Checking occlusion state)



(f) Lane 4 occludes lane 3, validating the departure
Lane 4: (Departure Detected state)



(g) Lane 4:
(Detection Disabled state)

Figure 3.11 Example of the states for a multiple lane departure in lanes 4, 5, and 6 with an occlusion of lane 5 on lane 4.

3.3 Experimental Test

This section presents the experimental test that was conducted using the low frame-rate images taken by a gate surveillance camera in the U.S. to evaluate the performance of the proposed algorithm. The algorithm was validated using one day's images that were screen-captured via the public web site and the images were taken from a gate surveillance camera at 0.2 fps during the hours of 6:00 am to 4:40 pm. Although the gate operates until 5:00 pm, there was no truck after 4:40 pm. A total of 138 blank images caused by internet delay or the image server's slow refresh rate were removed. Note that these blank images were collected at a rate lower than 0.2 fps. The remaining 6,567 images were used to evaluate the performance of the proposed algorithm. It is noted that the removal of the blank images would result in some discontinuous images in which truck movement is not captured completely. The blank image issue could potentially be resolved by accessing the image directly from the camera's IP address. The 6,567 images cover different lighting conditions, perspective occlusion, multi-lane departures, non-truck movements, etc. Each image has a resolution of 640*480 pixels. The proposed algorithm was evaluated by comparing the truck departure time detected using the proposed algorithm and the manual image review, which is considered as the ground truth. There were 1,133 truck departures observed by manually reviewing 6,567 images. The same images were processed by the algorithm written in Matlab at a speed of 0.24 second per image on a machine with dual core processors (Intel core i5 M520 2.40 GHz) and 4G RAM. The speed can be improved after converting the Matlab code into C++.

A truck departure is correctly detected and labeled as “True positive (TP)” if the truck departure time output by the algorithm and the manual review can be matched within a 10-second buffer in the same lane. The false detections are further divided into false positive (FP) and false negative (FN) detections, as usual. The proposed algorithm achieved correct truck departure detection (TP) in 1,093 out of 1,133 trucks, which corresponds to a 96.5% correct detection rate. There are 11 FP detections and 29 FN detections, which correspond to a 1% FP rate and a 2.6% FN rate. The respective results are summarized in Table 3.1. Further analysis shows that among the 29 FN detections, 19 can be attributed to discontinuous images in which the complete truck movement was not captured. As these 19 false negative detections are not related to the algorithm itself, the associated truck departures can be removed in order to present another set of results only characterizing the algorithm (Table 3.2). The proposed algorithm can achieve a 98.1% correct truck departure detection rate with only a 1% FP rate and a 0.9% FN rate. The remaining false detections are caused by trucks stopped for a while between the waiting line and the gate, very poorly contrasted trucks, trucks changing lanes, and operations vehicles and/or crews. Figure 3.12(a) shows an example of false negatives, and Figure 3.12(b) shows an example of false positives.

Table 3.1 Truck departure validation results (with blank images)

Lane	1	2	3	4	5	6	7	8	9	10	Total	%
Truck Departures	99	89	119	103	106	109	108	113	138	149	1133	
True Positive	95	83	113	98	104	106	107	109	135	143	1093	96.5%
False Positive	3	3	2	1	0	0	0	1	0	1	11	1.0%
False Negative	1	3	4	4	2	3	1	3	3	5	29	0.6%
False Negative (blank image)	0	0	2	4	1	3	1	2	3	3	19	

Table 3.2 Truck departure validation results (without blank images)

Lane	1	2	3	4	5	6	7	8	9	10	Total	%
Truck Departures	99	89	117	99	105	106	107	111	135	146	1114	
True Positive	95	83	113	98	104	106	107	109	135	143	1093	98.1%
False Positive	3	3	2	1	0	0	0	1	0	1	11	0.0%
False Negative	1	3	2	0	1	0	0	1	0	2	10	0.9%

(a) FN caused by a truck change in lane

(b) FP associated with regulation car traffic while the truck is arriving

Figure 3.12 Examples of FN/FP detections.

