# Optimized parameters for over-height vehicle detection under variable weather conditions

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***Abstract*:** Over-height vehicle drivers continuously ignore warning signs and strike onto bridges despite the number of preventative methods installed at low clearance bridges. In this paper, the authors present a new method for over-height vehicle strike prevention with a single calibrated camera mounted on the side of the roadway. The camera is installed at the height of the "over-height plane" formed by the average of the maximum allowable heights across all lanes in a given traffic direction; the error caused by the road gradient is assumed to be negligible and absorbed through the calibration process. At that height, the over-height plane can be safely approximated as a line in the camera view. Any vehicle exceeding this line is consequently over-height. The camera position and orientation is determined via a calibration process proposed. Instances of over-height vehicles are detected via optical flow monitoring. Evaluation of the system resulted in a height accuracy of ±2.875 mm; outperforming the target accuracy of ±5 cm, OH detection accuracy of 68.9%, and classification performance of 83.3%. While its accuracy is comparable to existing laser beam systems, it outperforms them on cost which is an order of magnitude less due to eliminating the need for new permanent infrastructure.

***Keywords:*** Bridge collision, over-height bridge strike, over-height detection system, over-height vehicle, tunnel strike.

## Introduction

An over-height vehicle strike (OHVS) is an incident in which a vehicle, typically a lorry (truck) or double-decker bus, tries to pass under a bridge or tunnel that is lower than its height, subsequently colliding with the structure. Accidental collisions between over-height (OH) vehicles and bridge superstructures are a global and frequent phenomenon occurring throughout transportation networks worldwide (Xu *et al.* 2012, El-Tawil *et al.* 2005, Fu *et al.* 2004). The US Federal Highway Administration reports that the third most common cause of bridge failure is vehicle or vessel collision (Federal Highway Administration 2013). These strikes lead to traffic delays, damage to bridge structures, bridge closures and injuries. In the worst-case scenario, derailments, immediate collapse of bridge structures, and fatalities may occur (Ghose 2009, Washington State Department of Transportation 2013).

Managing OHVS requires attention in three domains: prevention (discouraging strikes in the first place); detection (accurately recording strikes that do occur); and reporting (efficiently communicating OHVS details to the relevant authorities). The latter two aspects of OHVS management are effectively managed by current systems. Many OHVS technology that currently exist on the market is targeted towards preventing OHVS from occurring in the first place. Very few systems are designed to mitigate OHVS impact, as asset owners are interested in protecting the structure and limiting any risk of structural instability.

Current prevention systems are categorized into *passive*, *sacrificial,* and *active* types. Practitioners favor quick, cheap, and accessible passive methods such as signage, bridge markings, and flashing beacons as an initial attempt to warn drivers. These passive interventions are readily available, easily installed, and minimize additional infrastructure installation. They prevent ~10-20% of strikes, meaning that additional complimentary systems are necessary for higher prevention rates (Cawley 2002). Where strikes have persisted, practitioners incorporate sacrificial or active systems. Sacrificial systems (also known as rigid passive systems) are ideal for asset owners as post-installation maintenance is minimal and further discussed in Section II.

Active systems, also known as Early Warning Detection Systems (EWDS), detect and notify vehicle operators ahead of the presence of low structures. Current systems consist of a transmitter and a receiver, placed directly across the lane(s) of traffic with an inductive loop to detect presence of a vehicle in advance of the warning sign (TRIGG Industries International 2015). Asset owners in the US, Australia, China, Canada and Netherlands have deployed the active systems using laser or infrared light warning systems at low clearance locations (New York State 2015, LaserVision 2015, Sina 2012, Alberta Infrastructure & Transportation 2008, Dutch Ministry of Infrastructure, & Environmental Department of Waterways and Public Works 2015). However, at non-critical low height locations, most asset owners have chosen not to use EWDS due to unfavorable cost-benefit analyses. The reported installation costs range in the hundreds of thousands of dollars therefore limiting the widespread adoption of EWSD due its high costs associated with the physical infrastructure requirements (Sandidge, unpublished thesis, 2012, Dai *et al.* 2015, Singhal, unpublished data, 2015). The biggest issues for asset owners are affordability and reliability, without compromising the accuracy and performance of such a system. Many systems exist on the market; none cover the three aspects of OHVS management affordably.

In this paper, the authors propose a potentially viable solution for OH vehicle detection, specifically addressing the *prevention* problem. The paper is organized as follows: Section II describes the ideal framework for OHVS management, followed by non-rigid and rigid passive methods, and leading (active vs. passive) and lagging sensing methods. Section III introduces the overall framework with the proposed geometry, camera installation procedure, and detection algorithm. An evaluation of the system is presented in Section IV with results, discussion and concluding remarks.

## Background

As vehicle heights are continually increasing, and bridge structures built by standards that are decades out-of-date and often inadequate today, the problem of OHVS is an ongoing nuisance for asset owners. One of the earliest systems designed to deal with the problem date back to 1906, patented by the American engineer

James H. Donaldson (1906). The guard system was invented to warn drivers that the train is about to pass into a tunnel or under a bridge. The guards consisted of a number of strips of flexible material attached to a wire stretched across the track striking the top of the train, and warning drivers to stop to allow for the train to pass. Over the years, this type of OH vehicle detection and early warning system has evolved into the commonly used OHVS prevention tools still with us today.

