A Vision-based Method for On-Road Truck Height Measurement in Proactive Prevention of Collision with Overpasses and Tunnels

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Abstract: Over-height trucks are continuously striking low clearance overpasses and tunnels. This has led to significant damage, fatalities, and inconvenience to the public. Smart systems can automatically detect and warn oversize trucks, and have been introduced to provide the trucks with the opportunity to avoid a collision. However, high cost of implementing these systems remains a bottleneck for their wide adoption. This paper evaluates the feasibility of using computer vision to detect over-height trucks. In the proposed method, video streams are collected from a surveillance camera attached on the overpass/tunnel, and processed to measure truck heights. The height is measured using line detection and blob tracking which locate upper and lower points of a truck in pixel coordinates. The pixel coordinates are then translated into 3D world coordinates. Proof-of-concept experiment results signify the high performance of the proposed method and its potential in achieving cost-effective monitoring of over-height trucks in the transportation system. The limitations and considerations of the method for field implementation are also discussed.

Keywords: Accident avoidance; computer vision; height measurement; low clearance; over-height truck

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1. Introduction

Semi-trucks are a major form of transportation unit in the United States delivering nearly 70 percent of all freight tonnage [1]. The large percentage of tonnage signifies the importance of unhindered flows of these trucks across the nation. One of the areas where this evolves into a problem is during the transportation of freight on routes with low clearance overpasses (a bridge, road, or railway that crosses over another road or railway) and tunnels. There are a considerable number of old low clearance overpasses in the U.S. and the world, which cause accidents associated with collisions of trucks with overpasses. In a study conducted by the University of Maryland where all states were polled and 29 states responded, 18 of those 29 or 62% stated they consider over-height collisions a serious problem [2].

Accidental crashes of over-height trucks with overpasses and tunnels have been continuously reported over the years [3,4,5,6,7]. Even though the frequency of these accidents might not be thought significant, the costs they involve are considerably high. The damages involve direct costs related to injuries or fatalities for drivers or pedestrians and clearing/restoring the overpass/tunnels and underway roads, as well as indirect costs charged due to traffic delays. For example, an over-height truck collision with the Melbourne's Burnley tunnel on April 17, 2013 led to a damage loss and traffic jam cost which was up to one million dollars [6]. In terms of the frequency of over-height collisions, 14 (3%) out of 503 bridge failures in 1989-2000 were due to vehicle /structure collisions [8]. Agrawal et al. [9] reported that bridges in New York State have been experiencing approximately 200 strikes annually by over-height trucks. In Beijing, it was reported that approximately 20% of the overpasses are associated with over-height collisions [3]. Based on these statistics, and despite the fact that occurrences of over-height truck collisions are not as frequent as other traffic accidents such as vehicle collisions, the consequence of over-height collisions are usually quite severe [2].

In order to avoid these accidents and to reduce involved costs, it is beneficial to have a warning system that detect an over-height truck and notify its driver ahead of the presence of the low clearance overpass/tunnel. In the United States, many states have started deploying warning systems using laser or infrared light [10]. The systems (except for laser profiling units) generally consist of 1) a transmitter and

2) a receiver mounted on opposite sides of the road, 3) loop detectors under the road, and 4) a visual/aural warning system [11]. However, the high cost of implementing the systems constraints the wide use of those technologies [12]. In addition, the installation of loop detector requires temporary road closure causing another indirect cost. In contrast to the laser- or infrared-based systems, a vision-based system can be a cost-efficient alternative and resistant to false alarms. In the system, the aforementioned three components 1)-3) can be replaced with one or more cameras and an embedded processor running computer vision algorithms. This paper introduces an overall framework of the system and evaluates a vision-based method for measuring truck heights as a part of the framework. The method combines line segmentation and blob tracking in order to detect lines on the top and bottom of the truck. Two points are selected as they comprise a vertical line perpendicular to the road plane. The length of the line determines the truck height in 2D coordinates which can then be translated into 3D space. This process also involves unit conversions from pixel to a length unit such as meter or feet by use of a fixed reference object height. The present research signifies the potential of achieving cost-effective solution of preventing possible collision between over-height trucks and low-clearance overpass/tunnels by simply utilizing existing surveillance systems. Furthermore, the low cost will allow the system's broader applications. For instance, it can be applied at the entrance to parking decks where over-height vehicles are prohibited. The proposed system is also applicable to luggage handling systems in airports.

2. Background

2.1 Protective measures for overpass/tunnel crash accidents prevention

To prevent the over-height collisions, a couple of protective measures have been implemented. For example, in the United States, permits are required for the trucks over 13'-6" (4.12 m) [13]. 13'-6" is the allowed legal height of trucks. In general, the protective measures can be categorized as: 1) providing a listing of restricted structures on federal/state-maintained roadways for truck drivers to plan their travel routes ahead of time, to avoid where low clearance overpass/tunnels may occur, 2) installing signs along the road or on the overpass/tunnel, informing drivers of the low clearance of the structure, 3) enforcing detour of the over-height trucks and providing get-around directions over the road, and 4) installing a sacrificial system in which an audible alarm is made when over-height vehicles hit a physical obstruction [14] such as chains, metal strips, or sacrificial beams installed at the overpass/tunnel height in advance of the overpass/tunnel. These measures play a positive role in protecting existing structures from over-height truck collisions. However, their effects are limited. The measures 1)-3) highly rely on drivers' attention and do not eradicate the collision problem. It is still drivers' responsibility to confirm clearance heights along their routes. As a result, crash accidents continue to occur in that truck drivers often accidentally ignore the structure clearance [2, 6]. In addition, outdated low clearance overpass/tunnels exist that have not been marked on the drivers' maps. As to the measure 4), although sacrificial beams cause damages on trucks, a statistically high detection rate and a low false alarm rate may be achieved. A truck driver would appreciate that a little damage incurred to the truck will prevent catastrophic damages. However, if the driver has noticed a low clearance ahead while still needing to hit the detecting chains and metal strips to let the truck pass through, the inconvenience of being hit or a small damage becomes a disadvantage of this approach. Moreover, chains and metal strips may not provide an alarm loud enough to be heard inside trucks [15]. A more preventive way is having a warning system that can detect an over-height truck and notify its driver ahead of the presence of the low clearance overpass before a collision occurs [16]. The remainder of this section first reviews the implementation of existing over-height warning systems, the context within which this paper lies. The review is then followed by current research in vision-based height measurement, on which this paper is based.