The experimental test results have demonstrated the proposed algorithm is a promising method to detect truck departures using images taken by surveillance cameras at the gate. With a 98.1% correct truck departure detection rate, sufficient service times can be extracted using the proposed algorithm to represent the overall truck service time at the gate, and the variability and distribution of the service time can be identified.

3.4 Analyses of the Service Time Data

The service time data extracted from the actual images is at a detailed level (for each truck) with full coverage (all lanes), and covering a long period of time. In this section, a few analyses are presented to demonstrate the value of utilizing the service time data with a high granularity. Figure 3.13 shows the service time distribution by lane on one day. The service times for each lane are plotted in blue bars, and the red line represents the average service time (5.4 minutes) for all lanes. The lower services times can be observed on Lanes 9 and 10, which processed the most of the transactions, 139 and 144, respectively. The higher service times can be observed on Lanes 1 to 4, with the services time ranging from 5.9 minutes to 6.3 minutes. This information can help the mangers identify the operation issues (e.g. trouble transactions in particular lanes) and explore the potential improvements.

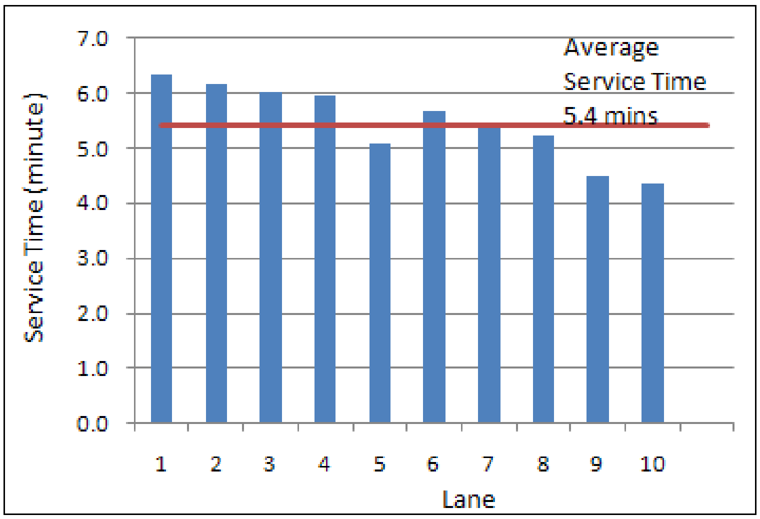
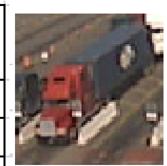


Figure 3.13 Service time by lane.

The abnormal service times can also be identified using this data set. The detailed information, including the time, lane, service time, as well as images, can be provided for investigating the causal factors that will be extremely valuable for exploring potential improvement. Cases of abnormal service times are presented in Figure 3.14. Figure 3.14(a) shows a dashboard indicating abnormal service time along with the time it occurred and the lane information. The slot (12:00-13:00 on Lane 1) highlighted in red have three trucks with a service time greater than 10 minutes, while most of the lane-hours have zero or one truck with a high service time. The highlighted slot can be linked with detailed information, as shown in Figure 3.14(b). The information, including the time the truck arrived and departed at the waiting line, and the images, can be provided for further investigation. This information would be of value to the gate managers who wish to identify the issues and explore the opportunities for improvements.

Hours	Lane 1	Lane 2	Lane 3	Lane 4
9-10	0	0	0	1
10-11	0	1	0	1
11-12	0	0	0	0
12-13	3	2	2	1
13-14	0	0	1	1

Arrival Time	Departure Time	Service Time
12:06:14	12:17:00	0:10:46
....		
12:21:01	12:31:13	0:10:12
....		
12:40:38	12:56:17	0:15:39



(a) Slot with high number of abnormal service times (b) Detailed information

Figure 3.14 Cases of abnormal service times.

CHAPTER 4:
PROPOSED VISION-BASED, GATE DATA ACQUISITION MODULE

To extend the use of the service time extraction algorithm to extract truck wait times, a vision-based multi-view gate data acquisition module is proposed to collect the images at one terminal gate, Gate 4, at the Port of Savannah, for extracting and validating wait times. This chapter presents a review of the operation at Gate 4 and the proposed vision-based multi-view gate data acquisition module. The review focuses on the layout and the business and logistic processes at the gate to thoroughly understand the operation and truck movement at the gate. Based on the review, multiple cameras on a mobile tower were designed to capture truck queues at various critical locations at Gate 4. The camera configurations, including location, resolution, angle, and focal length, are presented.