Figure 1 depicts a more recent schematic layout of the OH vehicle detection and warning system. The system employs the main components: sensing technology (*1*), warning device (*2*), alternative route (*3*), detection sensors (*4*) and, collision reporting (*5*) positioned upstream of low bridge. Components (*1*), (*2*), and (*3*) cover the prevention aspect of OHVS management by installing a sensing device to detect the OH vehicle and a warning device to warn the OH driver. These methods are considered to be leading methods. Adequate latency is required between data processing and warning issuance, to provide the driver of an OH vehicle with sufficient time to react, brake or exit. In ideal situations, an alternative route is provided for a quick and safe exit. Components (*4*) and (*5*) are lagging methods covering the detection and reporting aspects of the system. Detection sensors are mounted on the bridge structure to record any frequencies caused by strike and real-time collision reporting technologies are used to notify authorities of the strike. The system presents a holistic solution for early warning and detection system for OH vehicles. Asset owners seek an affordable method that will cover prevention (with an accuracy of ±5 cm), detection (and concomitant emergency services response), and real-time reporting.

**A) Prevention Methods**

**1) Passive Non-Rigid and Rigid Methods**

Non-rigid passive methods include flashing beacons and bridge markings. Flashing beacons are commonly used at low bridge approaches to warn drivers of an oncoming ‘hazard’ and typically paired with other preventative methods such as bridge markings to emphasize the warning. A study by Horberry *et al.* (2002), tests various designs of bridge markings to reduce the risk of OHV strikes. The study attempts to optimally redesign bridge markings to appear lower and more confined, making drivers more reluctant to pass underneath. Although this preventative initiative makes drivers more cautious, it only addresses part of the OHVS management problem therefore relying on drivers to take appropriate precautions; additional preventative mechanisms are required.

At the policy level, asset owners have attempted to manage the problem of OHVS by implementing permits, axel load restrictions, fines, driver education and awareness programs, good practice manuals and newsletters. Although these strategies may not directly prevent OHVS from occurring, increased awareness plays a positive role and can be effective for passengers, professional drivers and transport managers.

Rigid passive methods are typified of crash beams, metal hanging chains and road-narrowing techniques. Crash beams act as a 'cushion' to the bridge structure (Yang and Qiao 2010); energy transferred by the strike is dissipated by the beam therefore reducing damage to the main structure. Crash beams are costly and an effective mitigation strategy but they too only solve part of the problem; the beams do not warn vehicle operators and are protective rather than preventative. An alternative option is the use of metal hanging chains and road-narrowing (calming) techniques such as speed bumps, rumble strips and chicanes. Weathering causes major damage to the metal chains and calming techniques require major road reconfiguration; two non-ideal cases.

**2) Active vs. Passive Sensing Methods (Leading)**

Preventative methods are actively being researched in order to find an effective solution, from the perspective of high performance and low cost. This section reviews the research, concentrating on preventative methods that are based on imaging or electromagnetic waves. Imaging-or vision-based sensing solutions are divisible into two categories based on the sensor modality used. The first involves sensors with active illuminators or active emission of electromagnetic waves, for which lasers and radar are prominent examples. The second involves sensors that passively measure the ambient electromagnetic energy, the standard video camera being the main example. The review of passive prevention methods will be further decomposed into active sensing and passive sensing strategies.

Active methods consist of optoelectronic single- or dual-eye infrared, visible beam, radar or laser beam detection systems, all of which detect OH vehicles when the laser or light beam is interrupted (Sinfield, unpublished data 2010). In Massoud (2013), a laser system was shown to function well, and was recommended over equivalent mechanical methods. Such sensing technology methods are representative of those currently on the market and provide little incentive for asset owners since the outdoor infrastructure installation requirements are financially prohibitive. Outdoor infrastructure entails the installation of new permanent poles, typically a receiver and transmitter for laser-based cases. Urazghildiiev *et al.* (2002; 2007), proposes overhead installation of a microwave (MW) radar system for detecting both the height and the vertical profile of passing vehicles in the sensing lane (a single lane per radar). The radar measurement system performed well under most weather conditions and to vibrations still requires the installation of additional outdoor infrastructure. One unit is required for each lane therefore increasing the overall cost of installation, which is suboptimal for asset owners.

Passive sensing methods utilize vision-based methods, such as those currently used in several IT systems developed for vehicle detection, vehicle classification, and license plate recognition (Anagnostopoulos *et al.* 2006). As part of these systems, the utilization of vision and imaging methods have been extensively researched for scene change detection (background subtraction), vehicle tracking and motion detection, all of which are essential for OH vehicle detection (Piccardi 2004, Coifman *et al.* 1998, Jazayeri *et al.* 2011). Researchers have studied alternative approaches using vision-based methods to extract vehicle height measurements but to-date, no active vision-based system exist on the market. The research has been somewhat limited but provides a solid starting point in determining the potential for further development.

Khorramshahi *et al.* (2008) presents a passive vision-based method for OH detection. Their algorithm uses a cubic detection zone to obtain vertical projections of feature points of blobs in 2D coordinates. The feature points over a specified threshold are tracked as OH vehicles. Although this method satisfies the economic efficiency criterion, the method is less robust when occlusions and shadows are present which can result in false negative detections. Other methods of OH detection are presented in Kanhere and Birchfield (2008), Shao *et al.* (2010), Criminisi *et al.* (2000), Sturm and Maybank (1999) using vanishing lines and reference objects to extract height measurements of vehicles and objects. These passive methods presented consist of the same underlying concept that given a known ground plane and upper and lower limit, the vision-based methods are able to recover the height of objects. The computer vision methods rely on geometric shapes and structures to recover usable information in complex scenes that increases the set of confounding factors such as the need for ground plane information. For example, Dai *et al.* (2015) contributed the most recent research to OH vehicle detection using line detection and blob tracking to estimate heights of box-shaped vehicles. The top and bottom boundaries are determined in 2D pixel coordinates and converted into 3D height measurements. The research shows promise as a novelty approach; however, the method does not perform well during scenes of occlusions or nighttime conditions. When vehicle shadows and occlusions were present, it impacted the reliability and accuracy causing incorrect extractions of height measure leading to false positive and negative detections. In contrast, Nguyen *et al.* (2016) presented an improved method that eliminated the need for physical vehicle height extractions. The method uses a vision-based approach set at the height of the low bridge. The camera (when calibrated) acts like a laser-beam; any moving motion over that height is further analyzed to correctly classify the motion as a positive instance *i.e.* OH vehicle. The OH detection method was tested under ideal conditions: sunny, non-windy weather conditions resulting in an overall detection accuracy of 99.9% with a false positive rate of 0.1%. The method performed well under ideal weather conditions but has not been tested under more vigorous weather conditions. Vehicle occlusions and shadows do not interfere with the detection process since the camera is situated at a height where occlusions and shadows are non-existent or less frequent. The viability of the method is premature, further real-time testing is needed to show its robustness and true value.

