1 **Evaluation of Computer Vision for On-Road Truck Height Measurement in Proactive Prevention**

2 **of Collision with Overpasses and Tunnels**

3 Fei Dai [a], Man-Woo Park [b,*], Matthew Sandidge [c], and Ioannis Brilakis [d]

4 *[a] Department of Civil and Environmental Engineering, West Virginia University, 635 Engineering*

5 *Sciences Building, 395 Evansdale Drive, Morgantown, WV 26506, USA, Email: fei.dai@mail.wvu.edu*

6 *[b] Department of Civil and Environmental Engineering, Myongji University, 116 Myongji-ro, Cheoin-gu,*

7 *Yongin, Gyeonggi-do, 449-728, South Korea, Email: mwpark@mju.ac.kr*

8 *[c] E.I.T., AMEC US Nuclear Services, 1979 Lakeside Parkway, Suite 400, Tucker, GA 30084, USA,*

9 *Email: matthew.sandidge@amec.com*

10 *[d] Department of Engineering, University of Cambridge, BC2-07, Trumptington Street, Cambridge CB2*

11 *1PZ, UK, Email: ib340@cam.ac.uk*

12 **Abstract:** Over-height trucks are continuously striking low clearance overpasses and tunnels. This has led

13 to significant damage, fatalities, and inconvenience to the public. Smart systems can automatically detect

14 and warn oversize trucks, and have been introduced to provide the trucks with the opportunity to avoid a

15 collision. However, high cost of implementing these systems remains a bottleneck for their wide adoption.

16 This paper evaluates the feasibility of using computer vision to detect over-height trucks. In the proposed

17 method, video streams are collected from a surveillance camera attached on the overpass/tunnel, and

18 processed to measure truck heights. The height is measured using line detection and blob tracking which

19 locate upper and lower points of a truck in pixel coordinates. The pixel coordinates are then translated

20 into 3D world coordinates. Proof-of-concept experiment results signify the high performance of the

21 proposed method and its potential in achieving cost-effective monitoring of over-height trucks in the

22 transportation system. The limitations and considerations of the method for field implementation are also

23 discussed.

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

* Corresponding author. Tel.: +82 31 330 6411; fax: +82 31 336 9705. *E-mail address:*
mwpark@mju.ac.kr (M.-W. Park)

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

51 2) a receiver mounted on opposite sides of the road, 3) loop detectors under the road, and 4) a visual/aural

52 warning system [11]. However, the high cost of implementing the systems constraints the wide use of

53 those technologies [12]. In addition, the installation of loop detector requires temporary road closure

54 causing another indirect cost. In contrast to the laser- or infrared-based systems, a vision-based system

55 can be a cost-efficient alternative and resistant to false alarms. In the system, the aforementioned three

56 components 1)-3) can be replaced with one or more cameras and an embedded processor running

57 computer vision algorithms. This paper introduces an overall framework of the system and evaluates a

58 vision-based method for measuring truck heights as a part of the framework. The method combines line

59 segmentation and blob tracking in order to detect lines on the top and bottom of the truck. Two points are

60 selected as they comprise a vertical line perpendicular to the road plane. The length of the line determines

61 the truck height in 2D coordinates which can then be translated into 3D space. This process also involves

62 unit conversions from pixel to a length unit such as meter or feet by use of a fixed reference object height.

63 The present research signifies the potential of achieving cost-effective solution of preventing possible

64 collision between over-height trucks and low-clearance overpass/tunnels by simply utilizing existing

65 surveillance systems. Furthermore, the low cost will allow the system's broader applications. For

66 instance, it can be applied at the entrance to parking decks where over-height vehicles are prohibited. The

67 proposed system is also applicable to luggage handling systems in airports.