4.1 Review of the Port of Savannah

The Port of Savannah is located approximately 18 miles from the Atlantic Ocean on both sides of the Savannah River. Operated by the Georgia Ports Authority (GPA), the Port of Savannah featured 2.4 million TEUs in 2009, and it is the fourth largest seaport in the U.S (*44*). On average, approximately 92,000 tons of cargo moved through the port daily in 2010, with the top five export commodities being wood pulp, paper and paperboard, food, clay, and chemicals. The port has experienced 17 years of consecutive container throughput increase, an average increase rate of 15% (*44*); it is expected to reach 6.5 million in 2020 (*45*). Two major terminals, the Garden City Terminal and the Ocean Terminal, serve the Port of Savannah. Gate 4 at the Garden City Terminal is a containerized-transactions-only gate and processes more than 60% of the transactions at the Port of Savannah. An interview with the GPA also shows the operation at Gate 4 reflects the typical GPA gate business processes. Thus, Gate 4 is proposed as the test site for the vision-based gate data acquisition module. The layout and the business and logistic processes at Gate 4 are reviewed in this section to thoroughly understand the operation and truck movement at the gate.

Figure 4.1 shows the physical layout of Gate 4. The main entrance is located at the intersection of Bourne Avenue and South Costal Highway (US 25). According to GPA Process Mapping Documents (*46*), a truck arrives at the gate from the local network and sequentially enters the portal, pedestal, and inspection canopy for security check, pre-gate information validation, and container inspection, respectively. After these processes, the truck can proceed to the yard to drop off or pick up the desired containers. Occasionally, if a truck does not pass the pre-gate validation, a trouble ticket will be issued and the truck has to enter the Trouble Kiosk to solve the issue, which is described in the trouble ticket resolution process. Detailed business and logistic processes, including pre-advise, portal, pedestal, gate inspection, and trouble ticket resolution, at Gate 4 are presented in the following paragraphs.