## B. Collision Detection and Reporting Methods (Lagging)

Practitioners have access to readily available systems for the detecting and reporting aspects of OHVS management, but the devices alone will not prevent strikes; the main area of concern lies with prevention. Devices that could be used as complementary detection and reporting methods are structural monitoring and impact detection sensors and accelerometers that are installed on the bridge structure to record changes in frequencies caused by vehicular impact, hence 'lagging' method (Park *et al.* 2000). Many strike accidents that occur today are not reported, and asset owners are left to remedy the damage caused by drivers.

Companies such as Strainstall and Trimble help to rectify this problem by providing a web-based structural monitoring product for real-time access to data (Strainstall 2015, Trimble 2015). The sensors are used as a data acquisition system, collecting data at a single node for centralized processing. An accelerometer can be used to parameterize a model of the structure: when damage occurs on the bridge structure, the parameters of this model changes (Xu *et al.* 2004). Connectivity to a wireless network enables the device to send the measurements to a remote location for processing and decision-making. Collision notification technology relays the message to the control room.

## C) Related Computer Vision-based Methods

The capability for intelligent transportation systems to detect and track moving objects still presents a challenge using vision-based systems. However, with the increased computational speed of processors today, this has enabled the applications of vision technology possible. Below presents related methods for detecting OH motion and feature detection, tracking & classification.

### 1) Optical Flow (motion)

Yoo and Park (2008) presents a novel approach for detecting moving objects in the camera view using a differencing method, Earth Mover's Distance to find motion patterns in a given region. The algorithm works such that it finds motion patterns by subtracting two consecutive frames and assigning motion blocks to detect regions with movement showing robustness with local illumination changes.

Similarly, researchers Mittal and Paragios (2004) present a patented technique for modeling dynamic scenes using a novel kernel-based multivariate density estimation for motion detection. The technique performs well under adverse weather conditions and motion with vigorous moments such as moving trees and bushes; the algorithm is able to minimize background noise therefore presenting a good foundation for OH vehicle detection.

Niu & Jiang (2008) presents an improved adaptive background subtraction detection method using a Gaussian mixture model to minimize shadow interference of moving objects. The method shows robustness to shadow removal and lighting sensitivities. The adaptive background subtraction is promising for OH vehicle detection in variable weather conditions.

**2) Feature Detection, Tracking & Classification**

Researchers Zheng & Chellappa (1995), Yao & Chellappa (1994), Tomasi and Kanade (1992) and Chetverikov & Verestói (1999) have shown effective methods to detect moving objects using feature-based detection, tracking & classification. Of those, researchers Tomasi and Kanade present a widely used method using factorization to track the motion of features in an image stream. The method utilizes the size of eigenvalues to detect corners and regions with high spatial frequency content, second-order derivatives and intensity variance. The method compares past and present fixed-sized feature windows by taking the sum of the squared intensity differences over the windows and finding the displacement of one frame to the next using texture-rich pixels. The method shows robustness to occlusions and noisy images – both of which are ideal for effective OH vehicle detection and tracking.

Feature detection and tracking is a crucial step in preventing false positive detections for OH vehicle detection. Vision-based methods shows promise for OHVS; however, despite the favorable affordability criterion, asset owners are not yet convinced that vision-based systems are suitable to handle the vigorous outdoor conditions while meeting its performance accuracy. Further testing is required to achieve and demonstrate the true effectiveness and value of the approach. In essence, if the system is able to achieve the accuracy target of ±5 cm, a low cost vision-based system (paired with complimentary detecting and reporting tools) could provide a holistic solution to the problem of bridge and tunnel strike prevention.

**Proposed solution framework**

Existing EWDS are the most accurate warning systems, yet are not cost effective due to their significant physical infrastructure requirements. Cost considerations drastically limit their adoption and suitability. New EWDS are needed that can bring the cost down by at least one order of magnitude to make them attractive to infrastructure owners. Therefore, this paper presents a new solution for OH vehicle detection using perspective projection, inspired by the laser beam method. The objective is to replace the transmitter, receiver, and loop detectors with a single camera mounted upstream of a low bridge.

The proposed method adopts a previously developed method Nguyen *et al.* (2016); however, the study expands the method using optimized parameters under variable weather conditions. The method is based on the following geometric principle: when a camera is properly mounted at the height of the bridge clearance relative to the local roadway, then the OH plane will appear as a line in the camera image. The method is suitable for various shapes and sizes of vehicles, numbers of laneways, and illumination conditions (day and night time). The camera placement is crucial; this step minimizes any potential captures of noisy motion that may contribute to triggering false positive alarms. The camera location should be free of potholes (to minimize height variations), vegetation, branches, trees, and over-head cables. According to the mathematical modelling of perspective projection, if the object is less than the set camera height, it will not be detected within the ROI despite distance from the camera (this includes buildings and occupant motions from across the roadway). However, if the occupants are on the second floor and captured within the ROI, the practitioners should find an alternative location to minimize the potential unwanted noise. If alternative locations are not possible, the threshold will need to be adjusted to account for the noise (further explained under Evaluation of System).