68

69 **2. Background**

70 **2.1 Protective measures for overpass/tunnel crash accidents prevention**

71 To prevent the over-height collisions, a couple of protective measures have been implemented. For

72 example, in the United States, permits are required for the trucks over 13'-6" (4.12 m) [13]. 13'-6" is the

73 allowed legal height of trucks. In general, the protective measures can be categorized as: 1) providing a

74 listing of restricted structures on federal/state-maintained roadways for truck drivers to plan their travel

75 routes ahead of time, to avoid where low clearance overpass/tunnels may occur, 2) installing signs along

76 the road or on the overpass/tunnel, informing drivers of the low clearance of the structure, 3) enforcing

77   detour of the over-height trucks and providing get-around directions over the road, and 4) installing a

78   sacrificial system in which an audible alarm is made when over-height vehicles hit a physical obstruction

79   [14] such as chains, metal strips, or sacrificial beams installed at the overpass/tunnel height in advance of

80   the overpass/tunnel. These measures play a positive role in protecting existing structures from over-height

81   truck collisions. However, their effects are limited. The measures 1)-3) highly rely on drivers' attention

82   and do not eradicate the collision problem. It is still drivers' responsibility to confirm clearance heights

83   along their routes. As a result, crash accidents continue to occur in that truck drivers often accidentally

84   ignore the structure clearance [2, 6]. In addition, outdated low clearance overpass/tunnels exist that have

85   not been marked on the drivers' maps. As to the measure 4), although sacrificial beams cause damages on

86   trucks, a statistically high detection rate and a low false alarm rate may be achieved. A truck driver would

87   appreciate it that a little damage incurred to the truck will prevent catastrophic damages. However, if the

88   driver has noticed a low clearance ahead while still needing to hit the detecting chains and metal strips to

89   let the truck pass through, the inconvenience of being hit or a small damage becomes a disadvantage of

90   this approach. Moreover, chains and metal strips may not provide an alarm loud enough to be heard inside

91   trucks [15]. A more preventive way is having a warning system that can detect an over-height truck and

92   notify its driver ahead of the presence of the low clearance overpass before a collision occurs [16]. The

93   remainder of this section first reviews the implementation of existing over-height warning systems, the

94   context within which this paper lies. The review is then followed by current research in vision-based

95   height measurement, on which this paper is based.

96

97   **2.2 Over-height vehicle warning systems**

98   Over-height vehicle warning system, also called Early Warning Detection System (EWDS) is an active

99   system. It automatically detects the existence of an over-height vehicle for a particular tunnel or overpass

100 and warns the driver of the vehicle of the pending danger before a collision with the structure occurs.

101 Sinfield [17] provided an overview on existing commercially available EWDSs and the state of their

102 implementation in U.S. Based on his review, the majority of existing systems fall into the categories of

103 utilizing the sensing technologies of visible beam, laser (acronym for Light Amplification by Stimulated

104 Emission of Radiation), or infrared, all of which rely on the interruption of a beam or sheet of light to

105 identify a vehicle exceeding a predefined height threshold or to construct the profile of a vehicle that can

106 be translated into accurate vehicle dimensions.

107   Visible beam systems are the types of optoelectronic sensors. They operate by emitting a beam of

108 visible light from a source unit to a detection unit that either processes the light or reflects it back. In

109 general, the cost of visible beam systems is low, but they are unreliable to ambient light and inclement

110 weather that are particularly common in outdoor conditions. Systems that utilize laser are generally

111 divided into laser sheet systems [18] and laser profiling systems [19]. The former works by generating a

112 plane of one or more laser beams that is interrupted by a passing object. The latter reconstructs the point

113 cloud of a passing object such that the object's height can be easily interpreted. It is worth mentioning

114 that the cost of laser profiling systems is particularly high and the effect of these systems is limited to

115 moving traffic with slow speed. As a result, they tend not to be used solely for overheight vehicle

116 detection. Similar to laser systems, infrared systems work by directing a focused beam of light in the

117 infrared region of the optical spectrum from a transmission unit to a reflective target or detection unit.