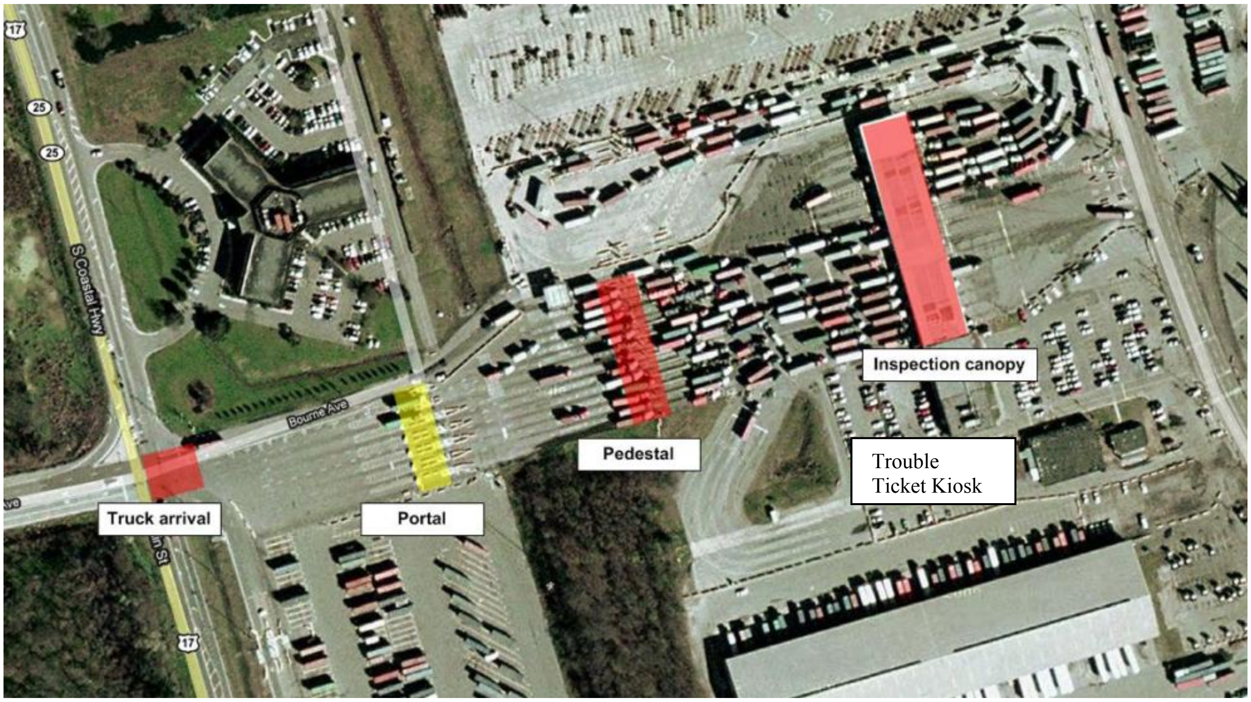


Figure 4.1 Layout of Gate 4.

Pre-Advise

Pre-advise is the process of submitting gate transaction information before a truck arrives at the gate. This process increases security and helps speed up the gate process. Transaction information, such as truck license number, trucking company, container number, and chassis number, is entered to the WebAccess system prior to a truck's arrival at the gate. The truck and driver are validated before being allowed entry to the port. The user (e.g. trucking company) logs into the WebAccess before the truck physically arrives at the gate. According to the system instruction, the user is instructed to fill in all the necessary transaction information. After the submission of the input information, the system will confirm it and generate a personal identification number (PIN) for each transaction. The truck driver will use the PIN to uniquely indicate the transaction when the truck arrives at the gate. The PIN is valid for 72 hours, and there is no lead time for obtaining a PIN. This means the earliest time the user can obtain a PIN for the transaction is 72 hours before truck arrival.

Portal

Portal is a process established after the implementation of the automated terminal asset management system (ATAMS) in the GPA. The portal process includes two steps: manual GPA credential check and automatic truck and container identification. At the first step, a security officer will check the truck's GPA credentials (a badge issued by GPA that allows the drivers to enter the GPA facility) and match the face with the photo on the credentials. This check takes approximately 5 to 10 seconds. At the second step, the truck will proceed at a slow speed (typically 5 mile per hour) to the ATAMS lanes. There are six ATAMS lanes at the portal, and the number of open lanes is determined by the arrival truck volume observed by the gate officers. Each lane is equipped with OCR-smart cameras and RFID-reading equipment to capture the container number, chassis number, and truck ID. Three cameras at different heights and angles are used to capture the container number and chassis number on the truck, and the OCR is used to automatically recognize the numbers. A typical RFID is mounted under the truck. About 95% of trucks are equipped with this type of RFID, storing the basic truck information. Approximately 80-90% of the trucks equipped with an RFID tag can be identified automatically at the portal.

Pedestal

Pedestal is a check-in process before a truck is allowed entry to the port. The pedestal is equipped with a telecommunication system that allows the truck drivers to communicate with the terminal, to validate the pre-advised transaction information, and to acquire the necessary tickets for the designation of container pick-up and drop-off locations. There is no security inspection required at this stage. The operation process at the pedestal consists of the following steps:

- Driver drives on to the scales at the pedestal after waiting in line in the queue and the weight of the truck is acquired.
- Driver then scans an ID card (i.e. GPA credentials). If the ID card is recognized by the system as being valid, the truck will continue to the gate process. If an invalid card or no card is presented, the gate clerk at the remote office will generate a trouble ticket and the driver will be sent to the Trouble Kiosk.
- Driver continues to press the call button to communicate with the gate clerk over the phone by providing his truck's tag (state license) number and the PIN number generated during the pre-advise process. Meanwhile, at the gate clerk's office, the information is collected and identified at the portal, including container and chassis number, will be displayed.
- The gate clerk will compare the information provided by the driver through the phone with the information collected at the portal. If the information matches, the gate clerk will commit the transaction, and the system will print a ticket for the driver. With the printed ticket, the truck will proceed to the gate for inspection. If the information does not match, the gate clerk will make necessary corrections to the container number, size, and type. If the truck has multiple transactions, both drop-off and pick-up, a separate ticket for each transaction will be printed following the aforementioned procedures.
- Trouble tickets are issued at the pedestal from time to time due to a driver's lack of an ID card, lack of PIN, etc. Approximately 5% of the tickets printed at the pedestal are trouble tickets. The processing time at the pedestal varies depending on the communication between drivers and the gate clerks. Based on observation, the average processing time for a truck at the pedestal (including non-trouble tickets and trouble tickets) is 2 to 3 minutes.