The primary innovations are the specialized camera placement relative to the roadway and the associated setup procedure that minimizes installation efforts. All components of the system thus far described are intended to minimize inspection, maintenance and repair costs. If the proposed solutions achieve the accuracy of laser-based systems and maintains the low cost of typical passive vision-based systems, then pairing the proposed prevention method with complimentary detecting and reporting methods will provide a holistic solution to the problem of bridge and tunnel strikes. The proposed solution is also applicable to low-deck parking garages and shipping barges with low height restrictions.

The overview process for OH vehicle detection is presented in Figure 2. Video is converted into image frames, which are then used as inputs for the OH detection process. The MATLAB code uses the VideoReader to read video files. The elapse time is 36.8658 seconds to process 30 frames, equating to 1.2289 fps. A frame grabbing code is used to convert the video files into image frames. After the frame is converted, each frame is passed through the image blur metric (Do 2009). If the frame is identified as blurry, the code discards the frame and uses the succeeding frame. The blur metric works such that the images are passed through several filters and assigned a 'blur annoyance' rating estimated using neighboring pixels. If this variation is high, the initial image is considered sharp. If the variation is moderate or low, the initial image is blurry. The blur perception is calculated based on the sum of the coefficients and selected using the vertical and horizontal blur value, resulting in a binary solution (0 and 1) for the best and the worst quality images (Crete *et al.* 2007).

An OH vehicle is typically in the scene for 2 seconds. If the camera is set at 30 fps then this equates to 60 frames to be processed. In order for an alert to be triggered, only one OH instance is required. When the message board is on 'active' alert, any positive OH instances are considered redundant. If the message board is no longer 'active', any positive OH instance will re-trigger the message board to warn the driver. The system does not count (the frames that is), there is a simple if elseif statement (if this is true then execute this, else if this is true then execute this) that works such that if the message board is active then disregard any positive instance else if the message board is inactive then turn the message board *on*.

When an OH vehicle is detected, recording of cameras and accelerometers are activated; a message is issued on the display unit, warning the driver of the low bridge. The driver warning process may take one of two paths: 1) if the driver exits or stops, and no impact is detected, then video data is discarded and accelerometers are deactivated; 2) if the driver continues and an impact is detected, then the vehicle license plate number is extracted from the recorded video and impact data from the accelerometer is stored. The collision report (video segment, license plate, and accelerometer data) is sent to the relevant authorities.

**C. Camera Geometry and Detection Policy**

The method models an active laser sheet using passive vision methods. Figure 3(a) depicts the scenario displaying a crop version of the infinite OH plane offset from road plane by bridge clearance height *h*, where the camera coordinate system is $X^c$, $Y^c$, $Z^c$ and world coordinate system is *x*, *y*, and *z* axes. The camera rotation is defined as $\theta_{yaw}$, $\theta_{pitch}$, $\theta_{roll}$. The OH plane is defined by offsetting the local road plane by the height *h*, and the camera is placed such that the optical center lies on the plane. The light rays of object points located on the OH plane will project to a line. The plane divides the world into two regions, those above and those below. Likewise, the line in the image divides the image into object points below- or above- the line. The method assumes that the lanes are approximately planar across the road width of each direction, trucks are located to the right except to pass and that camera lens distortions are rectified through camera calibration.

Figure 3(b) depicts a side view of the OH scenario with an OH region of interest (ROI indicated in red). The $\theta_{pitch}$ of the camera is shown tilted downwards ($\theta_{pitch} \geq 0$) to minimize any illumination reflection on the lens caused by sunlight. This volume projects onto the image as a band. Any OH vehicles passing through the sense scene will cross the line in the image view and project into the band, thereby triggering an OH detection. Vehicles not tall enough to strike the bridge will not project into the band, and can therefore be ignored. In this sense, the proposed geometric setup resembles that of an active laser sheet. Figure 3(c) displays the top view of the camera setup. The optical axis of the camera $Z^c$ intersects with the road plane along the *y*-axis at $p = (0, h\ cot\ \theta_{pitch}, 0)$. All figures use the right-handed system, such that $x$ and $X^c$ are into the page in the side view, while $y$ is coming out of the page in the top view figure 3(c), noted by the red dot.

## D. Camera Installation Procedure

This section summarizes the mechanics of the proposed methodology. There are two aspects to the calibration process involving the intrinsic and extrinsic parameters of the camera. The intrinsic parameters are constants that hold irrespective of the placement of the camera, whereas the extrinsic are fundamentally tied to the placement of the camera in the world. The installation requires the extrinsic parameters to be specifically determined by the local roadway and the desired OH value $h$. However, there is some dependence on the intrinsic parameters, thus they should be established first.

The intrinsic parameters, being independent of placement, can be estimated anywhere. This should be done away from the installation site where the necessary calibration infrastructure may be better controlled for accuracy. The standard method for intrinsic parameter calibration involves a calibration pattern. Taking pictures of the calibration pattern at different positions and orientations enables the estimation of the intrinsic components of the camera such as focal length ($f^x$, $f^y$), camera center ($c^x$, $c^y$) and radial distortion coefficients ($k^1$, $k^2$) of the camera (two coefficients are typically sufficient for compensation of radial lens distortion (Heikkila and Silvén 1997).

The extrinsic parameters represent the transformation from the 3D world coordinate system to the 3D camera coordinate system centered at the optical center; the two parameters, the extrinsic and intrinsic describes the transformation from 3D world points to 2D image points (Fathi and Brilakis 2014). The camera installation and extrinsic calibration process will configure the OH system with the desired extrinsic camera parameters in a controlled and repeatable manner. The process relies on the facts that installation involves controlling for two variables, camera height $h\_c$ and camera roll $\theta_{roll}$ and that a plane is defined by three non-collinear points lying on the plane.