2.2 Over-height vehicle warning systems

Over-height vehicle warning system, also called Early Warning Detection System (EWDS) is an active system. It automatically detects the existence of an over-height vehicle for a particular tunnel or overpass and warns the driver of the vehicle of the pending danger before a collision with the structure occurs. Sinfield [17] provided an overview on existing commercially available EWDSs and the state of their implementation in U.S. Based on his review, the majority of existing systems fall into the categories of utilizing the sensing technologies of visible beam, laser (acronym for Light Amplification by Stimulated Emission of Radiation), or infrared, all of which rely on the interruption of a beam or sheet of light to identify a vehicle exceeding a predefined height threshold or to construct the profile of a vehicle that can be translated into accurate vehicle dimensions.

Visible beam systems are the types of optoelectronic sensors. They operate by emitting a beam of visible light from a source unit to a detection unit that either processes the light or reflects it back. In general, the cost of visible beam systems is low, but they are unreliable to ambient light and inclement weather that are particularly common in outdoor conditions. Systems that utilize laser are generally divided into laser sheet systems [18] and laser profiling systems [19]. The former works by generating a plane of one or more laser beams that is interrupted by a passing object. The latter reconstructs the point cloud of a passing object such that the object's height can be easily interpreted. It is worth mentioning that the cost of laser profiling systems is particularly high and the effect of these systems is limited to moving traffic with slow speed. As a result, they tend not to be used solely for overheight vehicle detection. Similar to laser systems, infrared systems work by directing a focused beam of light in the infrared region of the optical spectrum from a transmission unit to a reflective target or detection unit. Both laser and infrared systems present more robust features for outdoor use than visible beam systems. A typical infrared/laser system (except for the laser profiling system) consists of 1) a transmitter and 2) a receiver mounted on opposite sides of the road, 3) loop detectors under the road, and 4) a visual/aural warning system [11]. In this system, the transmitter mounted on a pole at the height of the bridge clearance emits the laser or infrared beam. The interference of the beam due to the appearance of a truck activates a warning system that informs the driver with flashers and/or audible alarms. Loop detectors identify the appearance of a vehicle and their lanes [11]. The identification is used to remove false detections caused by non-vehicles such as birds and flapping tarps. Many states in the U.S. have started deploying warning systems using laser or infrared [10]. It is reported the decrease of accidents after the systems began operation [12]. The use of infrared light is more dominant than laser in these systems, being considered safer and more durable in various environments than laser (e.g., better penetration of rain and fog). However, the high cost of implementing the systems restricts the wide use of these technologies [20]. For example, the deployment of the system in both directions of a road in Maryland cost a total of $146,000 [21]. Moreover, the installation of loop detector needs temporary road closure causing another indirect cost.

2.3 Computer vision based height measurement

As an alternative to the laser- or infrared-based system, a vision-based over-height vehicle detection system has the potential of being cost-efficient since it can identify truck heights only with one or more cameras for each direction, equipped with a processor unit. As video is one of the major data types that most DOTs daily collect, continuous research efforts have been made on the application of computer vision algorithms for intelligent transportation systems (ITS). For instance, automated detection [22,23] and tracking [24,25] of vehicles have drawn great interests and been extensively investigated for counting vehicles and extracting their trajectories, which are essential information in monitoring and analyzing traffic conditions.

The vision-based vehicle monitoring generally works as follows. Once the cameras are positioned, their video streams are processed by an embedded processor unit to identify and locate vehicles. This processing involves three steps: camera calibration, vehicle detection, and vehicle tracking. Camera calibration provides a transformation between image pixel coordinates and real-world road-plane coordinates [26]. The transformation is necessary to obtain the width and height of a vehicle in metric units and to identify which lane the vehicle appears in. Vehicle detection recognizes a new vehicle entering the view, and the detected vehicles are tracked by a tracking method.

Measuring the height of on-road vehicle in videos has been investigated in a few research works [27, 28]. In Khorramshahi et al.'s work [27], feature points on a truck are located and tracked while the truck passes through a cubic virtual zone which is as high as clearance. Based on the relative positions of the tracked feature points and the virtual zone, it judges whether the truck height is over the clearance or not. However, creating the virtual zone, which acts an important role in calibration, requires manual marking in the captured video frames. The marking refers to the bounding box that defines the length, width, and height of the virtual zone. It should be done based on the dimension of any vehicle that passes the zone. Therefore, it needs a priori knowledge about the vehicle dimension. In addition, because this method deals with the detection in the image pixels and through comparison with the predefined bounding box, it does not calculate the exact height of a vehicle. Shao et al. [28] proposed an automated method to identify the height of moving objects from un-calibrated videos by use of vanishing line of the scene. In this method, trajectories of moving objects are statistically modeled to determine the vanishing lines of scene. Despite its novelty, it is not applicable to general roadway scenes because two vehicles moving in two non-parallel directions should be present in the views for their automated calibration method. There is a need for creating a new method that is capable of utilizing existing roadway features available for measurement of on-road truck heights.

3. Methodology

The objective of this paper is to propose an automatic, ubiquitous, and inexpensive method to determine the height of on-road trucks in digital video collected from a fixed camcorder. Vision-based systems currently have a limitation of low performance in night time. However, night time imaging technologies are continuously advancing, increasing the applicability of the computer vision technologies. In other words, vision-based systems have a potential to be a valid tool for night time applications in near future. An additional obstacle is inclement weather which is reported also as an obstruction to infrared/laser system [29]. Low cost allows for wide spread implementation of vision-based systems, and the value of the information it can provide is expected to outvalue the cost. Also, for the states that have already employed the infrared/laser system, the vision-based approach can be a cost-effective supplement to the infrared/laser system enhancing the detection accuracy. It should be noted that this research focuses on flat, single or double lane per direction roadways, daytime lighting, and one-directional flow for video processing.