Gate Inspection

The gate inspection process is to inspect incoming equipment (chassis and container) to note any damage or broken seals. GPA liability is reduced when damage that occurred before the truck entered the port is discovered and noted. The inspection is performed by an International Longshoremen's Association (ILA) clerk. For the bobtails, the inspection is not required. The operation procedures for the gate inspection process are described below:

- Driver arrives at the inspection canopy and gives the drop off ticket to the clerk (for Gate 4 without bobtail entrance).
- The clerk enters the truck information, including ID number and transaction number, from the drop off ticket into a remote, handheld device, the radio data terminal (RDT).
- The clerk then physically inspects the chassis and container and enters any damage found into the RDT.

- The clerk commits the transaction, and the interchange receipt (EIR) is printed for both damaged and undamaged containers and/or chassis and for a truck requiring special handling.
- The truck proceeds to the location designated on the EIR.

Trouble Ticket Resolution

The driver is sent to the Trouble Kiosk to resolve the matter if a trouble ticket is issued at the pedestal. The gate operation officers will work with the driver to resolve the issue and correct the information in the system. The location of the Trouble Kiosk is shown in Figure 3.2. The operation procedures at the Trouble Kiosk are described below:

- Driver arrives at the Trouble Kiosk and uses a specific phone to make calls to resolve the trouble ticket. If the trouble ticket is due to an invalid ID card, the security phone is first used to obtain a visitor's pass before the trouble ticket can be solved. In other cases, the driver needs to call the gate operation office using the house phone and let the office contact the shipping line for additional information. The driver might need to phone his dispatcher to correct or receive numbers or other information to present to the gate operation office.
- After the data is collected, the gate operations office performs research and determines whether the trouble ticket can be resolved. If not, the driver must exit the port.
- The clerk accesses records using the transaction number and corrects the information in the database following instructions from the Gate Operations Office. A valid drop-off or pickup ticket or both are printed.
- Driver receives the newly printed tickets and proceeds to the inspection lanes.

Rapid Dispatch Service

GPA provides rapid dispatch services for the local retailers, such as Home Depot, Wal-Mart, and Dollar Tree, which have special arrangements with the port. Their containers are all stored on chassis in the rapid dispatch yard in slots designated for these particular retailers. All the trucks will have to go through the regular gate processes to enter the port. The difference between the regular truck and the rapid dispatch truck is rapid dispatch trucks do not need to exchange chassis, but directly pick up the containers on the chassis and leave the terminal. This rapid dispatch service helps retailers improve their truck operation speed. Currently, rapid dispatch is operated by Gateway Terminals, Inc., a consortium of the four stevedoring companies doing business at the GPA facilities. The rapid dispatch facility at the Garden City Terminal handles 200 to 300 containers per day, about 4% of the total containerized transactions.

4.2 Design of the Vision-Based Multi-view Gate Data Acquisition Module

Based on the review of the gate operation, a vision-based data acquisition module is proposed to collect the images in support of extracting wait times at Gate 4. A multi-camera mobile system, as shown in Figure 4.2, is chosen to cover the four critical locations, including the entrance, portal, pedestal, and gate inspection; it does not interrupt or distract the gate operation. Through field visits, a spot at the corner of the rapid dispatch yard with an open view to the four observation locations and their respective queues is proposed to set up the mobile tower, shown as a red dot in Figure 4.3. The proposed location, 750 feet from the center of the inspection canopy, is the closest available location; the distance to the intersection is about 700 feet. The proposed location is within the paved rapid dispatch yard and can provide a stable base for the mobile tower.