118 Both laser and infrared systems present more robust features for outdoor use than visible beam systems. A

119 typical infrared/laser system (except for the laser profiling system) consists of 1) a transmitter and 2) a

120 receiver mounted on opposite sides of the road, 3) loop detectors under the road, and 4) a visual/aural

121 warning system [11]. In this system, the transmitter mounted on a pole at the height of the bridge

122 clearance emits the laser or infrared beam. The interference of the beam due to the appearance of a truck

123 activates a warning system that informs the driver with flashers and/or audible alarms. Loop detectors

124 identify the appearance of a vehicle and their lanes [11]. The identification is used to remove false

125 detections caused by non-vehicles such as birds and flapping tarps. Many states in the U.S. have started

126 deploying warning systems using laser or infrared [10]. It is reported the decrease of accidents after the

127 systems began operation [12]. The use of infrared light is more dominant than laser in these systems,

128 being considered safer and more durable in various environments than laser (e.g., better penetration of

5

129 rain and fog). However, the high cost of implementing the systems restricts the wide use of these

130 technologies [20]. For example, the deployment of the system in both directions of a road in Maryland

131 cost a total of $146,000 [21]. Moreover, the installation of loop detector needs temporary road closure

132 causing another indirect cost.

133

134 **2.3 Computer vision based height measurement**

135 As an alternative to the laser- or infrared-based system, a vision-based over-height vehicle detection

136 system has the potential of being cost-efficient since it can identify truck heights only with one or more

137 cameras for each direction, equipped with a processor unit. As video is one of the major data types that

138 most DOTs daily collect, continuous research efforts have been made on the application of computer

139 vision algorithms for intelligent transportation systems (ITS). For instance, automated detection [22,23]

140 and tracking [24,25] of vehicles have drawn great interests and been extensively investigated for counting

141 vehicles and extracting their trajectories, which are essential information in monitoring and analyzing

142 traffic conditions.

143   The vision-based vehicle monitoring generally works as follows. Once the cameras are positioned,

144 their video streams are processed by an embedded processor unit to identify and locate vehicles. This

145 processing involves three steps: camera calibration, vehicle detection, and vehicle tracking. Camera

146 calibration provides a transformation between image pixel coordinates and real-world road-plane

147 coordinates [26]. The transformation is necessary to obtain the width and height of a vehicle in metric

148 units and to identify which lane the vehicle appears in. Vehicle detection recognizes a new vehicle

149 entering the view, and the detected vehicles are tracked by a tracking method.

150   Measuring the height of on-road vehicle in videos has been investigated in a few research works [27,

151 28]. In Khorramshahi et al.'s work [27], feature points on a truck are located and tracked while the truck

152 passes through a cubic virtual zone which is as high as clearance. Based on the relative positions of the

153 tracked feature points and the virtual zone, it judges whether the truck height is over the clearance or not.

154 However, creating the virtual zone, which acts an important role in calibration, requires manual marking

6

155 in the captured video frames. The marking refers to the bounding box that defines the length, width, and

156 height of the virtual zone. It should be done based on the dimension of any vehicle that passes the zone.

157 Therefore, it needs a priori knowledge about the vehicle dimension. In addition, because this method

158 deals with the detection in the image pixels and through comparison with the predefined bounding box, it

159 does not calculate the exact height of a vehicle. Shao et al. [28] proposed an automated method to identify

160 the height of moving objects from un-calibrated videos by use of vanishing line of the scene. In this

161 method, trajectories of moving objects are statistically modeled to determine the vanishing lines of scene.

162 Despite its novelty, it is not applicable to general roadway scenes because two vehicles moving in two

163 non-parallel directions should be present in the views for their automated calibration method. There is a

164 need for creating a new method that is capable of utilizing existing roadway features available for

165 measurement of on-road truck heights.

166

167 **3. Methodology**

168 The objective of this paper is to propose an automatic, ubiquitous, and inexpensive method to determine

169 the height of on-road trucks in digital video collected from a fixed camcorder. Vision-based systems

170 currently have a limitation of low performance in night time. However, night time imaging technologies

171 are continuously advancing, increasing the applicability of the computer vision technologies. In other

172 words, vision-based systems have a potential to be a valid tool for night time applications in near future.

173 An additional obstacle is inclement weather which is reported also as an obstruction to infrared/laser

174 system [29]. Low cost allows for wide spread implementation of vision-based systems, and the value of

175 the information it can provide is expected to outvalue the cost. Also, for the states that have already

176 employed the infrared/laser system, the vision-based approach can be a cost-effective supplement to the

177 infrared/laser system enhancing the detection accuracy. It should be noted that this research focuses on

178 flat, single or double lane per direction roadways, daytime lighting, and one-directional flow for video

179 processing.