The schematic overview of the proposed vision-based EWDS is illustrated in Fig. 1. Each single surveillance camera is mounted on a fixed position facing the roadway traffic on each lane. Such deployment is to reduce the possibility of parallel vehicle occlusion. As a truck is measured and its height exceeds a predefined threshold, the warning bell will sound to signal the danger of an over-height collision. The sign message guides the truck driver to an alternative route where the driver can exit the current roadway and avoid collision with the overpass [17]. The warning bell and messages need to be delivered to the drivers early enough so that the trucks can smoothly enter the re-routing road without interrupting the traffic. The technical framework of the system is shown in Fig. 2. Video frames are obtained from each camera and Gaussian smoothing is applied to every frame to reduce image noise. The method then takes two parallel paths: field of view calibration and truck detection. The former reveals the principal axis and the Manhattan structure to establish field of view geometry, and the latter locates the truck region based on the motion and shape features. The results of the two paths are combined to calculate truck heights. The result is an estimate of a truck height, ready to be used in a EWDS. The details of these framework components are presented below.

Insert Figure 1 here

Insert Figure 2 here

3.1 Field of view calibration

Once a camera view is fixed, three orthogonal axes comprising of the Manhattan structure [30] in real world coordinate system have to be found. The three axes consist of the principal axis along the direction of the road (or the traffic flow) (x-axis), a vertical axis perpendicular to the road plane (z-axis), and the other orthogonal to the formers (y-axis). The orthogonal axes are defined by three vanishing points. The following describes the way to find the axes. First, all line segments in the camera view are detected using the Line Segment Detector (LSD) [31]. The detected line segments are then grouped as they converge to the same vanishing points. This framework recommends using the J-Linkage algorithm [32] together with the Expectation-Maximization (EM) [33] to perform the grouping. It is because, unlike other estimators such as multi-RANSAC [34], applying J-Linkage does not need to have the knowledge of the number of models (i.e., vanishing points) in the image, and using EM increases the resistance to errors that a set of line segments of a vanishing point is falsely divided into two groups [35]. A number of line segment sets and their corresponding vanishing points will be accordingly generated. In Fig. 3, the line segment sets are illustrated in different colors. It can be easily seen that the blue lines form the majority and are thus determined to be a principal axis. Following this, a set of line segments that are orthogonal to this principal axis is found by checking the orthogonality with the following equation.

$$v^T \omega v_m = 0$$

v is the vanishing point of the candidate line segment set, v_m is the vanishing point of the principal axis, and the ω is the Image of Absolute Conic (IAC) calculated via the 3 × 3 matrix of the camera internal parameters [36]. The camera internal parameters can be achieved through camera calibration. Next, a similar procedure is applied in search of the third set of line segments. In this procedure, the difference is that the framework takes the search objective as the minimum of the sum of squares of every two sets. This will result in the most orthogonal triplet of line segments, which makes up the Manhattan structure (Fig. 4). It is worthwhile to note that all calibration procedures are performed online and fully automated. This enables the flexibility of the surveillance video being installed, which allows for fine-tuning pan or tilt angles of the lens even after the camera has been installed on spot.

Insert Figure 3 here

Insert Figure 4 here

3.2 Truck detection

In order to calculate truck heights, truck regions in video frames have to be located. The truck detection employs two algorithms – blob detection [37,38,39] and HOG (Histogram of Oriented Gradients) detection [40]. First, the blob detection creates/updates a background model of static background scene and detects the regions of moving objects by comparing incoming video frames with the background model. The detected regions are called blobs. The blob detection narrows down the candidate regions of trucks and reduces false positives of the HOG detection. The HOG feature which is a well-known shape feature is used to locate the trucks within the detected blobs. The output is a bounding box enclosing the truck.

3.3 Truck height determination

This section deals with a new algorithm for calculating truck heights. This algorithm is applied to the regions of bounding boxes obtained by truck detection. The linear workflow of the algorithm is shown in Fig. 5. First, a line segment corresponding to the top boundary of a truck is obtained. All line segments inside a bounding box are detected by LSD method (Fig. 6(a)), and those whose direction is along the principal axis are selected. From the obtained line segments, the one whose left end point is closest to the top left corner of the bounding box is determined as a top boundary of the truck (Fig. 6(b)). The above works when the camera is placed, from the truck driver's perspective, to the right hand side of the truck. If the camera is positioned to the left hand side of the truck, the one whose right end point is closest to the top right corner of the bounding box will be selected as a top boundary of the truck. Second, the truck's bottom boundary is located. The blob image of the truck is obtained by using blob detection (Fig. 7(a)). Then, the boundaries (i.e., a set of pixel lines) of the blobs are extracted by applying the Canny edge detection [41] to the blob image (Fig. 7(b)). This allows for detection of the bottom boundary of the truck. The method first selects all edge pixels that are nearest to the bottom along the horizontal direction of the image. Then the top boundary is projected downward intersecting with the resulting pixel edges to determine the start and end locations of the bottom boundary. Fig. 7(b) indicates the bottom boundary of the truck annotated by yellow arrows. It is noteworthy that the blobs in this research result from the moving truck. Therefore, the trajectory of the truck wheels forms a region (Fig. 7(a)) in which the contacts of the truck wheels and the road surface result in a continuous and near-linear pixel line. The pixel line results from the truck wheel instead of shadow. It is used to detect the bottom boundary of the truck in the image. Fig. 8 shows an example of obtaining the bottom boundary when the area below the truck is not fully filled with the shadow. In this case, the height is determined by the bottom point of the wheels.