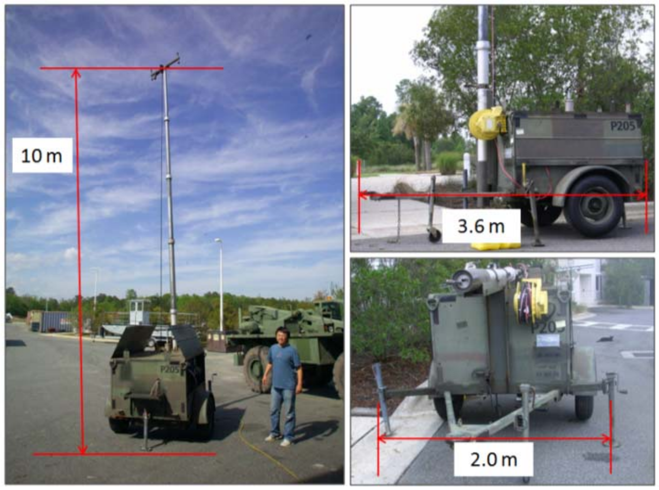


Figure 4.2 Proposed vision-based, multi-view gate data acquisition module.

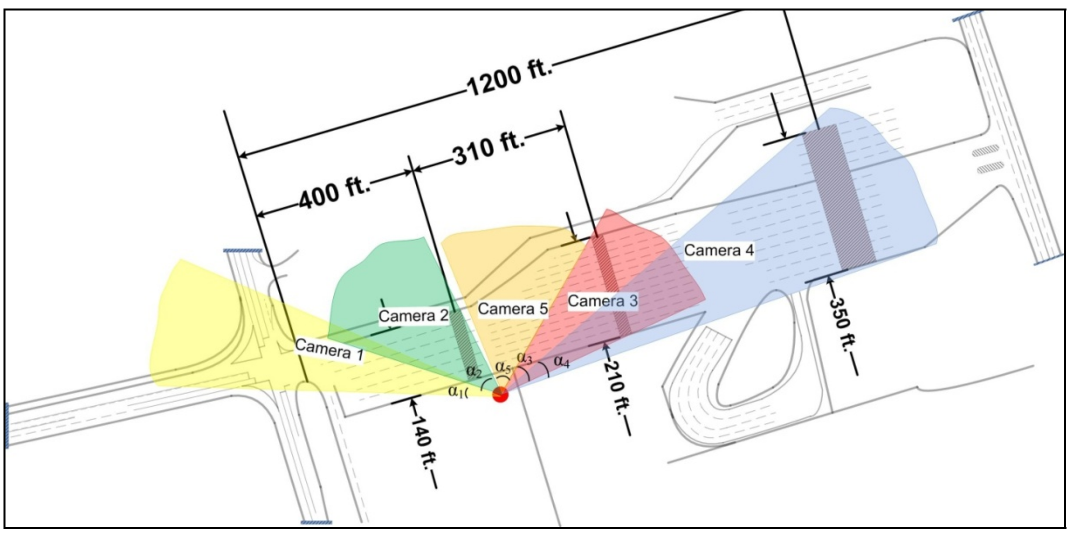


Figure 4.3 Location and camera configurations for the proposed vision-based, multi-view gate data acquisition module.

A total of five cameras are proposed to capture the truck movements in 1,200 feet, as shown in Figure 4.3. Based on a camera height of 30 feet and the cameras with 2/3 inches sensor, the camera system configuration can cover the area and capture an individual truck at different locations. The camera configurations, including orientation, lens, and resolution, are presented in Table 4.1 The inspection canopy, which is the most distant location from the camera location, is considered when determining the camera resolution. A truck at the inspection canopy occupies fewer pixels compared to a truck at other observation locations. Therefore, the requirement for camera resolution at the inspection canopy is higher than the requirements at other observation locations. A thirty-pixel resolution is considered a typical value for detecting a truck using the image processing algorithm. Table 4.2 shows the minimum resolution requirements for each of the five cameras to satisfy a 30-pixel truck occupation in the images with expected queue lengths. A 1024*768 resolution for all the five cameras in the multi-camera system is proposed.