180   The schematic overview of the proposed vision-based EWDS is illustrated in Fig. 1. Each single

181   surveillance camera is mounted on a fixed position facing the roadway traffic on each lane. Such

182   deployment is to reduce the possibility of parallel vehicle occlusion. As a truck is measured and its height

183   exceeds a predefined threshold, the warning bell will sound to signal the danger of an over-height

184   collision. The sign message guides the truck driver to an alternative route where the driver can exit the

185   current roadway and avoid collision with the overpass [17]. The warning bell and messages need to be

186   delivered to the drivers early enough so that the trucks can smoothly enter the re-routing road without

187   interrupting the traffic. The technical framework of the system is shown in Fig. 2. Video frames are

188   obtained from each camera and Gaussian smoothing is applied to every frame to reduce image noise. The

189   method then takes two parallel paths: field of view calibration and truck detection. The former reveals the

190   principal axis and the Manhattan structure to establish field of view geometry, and the latter locates the

191   truck region based on the motion and shape features. The results of the two paths are combined to

192   calculate truck heights. The result is an estimate of a truck height, ready to be used in a EWDS. The

193   details of these framework components are presented below.

194   <u>Insert Figure 1 here</u>

195   <u>Insert Figure 2 here</u>

196

197   **3.1 Field of view calibration**

198   Once a camera view is fixed, three orthogonal axes comprising of the Manhattan structure [30] in real

199   world coordinate system have to be found. The three axes consist of the principal axis along the direction

200   of the road (or the traffic flow) (x-axis), a vertical axis perpendicular to the road plane (z-axis), and the

201   other orthogonal to the formers (y-axis). The orthogonal axes are defined by three vanishing points. The

202   following describes the way to find the axes. First, all line segments in the camera view are detected using

203   the Line Segment Detector (LSD) [31]. The detected line segments are then grouped as they converge to

204   the same vanishing points. This framework recommends using the J-Linkage algorithm [32] together with

205   the Expectation-Maximization (EM) [33] to perform the grouping. It is because, unlike other estimators

8

206   such as multi-RANSAC [34], applying J-Linkage does not need to have the knowledge of the number of

207   models (i.e., vanishing points) in the image, and using EM increases the resistance to errors that a set of

208   line segments of a vanishing point is falsely divided into two groups [35]. A number of line segment sets

209   and their corresponding vanishing points will be accordingly generated. In Fig. 3, the line segment sets

210   are illustrated in different colors. It can be easily seen that the blue lines form the majority and are thus

211   determined to be a principal axis. Following this, a set of line segments that are orthogonal to this

212   principal axis is found by checking the orthogonality with the following equation.

213 $$v^T \omega v_m = 0$$

214   v is the vanishing point of the candidate line segment set, v_m is the vanishing point of the principal axis,

215   and the ω is the Image of Absolute Conic (IAC) calculated via the 3×3 matrix of the camera internal

216   parameters [36]. The camera internal parameters can be achieved through camera calibration. Next, a

217   similar procedure is applied in search of the third set of line segments. In this procedure, the difference is

218   that the framework takes the search objective as the minimum of the sum of squares of every two sets.

219   This will result in the most orthogonal triplet of line segments, which makes up the Manhattan structure

220   (Fig. 4). It is worthwhile to note that all calibration procedures are performed online and fully automated.

221   This enables the flexibility of the surveillance video being installed, which allows for fine-tuning pan or

222   tilt angles of the lens even after the camera has been installed on spot.

223   <u>Insert Figure 3 here</u>

224   <u>Insert Figure 4 here</u>

225

226   **3.2 Truck detection**

227   In order to calculate truck heights, truck regions in video frames have to be located. The truck detection

228   employs two algorithms – blob detection [37,38,39] and HOG (Histogram of Oriented Gradients)

229   detection [40]. First, the blob detection creates/updates a background model of static background scene

230   and detects the regions of moving objects by comparing incoming video frames with the background

231   model. The detected regions are called blobs. The blob detection narrows down the candidate regions of

232   trucks and reduces false positives of the HOG detection. The HOG feature which is a well-known shape

233   feature is used to locate the trucks within the detected blobs. The output is a bounding box enclosing the

234   truck.