A software installation prototype is created to help aid users perform the camera corrections needed in order to locate the three [xi, yi] points in the image view. The prototype functions such that it retrieves and undistorts a single image taken when the poles are at the respective marker locations (1) and (2). By using the mouse curser, the user clicks on the pole tip marker in the image. The prototype records the pixel locations of the points and compares their *y*-pixel values. If the *y*-pixel values do not match, the prototype instructs the user to adjust the camera by a specified amount. The same procedure is carried out for $\theta_{\mathrm{roll}}$ of the camera at marker locations (2) and (3). This process may require a series of iterations; this process may require a series of iterations; this process can take between 15 to 60 minutes. The process is designed to allow people with no prior experience/training perform the calibration process. The process can be performed with one person; however, two people are recommended. One person will handle the software while the other is will position the pole in its respective location; this will allow for maximized set-up time.

### 1) Camera Installation and Extrinsic Calibration Process

The camera installation and extrinsic calibration process will manipulate the projection of three specifically determined OH plane points until the two parameters are correct. The images in Figure 4 provide a visual narrative of the installation process. The red arrows contain text to indicate the corrections needed. Consider Figure 4(a), which depicts three non-collinear points [xi, yi, zi] set at the height of the bridge clearance *h*, relative to the local roadway. The light rays that make up the plane project onto the image view as three [xi, yi] points. When correctly installed, they will project onto a horizontal line in the image (which is the desired OH detection line) and referred to as the 'OH line'. Initially, this will not be the case. The installation process provides a means to arrive at a horizontal OH detection line object with a height equal to the height of the bridge clearance (tall pole with a bright marker at the tip). The pole method is an inexpensive, efficient, and readily available alternative to the total station method (access to which may be limited to a few).

Assume that the camera is to be installed at the height *h* above the road plane, and that the projection to the road plane is the road plane origin (0, 0, 0). First, the camera is placed (on an existing pole) at an approximated height to the desired height. Placing the camera on a pole limits the translational degrees of freedom to one. Then the following two rotations are set: $\theta_{\text{yaw}}$ is angled to capture license plates of vehicles and $\theta_{\text{pitch}}$ is angled downwards to allow for optimal positioning of the ROI, and less illumination interference. By performing these two rotations, the user has fulfilled two of the three rotational conditions: $\theta_{\text{yaw}}$ and $\theta_{\text{pitch}}$. Therefore, one degree of freedom ($\theta_{\text{roll}}$) remains.

At this point, the user should go out and perform two pole measurements. For the first point, the user should aim to capture a measurement towards the left side of the image. The second pole location should be located behind the first, which is achieved by walking away from the camera along the line defined by the camera installation point and the first pole point (both projected to the road plane). The simplest way to do this is to face the camera, then walk backwards with pole in hand. If the camera is at the pole height, then both of these pole locations will have the pole tip marker project to the same point in the image. If not, then there will be an offset determined by the true height of the camera relative to the desired OH plane. If it is below the OH plane, then the first point will appear "above" the second point and the camera should be lowered; this situation is depicted in Figure 4(a) with the red arrow denoting the correction to be made. If it is above the OH plane, then the opposite will hold. The measure and adjust process should be repeated until the two pole tip markers project to the same point.

At this point, the camera will be located at the proper height, however the OH detection line in the image will be at an angle determined by the camera roll relative to the road plane. The next step will modify the camera roll $\theta_{\text{roll}}$ so that the OH detection line is a horizontal line in the image. While not necessary, it is recommended as the additional step simplifies the OH detection computations. The user should then take a third measurement which projects to the right hand side of the image. The further to the right, the more sensitive the roll estimation process will be, and hence the more accurate. If the camera is at the correct roll, then the third point will lie on the same horizontal line as the first two points (their *y*-pixel coordinates will be the same). If not, then the line defined by the projected image coordinate of the first two pole tip points with the third will have a positive or a negative slope. A positive slope requires clockwise roll adjustment, and a negative slope requires counter-clockwise roll adjustment. The scenario is depicted in Figure 4(b). Some iteration may be necessary to arrive at the proper camera roll as depicted in Figure 4(c). For each iteration, two points will be needed, meaning that two pole tip measurements will be needed. One on the left side of the image and one on the right side, as depicted by marker locations (2) and (3) in Figure 4(b), respectively.

The camera is now located at the proper height and with the necessary roll needed for the OH detection line to be horizontal. However, this line may be located too low in the image. A low placement means that the camera is measuring more of the OH volume as opposed to the non-OH roadway volume. While it is theoretically not a problem based on the geometry, there are illumination factors to consider. Having the camera aimed too much at the sky leads to false automatic exposure compensation that would darken the roadway. Adjusting the camera pitch to minimize bright sky regions and also impossible to achieve OH detection volumes should indirectly improve visual processing by minimizing confounding and unrelated imaging factors. At this point, the user can adjust $\theta_{\text{pitch}}$ so that the OH detection line creates a favorable division of the image while still allowing for measurement of OH vehicles within the determined OH detection region (see Figure 4(c)).

**E. Detection Procedure**

The detection procedure uses the video from the camera that is then converted into image frames as the initial input data. Motion segmentation is used as the main feature extraction to detect and track moving objects within the ROI. The ROI is simply a pixel area set above the OH plane in the image that is sized accordingly to minimize the risk of false detections. The detection algorithm calculates the motion differences within the ROI between the current image frame and background model by utilizing vehicle motion when OH vehicles are present in the scene. Motion is detected by calculating the vector difference (optical flow) between the current image frame and background model as shown in Figure 5. The OH features points are automatically detected and tracked by using the Kanade Lucas Tomasi (KLT) algorithm (1981). The green circle represents the initial detected feature point detection in the image, *i* and the red cross represents the motion of that same detected point in the next consecutive image, *i++*. If no motion is detected, the circle and cross are matched. If movement is detected, a velocity displacement arrow is visible in blue showing direction of movement.