Insert Figure 5 here

Insert Figure 6 here

Insert Figure 7 here

Insert Figure 8 here

The subsequent step is to measure the truck height in pixel units. The height is measured by locating two points – one on the top boundary and the other on the bottom – that forms a vertical line (in z-axis direction). It should be noted that the top boundary in Fig. 6(b) is a straight line in the same direction of the principal axis (in vector image format) while the bottom one in Fig. 7(b) is winding (in raster image format). Hence, any point on the top boundary can be considered as a reference point, but finding the reference point on the bottom boundary is challenging. The remaining task is to find the correct part that lies on the actual bottom line corresponds to the top boundary. The following details the procedure of this task. The top boundary line is divided into n fragments by same length, which locates (n+1) points on the line. From each point, line scanning in z-direction (i.e., the vertical direction perpendicular to the road plane) is executed to search for the intersection with the bottom boundary. In this way, n sub-segments of the bottom boundary are obtained. From the sub-segments, one whose inclination is the closest (or the most parallel) to the top boundary line in the real world coordinate system is selected as the correct part of the bottom line. This also enables to avoid any falsely selected reference point that does not lie on the bottom boundary such as a small noise line segment. A small noise line segment may be generated from a road marking due to the imperfection of the blob detection algorithms. Next, the height in pixel units is measured simply by calculating the distance between an end point of the selected sub-segment on the bottom and the corresponding point on the top boundary line (Fig. 9).

Insert Figure 9 here

The final step is to convert 2D truck height in pixel units into 3D height in real world length units so as to compare with the overpass clearance. Single view metrology [42] is employed in this process. It takes known dimensions of objects in the camera view as input data. The road width and the length of the lane line pattern are good reference dimensions in y and x directions of the Manhattan structure, respectively. Based on the reference dimensions, the 2D height calculated in the image frames can be converted to a height value in real world units.

4. Implementation and Results

4.1 Implementation

A prototype was implemented to test the proposed method. This prototype was built upon a platform named "Gygax", which has been developed in house using Microsoft Visual C# in .NET Framework 4.0 Environment. Videos were recorded in an "mts" format using Canon VIXIA HF series camcorders. The "mts" format is then converted into an "avi" format from which "Gygax" can extract image frames in various formats such as "jpg" and "png". The original videos were recorded in 1280x720p resolution in color at the rate of 30 fps. During the process of video processing, they were converted to gray scale images as required. Fig. 10 shows the screenshots of applying the implemented prototype to measuring on-road truck heights in videos. Fig. 10(a) is the initial user interface of the prototype. Once a video is recorded and saved. The user can browse the folder to select the video into the prototype (Fig. 10(b)). Processing the video data in this prototype needs the user to click the "Truck Height Measurement" button in the "Tools" menu. Fig. 10(c) shows the result of the truck height measurement. Besides, the raw video and intermediate results such as Manhattan structure and blob detection are also provided on the result interface as shown in Fig. 10(c). It is worth mentioning that this prototype also implemented a dynamic-link library (DLL). It enables video streams to be directly read and transmitted from a camera to the prototype via wired connection. The DLL promises the automatic computing of the truck heights from video streams collected in real-time, making it potential for use in an Early Warning Detection System.

Insert Figure 10 here

In the process of implementing the prototype, the Manhattan structure algorithm, which searches the principal axis of the roadway and the three vanishing points, was validated on its accuracy and consistency. To this end, a two-minute video was recorded using a Canon VIXIA HF S100 camera. The camera was placed facing a road - Northside Drive in Atlanta, GA, which is located at prior to the intersection of the 17th street. The heading of the camera was configured to have an angle of 30 degrees with respect to the direction of the road. Having the camera angle fixed during video recording, fifty frames were extracted from the resulting stream. Based on each frame, the Manhattan structure algorithm found the principal axis and determined the vanishing points. Fig. 11 shows a summary of the obtained results from which the number of line segments along the principal axis and the cumulative histograms of the vanishing points' consistency errors were delineated. Fig. 11(a) shows the total number of detected line segments that belong to the maximum detection group in each frame. The group of line segments aligns along the same direction and serves as a basis for determination of the principal axis with the use of the Manhattan structure algorithm. Fig. 11(a) put here has two main purposes. First, it shows that the group in each frame used for determining the principal axis contains sufficient line segments. Second, it reveals the consistency of the algorithm in detecting the direction of the principal axis in each frame. Fig. 11(b) presents the cumulative histograms of the vanishing points' errors. It indicates the pixel accuracy and detection consistency of the algorithm for three Manhattan structure axes on each frame. For example, according to Fig. 11(b), the vanishing point #1 has the lowest pixel error and the most consistent performance in each frame. The average number of line segments along the principal axis was 295. The three vanishing points determined based on each frame have an average deviation of 3.24 pixels, 3.86 pixels, and 5.32 pixels respectively.

<u>Insert Figure 11 here</u>

The detection performance was also evaluated based on precision and recall. Precision is the ratio of the number of trucks retrieved to the total number of irrelevant and relevant records retrieved, while recall is the ratio of the number of trucks retrieved to the total number of trucks appeared in the video frames. The size of the HOG feature template was set as 104×136, and the bin size is set as 9. Depending on the hit threshold value, precision and recall vary as shown in Fig. 12. In this research, recall is more critical factor than precision since low recall increases the fraction of missed trucks. In other words, some trucks may not be detected and their heights will not be calculated at all. Therefore, it affects the overall performance of detecting over-height vehicles. In contrast, low precision increases the fraction of irrelevant instances retrieved. For example, other types of vehicles such as sedans and SUVs (Sport Utility Vehicles) are detected. However, it does not affect the overall performance as the irrelevant instances will be discarded in the next step if their heights are accurately calculated. Accordingly, the threshold is determined 0.4 which scores 0.996 of recall and 0.840 of precision. Fig. 13 shows examples of the detection results. Fig. 13(a), (b) and (c) show the cases when trucks were located accurately with bounding boxes while the Fig. 13(d) shows the cases when irrelevant instance (sedan) was detected. Fig. 13(c) is a result in a congested condition on a rainy day. Though the truck was moving extremely slowly with other vehicles on both the front and the rear sides, the whole truck face was clear in the view and the truck was detected successfully at a certain point on the road.