235

236   **3.3 Truck height determination**

237   This section deals with a new algorithm for calculating truck heights. This algorithm is applied to the

238   regions of bounding boxes obtained by truck detection. The linear workflow of the algorithm is shown in

239   Fig. 5. First, a line segment corresponding to the top boundary of a truck is obtained. All line segments

240   inside a bounding box are detected by LSD method (Fig. 6(a)), and those whose direction is along the

241   principal axis are selected. From the obtained line segments, the one whose left end point is closest to the

242   top left corner of the bounding box is determined as a top boundary of the truck (Fig. 6(b)). The above

243   works when the camera is placed, from the truck driver's perspective, to the right hand side of the truck.

244   If the camera is positioned to the left hand side of the truck, the one whose right end point is closest to the

245   top right corner of the bounding box will be selected as a top boundary of the truck. Second, the truck's

246   bottom boundary is located. The blob image of the truck is obtained by using blob detection (Fig. 7(a)).

247   Then, the boundaries (i.e., a set of pixel lines) of the blobs are extracted by applying the Canny edge

248   detection [41] to the blob image (Fig. 7(b)). This allows for detection of the bottom boundary of the truck.

249   Fig. 7(b) indicates the bottom boundary of the truck annotated by yellow arrows. It is noteworthy that the

250   blobs in this research result from the moving truck. Therefore, the trajectory of the truck wheels forms a

251   region (Fig. 7(a)) in which the contacts of the truck wheels and the road surface result in a continuous and

252   near-linear pixel line. The pixel line results from the truck wheel instead of shadow. It is used to detect

253   the bottom boundary of the truck in the image. Fig. 8 shows an example of obtaining the bottom boundary

254   when the area below the truck is not fully filled with the shadow. In this case, the height is determined by

255   the bottom point of the wheels.

256   <u>Insert Figure 5 here</u>

257   <u>Insert Figure 6 here</u>

258   <u>Insert Figure 7 here</u>

259   <u>Insert Figure 8 here</u>

260   The subsequent step is to measure the truck height in pixel units. The height is measured by locating

261   two points – one on the top boundary and the other on the bottom – that forms a vertical line (in z-axis

262   direction). It should be noted that the top boundary in Fig. 6(b) is a straight line in the same direction of

263   the principal axis (in vector image format) while the bottom one in Fig. 7(b) is winding (in raster image

264   format). Hence, any point on the top boundary can be considered as a reference point, but finding the

265   reference point on the bottom boundary is challenging. The remaining task is to find the correct part that

266   lies on the actual bottom line corresponds to the top boundary. The following details the procedure of this

267   task. The top boundary line is divided into n fragments by same length, which locates (n+1) points on the

268   line. From each point, line scanning in z-direction (i.e., the vertical direction perpendicular to the road

269   plane) is executed to search for the intersection with the bottom boundary. In this way, n sub-segments of

270   the bottom boundary are obtained. From the sub-segments, one whose inclination is the closest (or the

271   most parallel) to the top boundary line in the real world coordinate system is selected as the correct part of

272   the bottom line. This also enables to avoid any falsely selected reference point that does not lie on the

273   bottom boundary such as a small noise line segment. A small noise line segment may be generated from a

274   road marking due to the imperfection of the blob detection algorithms. Next, the height in pixel units is

275   measured simply by calculating the distance between an end point of the selected sub-segment on the

276   bottom and the corresponding point on the top boundary line (Fig. 9).

277   <u>Insert Figure 9 here</u>

278   The final step is to convert 2D truck height in pixel units into 3D height in real world length units so

279   as to compare with the overpass clearance. Single view metrology [42] is employed in this process. It

280   takes known dimensions of objects in the camera view as input data. The road width and the length of the

281   lane line pattern are good reference dimensions in y and x directions of the Manhattan structure,

11

282   respectively. Based on the reference dimensions, the 2D height calculated in the image frames can be

283   converted to a height value in real world units.