Table 4.1 Camera horizontal angle and focal length

Height: 36 ft.		Sensor Size: 2/3"		Object Percentage: 3%	
Location	Distance	Vertical Angle	Horizontal angle (α)	Focal length	Downward angle
Camera 1 (t2)	700 ft.	14.98°	19.97°	25mm	9.78°
Camera 2 (t3 & t4)	130 ft.	71.51°	95.35°	4.8mm	48.28°
Camera 3 (t5 & t6)	350 ft.	24.1°	32.13°	15mm	16.45°
Camera 4 (t7 & t8)	750 ft.	11.67°	15.56°	30mm	7.74°
Camera 5 (t5)	~350 ft.	24.1°	32.13°	15mm	16.45°

Table 4.2 Requirements for camera resolution

Location	Queue Length (foot)	Truck Length (pixel)	Minimum Resolution (4:3)
Camera 1 (t2)	90 ft.	30 pix.	320x240
Camera 2 (t3 & t4)	140 ft.	30 pix.	480x360
Camera 3 (t5 & t6)	210 ft.	30 pix.	640x480
Camera 4 (t7 & t8)	350 ft.	30 pix.	1024x768
Camera 5 (t5)	~210 ft.	30 pix.	640x480

CHAPTER 5:
CONCLUSIONS AND RECOMMENDATIONS

Truck congestion at port gates is of great concern to different stakeholders, including port authorities, motor carriers, and the public because it decreases the productivity of the port and truck fleets and increases the exhaust emissions. Actual truck traffic data at the gate, including arrival time, service time, and wait time, are essential for studying truck congestion at the gate. However, there is limited data available because data is currently manually collected. In this study, a service time extraction algorithm was developed to effectively acquire service time data from the video log images taken by the surveillance cameras at the gate, and validated with actual images.

While there are studies for traffic monitoring using image processing techniques, the layout and operation at the gate pose unique challenges in developing a robust service time extraction algorithm. These challenges include the image's low frame-rate, day-and-night lighting conditions, perspective occlusion caused by adjacent trucks, cast shadows, multi-lane departures, and non-truck movements made by operations vehicles and crews. The service time extraction algorithm integrates prior knowledge of the scene geometry and truck trajectory into three unique components to address the challenges. The proposed algorithm consists of three components: (1) a lane-based ROIs design, (2) a frame-differencing change-detection algorithm, and (3) a unique state transition model with a set of decision rules, considering perspective occlusion and other potential sources of false positive detections, to reliably detect a truck departure. The performance of the proposed algorithm was evaluated using 6,576 images captured at low frame-rate via internet from a live video feed from a gate surveillance camera. The proposed algorithm achieves a 98.1% correct truck departure detection rate, with only a 1% false positive detection rate and a 0.9% false negative detection rate. Preliminary results have demonstrated the robustness of the proposed algorithm by successfully detecting truck departures under various conditions, including day-and-night lighting conditions, multi-lane departures, perspective occlusion, and cast shadows. Also, the non-truck movements by operations vehicles and crews were successfully excluded from the truck departures.

Built upon the outcomes of the service time extraction algorithm, a vision-based, multi-view gate data acquisition module is proposed to collect the images at Gate 4 at the Port of Savannah to support the extraction and validation of wait times. Based on the review of the operation at the Port of Savannah, multiple cameras on a mobile tower were proposed to capture truck queues at Gate 4. The location, position, resolution, angle, and focal length for the cameras are proposed.

The following are the identified future research topics that could extend the application of the proposed vision technology:

- A comprehensive validation using a larger set of images with various congested conditions and weather conditions is needed for the full-scale implementation.
- An experimental test is needed to validate the proposed vision-based gate data acquisition module. The research team is in a discussion with the Georgia Ports Authority to conduct a test at Gate 4 in the Port of Savannah. The images to be collected at the Port of Savannah will

support the extraction and validation of the wait time data using the service time extraction algorithm.

- Built upon the outcomes of the service time extraction algorithm developed in this study, the research team will extend the proposed vision-based gate data gathering system to cover critical entry points to the port for monitoring and optimizing the truck traffic on the local road network near the port. A research project that involves the Georgia Institute of Technology, Centers for Logistics, and private sector, will be initiated in the near future to monitor and optimize the truck traffic on the local road network near Savannah Port.

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