Insert Figure 12 here

Insert Figure 13 here

Also, in the process of implementing the prototype, three methods of blob detection were implemented to find the best option for this specific case of detecting the bottom region of trucks. The methods are the median filter method [37], the mixture of Gaussian method [38], and the color co-occurrence method [39]. The results of this experiment are shown in Fig. 14. The primary criterion of selecting the blob detection method is the density since its main role is to extract the bottom boundary. Faint bottom edges often result in false or no detection of the bottom point of the height. Therefore, the selection is made mainly based on the density. The median filter method is selected as the most appropriate since it provides the most dense region detection on the bottom of trucks. The density was measured by GIMP (GNU Image Manipulation Program) [43]. The median filter method generated 37.4% white pixels (i.e., the ratio of the number of while pixels over the number of the entire pixels in the image), while the mixture of Gaussian method and color co-occurrence method generated 32.6% and 16.5% white pixels, respectively. The density and the noise of the blob detection can be controlled by adjusting the parameters associated with each method. The results in Fig. 14 were obtained by tuning the parameters in such a way that the density is increased and the noise is reduced on the bottom area of the truck. In terms of the parameter setting, the median filter method is easy to handle since it only has a single threshold parameter while the other two are associated with 4 or more parameters. Through the tests, the appropriate threshold parameter in the median filter method was determined to be 30, and this value was used consistently in the following experiments.

Insert Figure 14 here

This section does not particularly validate the detection accuracy of top and bottom boundaries of a truck. This paper directly validates the final truck height measurement, which indeed integrates the validity of the method in detecting the top and bottom boundaries of a truck. To test the performance of the implemented prototype, experiments were carried out in which twenty-five videos were collected at the locations of a low clearance (LC) bridge over the Northside Drive in Atlanta, GA prior to the intersection of 17th street, and a Personal Rapid Transit (PRT) bridge near the intersection location of the US 19 and Evansdale Drive in Morgantown, WV, respectively. Each video stream was 6-10 minute in length. The videos were collected using a Canon VIXIA HF S100 camera or a Canon VIXIA HF M50 camera. The cameras ware mounted on a heavy-duty tripod to prevent human involved movement or vibration during video recording. The detailed experimental setup concerning camera configuration and video collection is summarized in Table 1. Note in Table 1, the view angle refers to the angle between the camera light of sight and the roadway alignment.

Insert Table 1 here

Three parameters – (1) accuracy of height measurements in 2D pixel coordinates, (2) accuracy of height measurements in 3D real world coordinates, and (3) detection error rate – are considered to evaluate the performance of the proposed methodology. The parameters (1) and (2) are measured by comparing with actual ground truth data. The ground truth data for the parameter (1) is obtained by manual measurement. However, the ground truth data for the parameter (2), the actual height of a truck traveling on the road, is unknown. Therefore, a sample set of trucks with known heights was taken from the videos and tested separately for this purpose. Information regarding the heights of these trucks that serve as ground truth are obtained by referring to the truck manufacturers or moving equipment and storage rental companies such as U-Haul. These business companies' official websites provide specifications that clearly indicate the dimensions of their trucks. The tested trucks are categorized into two classes – semi-trucks with standard trailers and box trucks. Total 120 trucks, 60 for each category, were tested to measure the performance of the proposed method.

4.2 Results

The measurements of the three metric parameters are statistically analyzed, which are summarized in Table 2. Table 2 indicates the overall effectiveness of the proposed method. For the experiment at the bridge in Atlanta, the heights 58 trucks out of 60 were successfully measured. There were two instances of failure in measuring truck heights, which results in 3.3% of detection error rate. The detected 2D image height when compared to the actual 2D image height boasts a 97.52% accuracy rate for the 58 measured trucks. This accuracy rate for estimated 3D truck height when compared to the actual 3D truck height drops slightly to 96.59%. The experiment at the PRT bridge in Morgantown had a result that 57 truck heights out of 60 were successfully measured, leading to a detection error rate of 5%. Fig. 15 shows a snapshot of processing the PRT bridge video with Gygax. The detected 2D image height and 3D physical height of trucks yielded an accuracy rate of 96.23% and 94.96% respectively. It can be observed that the results of the two experiments are comparable to each other. The accuracy rate of the physical truck height is lower than that of the image truck height. This can be attributed to the inaccuracy of the vanishing line and point detection. The average accuracy record, which is around 96%, signifies that the proposed method is highly accurate in measuring the height of trucks from streaming videos. The fact that the method missed two/three trucks out of 60 calls for further enhancement, particularly in the performance of truck detection.

Insert Table 2 here

Insert Figure 15 here

4.3 Limitations and Considerations for Field Implementation

This method is developed for low-clearance roadways, and uses cameras installed on the overpass/tunnels. The premise of the proposed technique is that the roadways are straight and flat, trucks are fully covered in the camera view, and sufficient illumination such as daytime light is available. The experiments carried out herein were geared toward demonstrating that on-road truck heights are able to be measured with sufficient level of accuracy using the described methodology. As such, the proposed vision-based technique has the promise for field implementation. However, it should be noted that the proposed method described here was exercised in a relatively simple way, which may not fully represent the complexity of truck measurement in the field; namely that roadways present particular characteristics (e.g., curved pathways, sloped surfaces, and multiple intersections) and that trucks have irregular tops (e.g., a flatbed carrying a tarped load). Furthermore, depending on the road geometry and camera angles, trucks may be occluded in the field of view. As such, the proposed method may suffer false positive detection issues and that over-height trucks are therefore missed. To avoid the occlusion cases, it is recommended to use one camera for each lane. This is possible because roads with low clearance overpasses usually involve only one or two lanes per direction. By doing so, it prevents the occlusion of one truck by another in the other lane. In addition, the capability of the method to detect and measure a truck height in situation where the truck is changing its driving lane needs further validation.

Several research hurdles must be addressed before the proposed vision-based technique can be implemented into a field-deployable system readily for use in over-height collision prevention. Further studies are needed to determine required levels of brightness and proper types of cameras for night time applications. The authors have noticed that the most popular and well known method of performing low light vision is based on the use of image intensifiers. An image intensifier is a vacuum tube device that enables imaging to possess high sensitivity in ultra-low-light conditions. Recent research in low light imaging techniques primarily focuses on the military and crime surveillance. These applications have demonstrated the promise. A tangible extension that can be explored is the use of image intensifiers incorporated into the charge-coupled-device (CCD) cameras followed by the study of advanced image processing that allows for nighttime measurement.