The camera setup allows for OH vehicles to appear within the ROI; therefore any moving objects traveling at a more-or-less constant velocity in the direction of traffic are detected and tracked by the algorithm. A motion threshold value is determined by comparing the pixel differences and adjusted for sensitivity against noise and other moving objects such as trees that may interfere with the detection procedure. If an OH vehicle is detected, this will trigger a warning to the driver. Vehicle occlusions and shadows do not interfere with the detection process since the camera is situated at a height where occlusions and shadows are less frequent. For example, if the bridge clearance height is 6.0 m, then the ROI only detects vehicles over the height of 6.0 m. However, vehicle occlusions may occur when two or more OH vehicles are in the scene simultaneously; this occurrence will trigger one warning to both drivers. For vehicle shadows, they are generally on the road plane and out of range from the ROI, therefore posing no interference with the detection procedure. The other set of uncontrolled environmental drawbacks is the variable weather conditions: windy, rainy and cloudy conditions; hence an extension to the research study. The detection procedure is ideal for various shapes and sizes of OH vehicles. The common denominator is that their heights exceed a certain limit relative to the road surface. By exploiting this characteristic, the method avoids computing an exact height measurement of each vehicle, preferring a binary decision that returns one of two possible outcomes (*OH / non-OH*) for accurate detection. The camera geometry and its associated installation procedure overcome several of the current detection deficiencies associated to existing methods. In particular, it eliminates the requirement of a vision-based ground plane measurement, which most of the other solutions require. Further, since the visual processing focuses only on offending vehicles, the set of confounding factors is less than the current strategies, which will improve computation time and discrimination.

**Evaluation of System**

This section provides details of the experiments designed to evaluate the height and detection accuracy of the system. The implementation was conducted on two collector roadways with 2 and 4 lanes of traffic in sunny, cloudy and rainy weather conditions. A Canon EOS M camera was used to capture 2.5 hours of video data (1920 x 1080 resolution) at 30 frames per second (fps). The CPU is an Intel Core i7-4790. The camera was mounted at a fixed pole where the $\theta_{\text{yaw}}$ at 45° and $\theta_{\text{pitch}}$ at 10° were set to capture license plates and downwards to minimize sun glare on the camera lens. The camera was installed one km upstream of the low clearance structure at a height of 5.0m, to allow for: (1) detection of the OH vehicle, (2) issuance of driver warning message, and (3) sufficient time for the driver to react and take the nearest exit. The camera was located such that obstructions (excessive vegetation, trees, branches, overhead cables) are not visible in the field of view. The camera was offset from the roadway at 1.5 m to avoid any potential damage from the vehicles and to allow for a greater field of view. The latter risks the potential of vehicle occlusion when there is inadequate offset from the camera and roadway. The roadway selected was relatively planar; no potholes or rutting were present to minimize the errors during calibration and detection stage.

An 8 x 6 calibration checkerboard pattern with 26 mm squares was used as part of the intrinsic calibration process. EmguCV camera calibration was used to find the intrinsic matrix, Ψ and two radial distortion coefficients, $k^1$, $k^2$. These parameters were then used to undistort the images in order to find the [xi, yi] points on the image plane. The extrinsic calibration was performed using an extensible window washing pole set at the height of the bridge clearance *h* with an attached prefabricated levelling bubble set plumb to the road plane. The OH plane is determined based on the pole heights relative to the road plane; the error caused by the road gradient is assumed to be negligible and absorbed through the calibration process. The road gradient under most Department of Transportation's road design specifications require a minimum of a 2% road slope ("rise" to "run" ratio) for sufficient water runoff to nearest outlets *i.e.* catch basins, ditches, culverts. This process takes into account the road gradient despite whether the poles are parallel to the road surface's normal direction. For example, if the road grade is on a decline the camera will be tilted to the same degree, as the calibration process will correctly position and align the OH plane.

In Figure 6, the image shows a screenshot of the prototype at Points 1 and 2 (*i.e.* marker locations (1) and (2)) saved with its respective *y*-pixel values. The prototype compared the differences in *y*-pixel values: 329 and 319, and instructed the user to move the camera vertically upwards by 50 – 100 mm. When the two points arrive at the same *y*-pixel value, this ensures the camera is at the correct height for OH detection.

The first component of the experiment was performed 16 times to validate the installation procedure; a total station was used as ground truth data. A sanity check was performed after each experiment to ensure the installation procedure accuracy. The check consisted of capturing three undistorted photos at marker locations (1), (2) and (3). If the three world points projected onto the image view with the same corresponding *y*-pixel values, this would confirm that the camera was set at the correct height representing the OH plane.

The second component of the experiment determined the optimal parameters for accurate detection of OH vehicles using an iterative optimization process. The goal is to find the optimal filter pixel response value and window size by optimizing two control variables: 1) filter pixel response value *i.e.* an adaptive background differencing algorithm to accommodate for variable weather conditions and 2) vertical pixel height *i.e.* the ROI above the OH plane to detect OH vehicles. Table 1 shows the initial parameters for the optimization procedure: 1) dependent variable, *dv*(horz_ROI) horizontal axis (*x*) at 1920 pixels to maximize the camera field of view, and 2) control variables, cv(threshold) and cv(vert_ROI) respectively. The dependent variable dv(horz_ROI) relates to the horizontal pixel dimension of the region of interest and the two control variables cv(threshold) sets the filter pixel response value parameter and cv(vert_ROI) is the size (horizontal and vertical pixel dimensions) of the region of interest in which OH vehicles are present.