284

285   **4. Implementation and Results**

286   **4.1 Implementation**

287   A prototype was implemented to test the proposed method. This prototype was built upon a platform

288   named "Gygax", which has been developed in house using Microsoft Visual C# in .NET Framework 4.0

289   Environment. Videos were recorded in an "mts" format using Canon VIXIA HF series camcorders. The

290   "mts" format is then converted into an "avi" format from which "Gygax" can extract image frames in

291   various formats such as "jpg" and "png". The original videos were recorded in 1280x720p resolution in

292   color at the rate of 30 fps. During the process of video processing, they were converted to gray scale

293   images as required. Fig. 10 shows the screenshots of applying the implemented prototype to measuring

294   on-road truck heights in videos. Fig. 10(a) is the initial user interface of the prototype. Once a video is

295   recorded and saved. The user can browse the folder to select the video into the prototype (Fig. 10(b)).

296   Processing the video data in this prototype needs the user to click the "Truck Height Measurement"

297   button in the "Tools" menu. Fig. 10(c) shows the result of the truck height measurement. Besides, the raw

298   video and intermediate results such as Manhattan structure and blob detection are also provided on the

299   result interface as shown in Fig. 10(c). It is worth mentioning that this prototype also implemented a

300   dynamic-link library (DLL). It enables video streams to be directly read and transmitted from a camera to

301   the prototype via wired connection. The DLL promises the automatic computing of the truck heights from

302   video streams collected in real-time, making it potential for use in an Early Warning Detection System.

303   Insert Figure 10 here

304   In the process of implementing the prototype, the Manhattan structure algorithm, which searches the

305   principal axis of the roadway and the three vanishing points, was validated on its accuracy and

306   consistency. To this end, a two-minute video was recorded using a Canon VIXIA HF S100 camera. The

307   camera was placed facing a road - Northside Drive in Atlanta, GA, which is located at prior to the

12

308   intersection of the 17th street. The heading of the camera was configured to have an angle of 30 degrees

309   with respect to the direction of the road. Having the camera angle fixed during video recording, fifty

310   frames were extracted from the resulting stream. Based on each frame, the Manhattan structure algorithm

311   found the principal axis and determined the vanishing points. Fig. 11 shows a summary of the obtained

312   results from which the number of line segments along the principal axis and the cumulative histograms of

313   the vanishing points' consistency errors were delineated. Fig. 11(a) shows the total number of detected

314   line segments that belong to the maximum detection group in each frame. The group of line segments

315   aligns along the same direction and serves as a basis for determination of the principal axis with the use of

316   the Manhattan structure algorithm. Fig. 11(a) put here has two main purposes. First, it shows the group in

317   each frame used for determining the principal axis contains significantly sufficient line segments. Second,

318   it reveals the consistency of the algorithm in detecting the direction of the principal axis in each frame.

319   Fig. 11(b) presents the cumulative histograms of the vanishing points' errors. It indicates the pixel

320   accuracy and detection consistency of the algorithm for three Manhattan structure axes on each frame. For

321   example, according to Fig. 11(b), the vanishing point #1 has the lowest pixel error and the most

322   consistence performance in each frame. The average number of line segments along the principal axis was

323   295. The three vanishing points determined based on each frame have an average deviation of 3.24 pixels,

324   3.86 pixels, and 5.32 pixels respectively.

325   Insert Figure 11 here

326   The detection performance was also evaluated based on precision and recall. Precision is the ratio of

327   the number of trucks retrieved to the total number of irrelevant and relevant records retrieved, while recall

328   is the ratio of the number of trucks retrieved to the total number of trucks appeared in the video frames.