Another hurdle that needs to be addressed is the influence of vehicle shadows on the performance of the height detection. A vehicle shadow is an area where sunlight cannot reach due to obstruction of the vehicle. The accuracy of measurement on truck heights implemented at the image pixel level may be severely affected by truck shadows. As such, the impact of truck shadows on the measurement accuracy should be carefully measured and controlled. Removal of truck shadows could be a feasible solution which has been presented in several research papers [44,45,46]. However, validation and customization are desirable to enable the techniques in these papers amenable to EDWS field implementation.

5. Conclusions

This paper evaluated a vision-based EDWS which can be a cost-efficient alternative to the laser- or infrared-based systems. The system is comprised of four main processes – field of view calibration, detection, truck height measurement, and warning notice. Having the same warning system as the laser- or infrared-based systems, it can substitute cameras and embedded processor units for expensive equipment and infrastructure such as mounted poles, transmitters, receivers, and detect loops. As the core of the vision-based EDWS, this paper proposed a novel method to measure truck heights using a camera installed on an overpass. Given the detected region of a truck, the method locates top and bottom boundaries of the truck by using line detection and blob detection, respectively. The height is determined by measuring the distance between the boundaries and converting it to the real world length units. The method is implemented in C#, and tested on videos taken at two local roads in Atlanta and Morgantown. The experiment results demonstrated the promise of the proposed method for use in on-road over-height truck warning. The merit of this research was the creation of an automatic video based method which can provide height determination of trucks and is a low cost alternative to the current expensive laser and infrared detection systems. As described in the preceding section, several critical technical issues must be tackled before the proposed technique is deployable in the field. Further efforts, given the demonstrated capabilities, will be to detail cost comparisons and potential savings between the proposed video based approach and other height detection systems, in various operating environments, given that cost-efficiency is a primary driving force for the present study. Being able to project estimate savings in dollars may help further understanding of benefits and limits of the vision techniques versus other techniques. This proposed method could be the valid option for the budget limited DOTs that needs state-wide implementation of EWDS to protect state infrastructure such as bridges and tunnels. Nevertheless, the technical issues are more critical and urgent than the cost comparisons for the future work to address. Though this paper presented experiments on local and highway roads, its wide use can be expected in controlled conditions in terms of occlusion and illumination. For instance, the proposed system can be easily applied for prohibition of over-height vehicle at parking decks and luggage handling in airports.

6. Acknowledgement

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List of Figures

Figure1

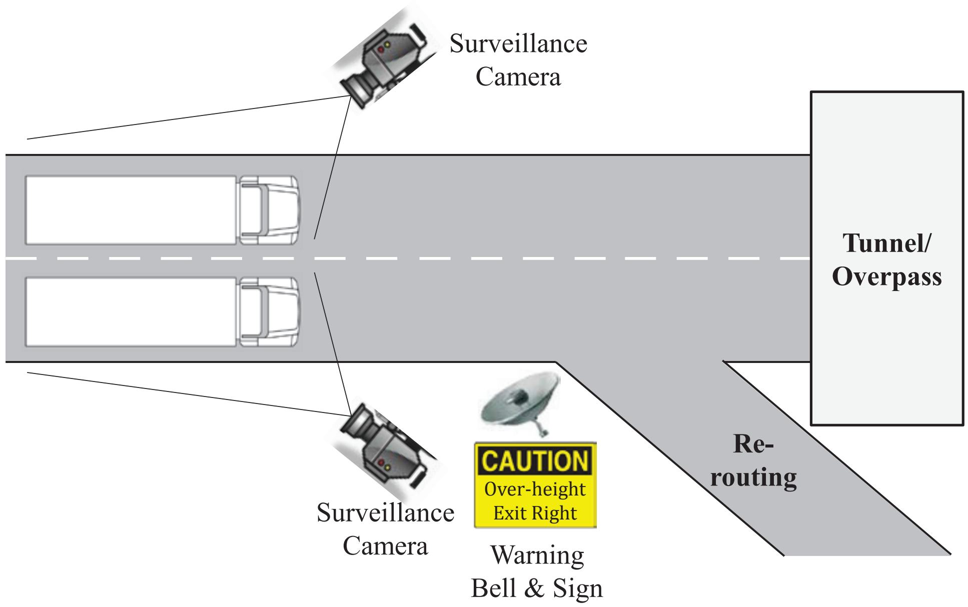

Surveillance
Camera
Tunnel/
Overpass
CAUTION
Over-height
Exit Right
Re-
routing
Surveillance
Camera
Warning
Bell & Sign

Figure2

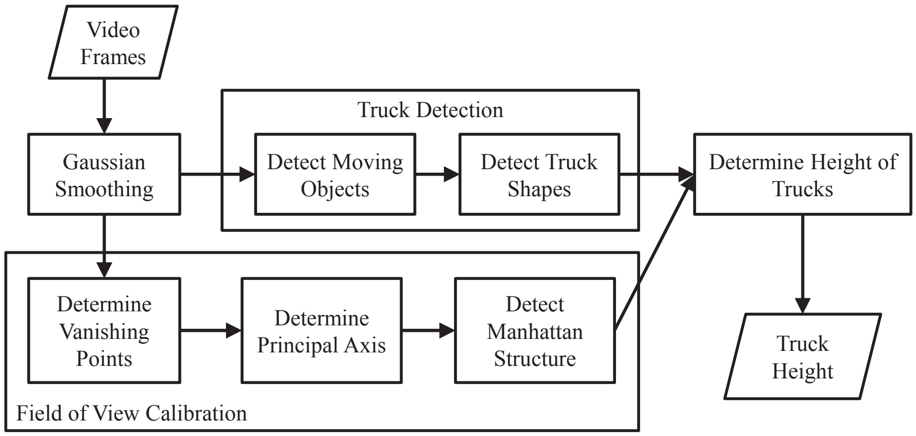

Video Frames
Gaussian Smoothing
Truck Detection
Detect Moving Objects
Detect Truck Shapes
Determine Height of Trucks
Determine Vanishing Points
Determine Principal Axis
Detect Manhattan Structure
Field of View Calibration
Truck Height