The optimization procedure functions such that, a video containing all positive (relevant *i.e*. OH vehicle is present) and negative (non-relevant *i.e*. OH vehicle not present) image frames are passed through the algorithm with two set parameters: 1) filter pixel response value (ranging from 0 to 255), and 2) ROI (vertical by horizontal window size). The purpose of the filter pixel response value is to detect moving objects within a specified ROI (area in which OH vehicles are present). White pixel values were used as trigger points to determine if there is motion within the ROI. White pixels are intensity values close or near 255. If motion is detected, the algorithm calculates the number of white pixels present in the current image within each region and returns a percentage value. If the percentage value is above or equal to a trigger point value, the KLT algorithm will detect the white pixel points which are displayed as the detected feature points. The relationship between the filter pixel response value and the KLT algorithm is such that when the white pixel values are present, the KLT algorithm detects and tracks these features throughout the ROI; this event will flag as a positive OH instance. The KLT feature tracker is applied as a post-processing stage to the *cv*(threshold) and *cv*(ROI), and mainly used to detect and track white pixel values > (greater than) the specified trigger points. Trigger point values are spaced at intervals from 10% to 100%. The purpose of the window size is to determine the appropriate size to detect OH vehicles while minimizing the amount of background noise. The dataset used a generality of 1.9% positive retrieval rate using negative and positive image frames. The negative frames are calculated based on the number of irrelevant items for a particular query (embedding size). The positive frames are the number of relevant items for a particular query (relevant class size). Refer to Table 2 for sample size calculation using the generality calculation (Huijsmans & Sebe, 2005).

Table 3 shows the results of the data using precision & recall metrics to assess the performance of the algorithm at each of the optimization iterations, where the "*positive*" class = 1 and "*negative*" class = 0. Ý is denoted as the estimate of the true class label Y. The recall value represents the measure of how many of the positive samples (OH vehicles) were indeed positive instances. Precision represents the amount of OH vehicles classified correctly from the positive instances. The acceptable recall rate for the system was set at 0.950 – 1.000 *i.e.* no more than 5% of missed OH vehicles to allow for high detection accuracy.

### A. Results: Height Accuracy (OH Plane)

Two methods were evaluated for the height accuracy of the OH plane – (1) via the pole method, and (2) via total station method. The ground truth data for method (1) was obtained by manual measurement and for method (2) a total station was used to validate the height. A total of three points were measured for each of the experiments. The height accuracies are summarized and analyzed in Table 4 and Figure 7, respectively. The two methods yielded an overall error of ±2.875 mm.

### B. Results: Detection Accuracy

Two performance metrics were considered for the detection accuracy: 1) precision and recall metrics to evaluate the performances of the control variables and 2) receiving operating characteristic curve (ROC) to evaluate the performance of the algorithm. Figure 8 shows the results of the optimization iterations using a binary classification to differentiate between relevant vs. non relevant instances of OH instances within a ROI. The optimization converged at a window size of 70 ± 3 x 1920 pixels and filter pixel response value of 142 ± 5. The average precision value was 0.689 (sunny: 0.751; cloudy: 0.631; rainy: 0.685) and recall of 1.000. The results showed that the minimum number of white pixel values required to detect an OH vehicle was 10% *i.e.* known as trigger points. Figure 9 shows the optimum performance of the filter pixel response value of 142 (window size 70 x 1920), resulting in an algorithm performance of 83.3% (area under the curve).

### C. Discussion/ Conclusions

The study focuses on presenting a holistic solution to the overall problem of OHVS management, with a specific contribution to the *prevention* problem. In this paper, the authors present an extended study of Nguyen *et al.* (2016) using optimized parameters for OH detection under variable weather conditions. The method models an active laser sheet using passive vision methods, as a major improvement to the existing laser beam method. The paper includes the installation and camera configuration procedure. The new method is based on a simple geometric principle: the OH plane, which appears as a line in the view of the camera, mounted at the height of the bridge clearance. Any vehicle exceeding the OH line in the image view is consequently OH. The proposed system demonstrates high performance with minimal installation efforts.

Evaluation of the system resulted in a height accuracy of ±2.875 mm; outperforming the target accuracy of ±5 cm, OH detection accuracy of 68.9%, and classification performance of 83.3%. This outperforms other vision-based system as the method eliminates the need to find the exact height of OH vehicles. The method uses a much simpler approach using a binary decision that returns one of two possible outcomes (*OH / non-OH*) for accurate detection. The parameters for the detection algorithm are not scene dependent. The calibration process is tuned for the specific low bridge and roadway (*i.e.* setting the OH plane) but the performance of the algorithm is optimized for any site chosen given the same camera specifications. The calibration process takes less than 60 minutes to perform, and once performed, does not have to be revisited unless the hardware is damaged.

The camera installation requires a bracket to be installed on an existing pole upstream of the low bridge and access to power and a processing unit; therefore, requiring a professional electrician. The calibration process can take between 15 to 60 minutes; however, this process may require a series of iterations. The camera setup is a permanent installation and meant to be used for many years. The camera is fitted with outdoor housing to endure the rugged winter conditions. The setup time is low in comparison to the overall time needed to derive value out of the system. Leading competitor laser-based systems require permanent infrastructure installation therefore requiring permit approvals, sub-contracting teams, engineers, planners, designers, road closures, road cuts and more. The vision-based system does not require any of the above therefore saving the infrastructure owner a significant amount of upfront costs.

The method performed as expected based on the predictions of the camera modeling (*i.e.* camera height and orientation) with an overall height error of ±2.875 mm. The box plot shows the one-sided error with a median height error of 2 mm and an upper height error of 8 mm. The preferred method of choice is the total station as the surveying station has a distance and height accuracy of 1/1000; however, total stations are expensive and requires specialized training to operate the system. Therefore, to overcome these challenges the accuracy of the "pole method" to the "total station method" were compared to determine if the accuracy provided by the pole method is acceptable without having to purchase expensive equipment to set the OH plane. The results demonstrated comparable accuracy between the pole installation and the total station method; therefore providing practitioners with more flexibility and accessibility without the burden of purchasing expensive total station equipment and requiring specialized training. On average, an OH vehicle was present in the scene 6.56 % of the time during a period of 2.5 hours of video data. The system was able to easily detect OH vehicles as the visual processing focuses only on offending vehicles therefore improving the computation time and performance of the system. Two special cases were detected where a truck carrying a ladder and pole exceeded the OH plane in the image view, activating a warning. Although the consequences are less damaging than a full-size truck striking into the bridge, this instance meets the criteria of an OH vehicle and therefore classified as a true positive.