Figure3

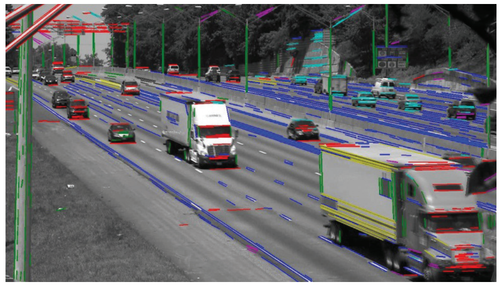


Figure4

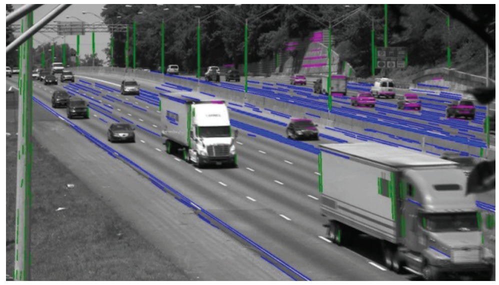


Figure5

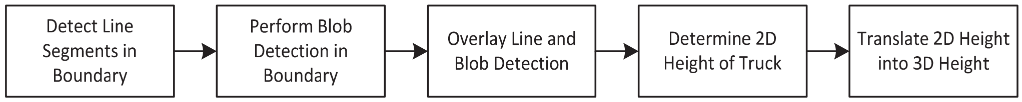
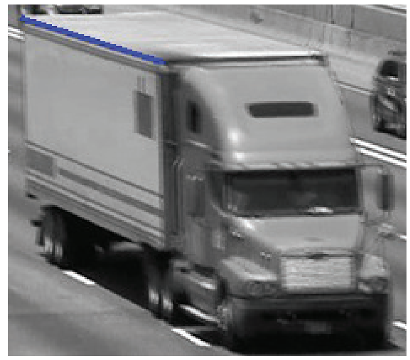

Detect Line Segments in Boundary
Perform Blob Detection in Boundary
Overlay Line and Blob Detection
Determine 2D Height of Truck
Translate 2D Height into 3D Height

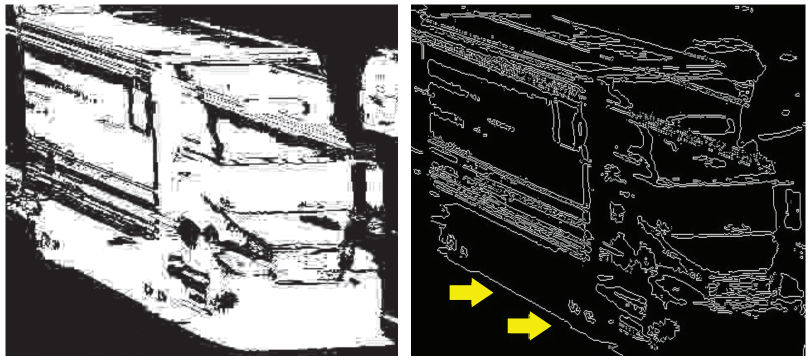
Figure6

(a)



(b)

Figure7



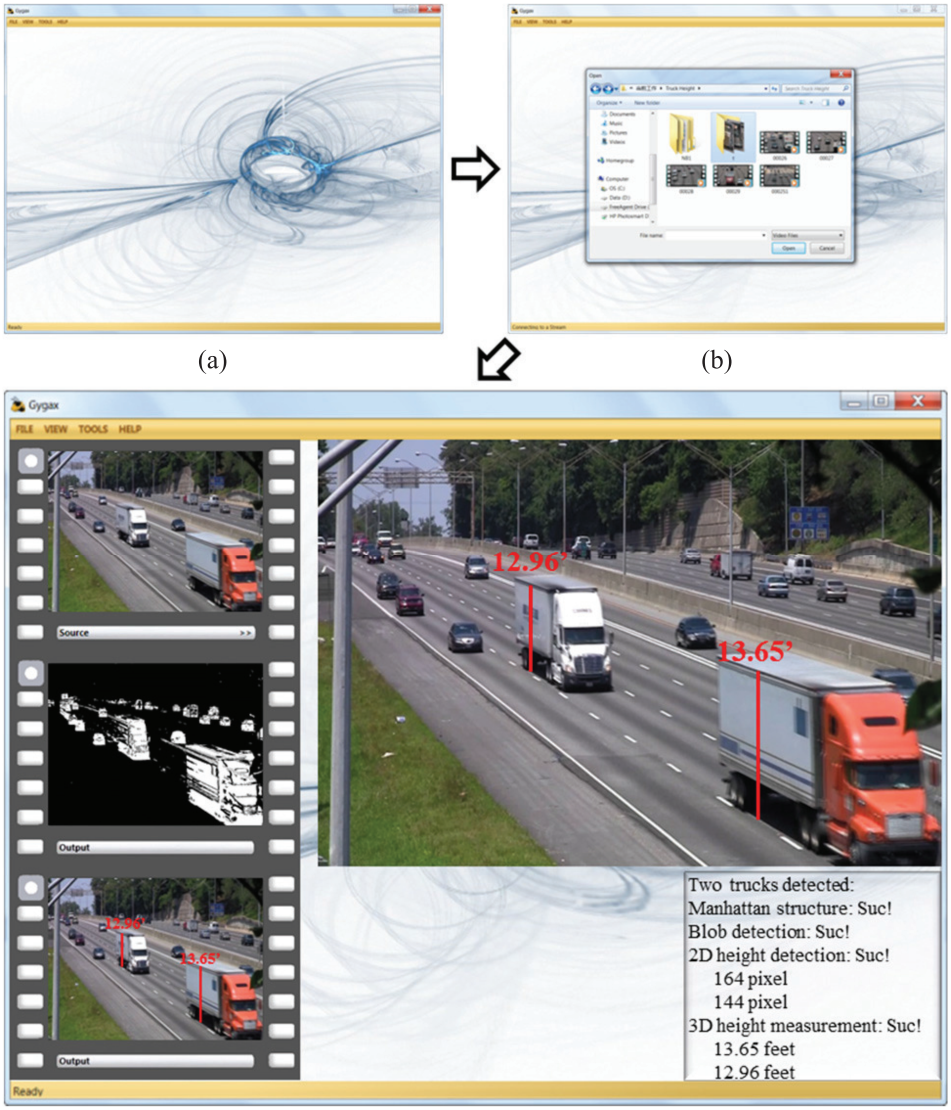
(a) (b)

Figure8

(a) (b) (c)

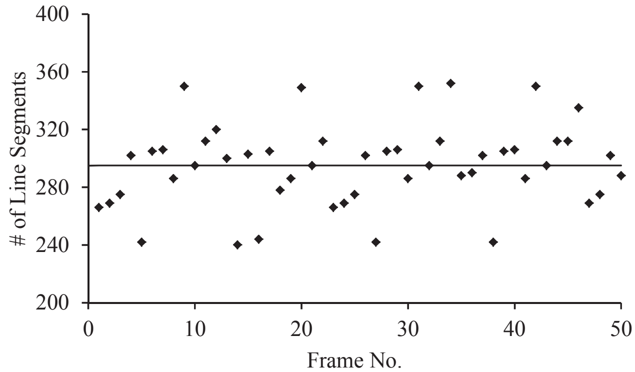
Figure9

Figure10



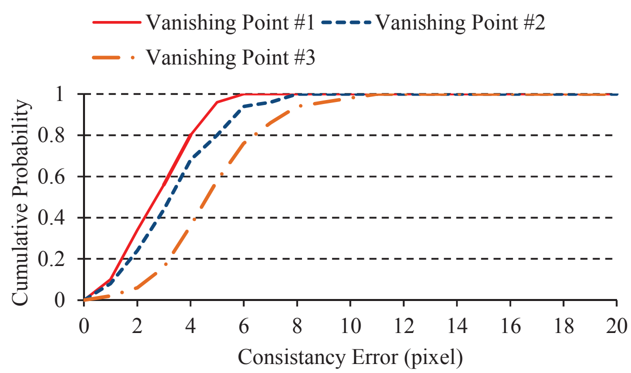
(a) (b) (c)

Figure11



400
360
320
280
240
200
# of Line Segments
0
10
20
30
40
50
Frame No.

(a)



Vanishing Point #1
Vanishing Point #2
Vanishing Point #3
1
0.8
0.6
0.4
0.2
0
Cumulative Probability
0
2
4
6
8
10
12
14
16
18
20
Consistancy Error (pixel)

(b)

Figure12

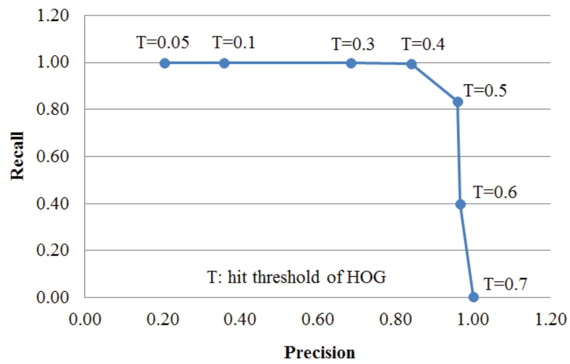
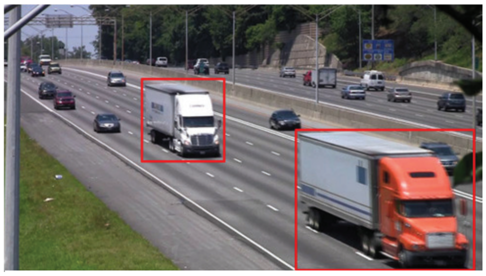

1.20
1.00
0.80
0.60
0.40
0.20
0.00
Recall
T=0.05
T=0.1
T=0.3
T=0.4
T=0.5
T=0.6
T=0.7
T: hit threshold of HOG
0.00
0.20
0.40
0.60
0.80
1.00
1.20
Precision

Figure13



(a)

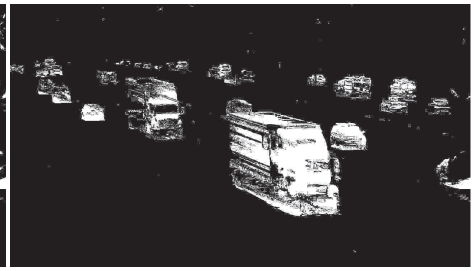
(b)

(c)

(d)

Figure14

(a) The median filter method



(b) The mixture of Gaussian method

(c) The color co-occurrence method

Figure15


Gygax
FILE VIEW TOOLS HELP
Source
Output
Output
13.62'
One truck detected:
Manhattan structure: Suc!
Blob detection: Suc!
2D height detection: Suc!
179 pixel
3D height measurement: Suc!
13.62 feet
Ready

Table

Table 1. Experimental Setup

	@ LC Bridge	@ PRT Bridge
Camera model	Canon VIXIA HF S100	Canon VIXIA HF M50
Resolution (pixel)	1280 × 720	1280 × 720
FPS (frames/second)	30	30
View angle (^{o})	25 ~ 30	30 ~ 35
# of video clips	10	15
Length of video clips (min)	6 ~ 8	6 ~ 10
# of trucks measured	60	60

Table 2. Summary of experimental results

		@ LC Bridge	@ PRT Bridge
# of trucks	Appeared	60	60
	Measured	58	57
% of detection error		3.3%	5%
% of accuracy (2D height measurement)	Mean	97.52%	96.59%
	Standard deviation	5.45%	4.89%
% of accuracy (3D height measurement)	Mean	96.59%	94.96%
	Standard deviation	4.75%	4.63%