In the event the vehicle's height is close to the OH plane (either above or below), this is important to note as the camera calibration plays a significant role in overall detection. The calibration process shows that the pole method can achieve millimetre accuracy when compared to ground truth data. The system error is 2.875 mm and the effect of the error to be ± 0.040 mm per pixel in the real world (on the assumption that the calibration steps have been carried out as described in the paper).

Recall values ranging from 0.950 to 0.100 were only considered while any values below were discarded in subsequent iterations of the optimization process to allow for high detection accuracy. As the window size increased more background noise was captured *i.e.* camera movement, swaying, vegetation etc. therefore, the optimization was required to determine the appropriate sized window to minimize the amount of additional noise. As for the filter pixel response value, the value started from 0 (restricted threshold) to 255 (relaxed threshold). The images are grayscale, therefore each pixel represents a single intensity value ranging from 0 = black to 255 = white (despite the depth). The intensity of a pixel is expressed within a given range between a minimum and a maximum in an abstract way (which is adopted by the image processing community); this value is not calculated by the method. The threshold value is predicted to be closer to 255 than 0 to minimize the amount of noise detected by the algorithm. At threshold value 132, the results show a predictiveness along the score of the model, arising from clustered observations of OH vehicles of similar sizes/ types and/or similarities in the background scenes. As the filter threshold response value increases, the values marginally improve while returning a classification performance of 83.3% at the final optimization iteration.

Based on the generality of 1.9%, the positive retrieval rate returned 31.1% of unuseful data *i.e.* false alarms caused by background noise. A false alarm in the essence causes no physical harm to the driver or infrastructure however, it decreases the accuracy of the system and may cause temporary confusion to the driver leading to the braking and stopping of the vehicle. The average precision value was 0.689 (sunny: 0.751; cloudy: 0.631; rainy: 0.685) and recall of 1.000. Although the algorithm was able to recall 100% of all OH vehicles, the precision of each individual experiments varied significantly when wind was a factor, as reflected in the results. The dataset was taken in moderate to severe windy conditions, where the detection algorithm encountered instances of operational issues which resulted in the swaying of the streetlight pole in the horizontal ($x$) and lateral ($y$) directions. The detection algorithm was unable to handle drastic pixel changes that contributed to false positive detections. Swaying in the horizontal axis had minimal effects on the OH line; however, if lateral displacements occur, offset of the OH line in the image view may occur, compromising the system accuracy.

The basis for future work includes the assessment of camera motion and stabilization in variable weather conditions to further minimize the number of false positive detection (false alarms given to the driver) for overall system performance. In addition, the trigger point optimized at 10%; this means that an object with motion is in the ROI, therefore this event will trigger a warning. Based on the results, the system was accurate 68.9% of the time for OH vehicle detection, however future works will be on improving the number of false positive detections. The KLT was used mainly to detect and track white pixel values > 10% across the ROI. An extension of this work is to evaluate and analyse the motion vectors through a number of 'checks' to minimize the number of false positive detections.

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| control variables | units | lower limit | upper limit |
|---|---|---|---|
| *cv*(threshold) | filter intensity threshold | 0 | 255 |
| *cv*(vert_ROI) | pixels | 1 | 275 |
| | | | |
| dependant variables | | | |
| *dv*(horz_ROI) | pixels | 1 | 1920 |

**Table 1.** Control and Dependent Variables

| Negative frames | Positive frames | Total frames | Generality frames | Expected random retrieval rate |
|---|---|---|---|---|
| 190303 | 3661 | 193964 | $\frac{3661}{193964}$ | 1.9% |

*where*

$c$ = number of irrelevant items for a particular query = embedding size (1)

$d$ = number of relevant items for a particular query = relevant class size (2)

$e$ = total number of items in the ranked database = database size = ($c + d$) (3)

**Table 2.** Sample Size Generality Calculation

| | relevant | nonrelevant |
|---|---|---|
| retrieved | true positives (*tp*) | false positives (*fp*) |
| not retrieved | false negatives (*fn*) | true negatives (*tn*) |

$$\text{precision} = tp/(tp + fp) = P(Y = 1 \mid \acute{Y} = 1) \quad (4)$$

$$\text{recall} = \text{sensitivity} = tp/(tp + fn) = P(\acute{Y} = 1 \mid Y = 1) \quad (5)$$

$$\text{specificity} = P(\acute{Y} = 0 \mid Y = 0) \quad (6)$$

**Table 3.** Precision- Recall retrieval performance metrics

| Experiment | Height of over-height plane using pole-method (mm) | Height of over-height using total station method (mm) | Diff (mm) | Error (mm) |
|---|---|---|---|---|
| 1 | 1784 | 1782 | 2 | 2 |
| 2 | 1803 | 1807 | -4 | 4 |
| 3 | 1810 | 1810 | 0 | 0 |
| 4 | 1756 | 1755 | 1 | 1 |
| 5 | 1880 | 1884 | -4 | 4 |
| 6 | 1768 | 1769 | -1 | 1 |
| 7 | 1813 | 1819 | -6 | 6 |
| 8 | 1800 | 1797 | 3 | 3 |
| 9 | 1756 | 1760 | -4 | 4 |
| 10 | 1791 | 1794 | -3 | 3 |
| 11 | 1821 | 1823 | -2 | 2 |
| 12 | 1981 | 1983 | -2 | 2 |
| 13 | 1795 | 1791 | 4 | 4 |
| 14 | 1897 | 1896 | 1 | 1 |
| 15 | 1765 | 1766 | -1 | 1 |
| 16 | 2319 | 2327 | -8 | 8 |
| Overall Average Error | | | | 2.875 |

**Table 4.** Height Accuracy