329   The size of the HOG feature template was set as 104×136, and the bin size is set as 9. Depending on the

330   hit threshold value, precision and recall vary as shown in Fig. 12. In this research, recall is more critical

331   factor than precision since low recall increases the fraction of missed trucks. In other words, some trucks

332   may not be detected and their heights will not be calculated at all. Therefore, it affects the overall

333   performance of detecting over-height vehicles. In contrast, low precision increases the fraction of

13

334   irrelevant instances retrieved. For example, other types of vehicles such as sedans and SUVs (Sport

335   Utility Vehicles) are detected. However, it does not affect the overall performance as the irrelevant

336   instances will be discarded in the next step if their heights are accurately calculated. Accordingly, the

337   threshold is determined 0.4 which scores 0.996 of recall and 0.840 of precision. Fig. 13 shows examples

338   of the detection results. Fig. 13(a), (b) and (c) show the cases when trucks were located accurately with

339   bounding boxes while the Fig. 13(d) shows the cases when irrelevant instance (sedan) was detected. Fig.

340   13(c) is a result in a congested condition on a rainy day. Though the truck was moving extremely slowly

341   with other vehicles on both the front and the rear sides, the whole truck face was clear in the view and the

342   truck was detected successfully at a certain point on the road.

343   Insert Figure 12 here

344   Insert Figure 13 here

345   Also, in the process of implementing the prototype, three methods of blob detection were

346   implemented to find the best option for this specific case of detecting the bottom region of trucks. The

347   methods are the median filter method [37], the mixture of Gaussian method [38], and the color co-

348   occurrence method [39]. The results of this experiment are shown in Fig. 14. The primary criterion of

349   selecting the blob detection method is the density since its main role is to extract the bottom boundary.

350   Faint bottom edges often result in false or no detection of the bottom point of the height. Therefore, the

351   selection is made mainly based on the density. The median filter method is selected as the most

352   appropriate since it provides the most dense region detection on the bottom of trucks. The density was

353   measured by GIMP (GNU Image Manipulation Program) [43]. The median filter method generated 37.4%

354   white pixels (i.e., the ratio of the number of while pixels over the number of the entire pixels in the

355   image), while the mixture of Gaussian method and color co-occurrence method generated 32.6% and

356   16.5% white pixels, respectively. The density and the noise of the blob detection can be controlled by

357   adjusting the parameters associated with each method. The results in Fig. 14 were obtained by tuning the

358   parameters in such a way that the density is increased and the noise is reduced on the bottom area of the

359   truck. In terms of the parameter setting, the median filter method is easy to handle since it only has a

14

360   single threshold parameter while the other two are associated with 4 or more parameters. Through the

361   tests, the appropriate threshold parameter in the median filter method was determined to be 30, and this

362   value was used consistently in the following experiments.

363   <u>Insert Figure 14 here</u>

364   This section does not particularly validate the detection accuracy of top and bottom boundaries of a

365   truck. This paper directly validates the final truck height measurement, which indeed integrates the

366   validity of the method in detecting the top and bottom boundaries of a truck. To test the performance of

367   the implemented prototype, experiments were carried out in which twenty-five videos were collected at

368   the locations of a low clearance (LC) bridge over the Northside Drive in Atlanta, GA prior to the

369   intersection of 17th street, and a Personal Rapid Transit (PRT) bridge near the intersection location of the

370   US 19 and Evansdale Drive in Morgantown, WV, respectively. Each video stream was 6-10 minute in

371   length. The videos were collected using a Canon VIXIA HF S100 camera or a Canon VIXIA HF M50

372   camera. The cameras ware mounted on a heavy-duty tripod to prevent human involved movement or

373   vibration during video recording. The detailed experimental setup concerning camera configuration and

374   video collection is summarized in Table 1. Note in Table 1, the view angle refers to the angle between the

375   camera light of sight and the roadway alignment.

376   <u>Insert Table 1 here</u>

377   Three parameters – (1) accuracy of height measurements in 2D pixel coordinates, (2) accuracy of

378   height measurements in 3D real world coordinates, and (3) detection error rate – are considered to

379   evaluate the performance of the proposed methodology. The parameters (1) and (2) are measured by

380   comparing with actual ground truth data. The ground truth data for the parameter (1) is obtained by

381   manual measurement. However, the ground truth data for the parameter (2), the actual height of a truck

382   traveling on the road, is unknown. Therefore, a sample set of trucks with known heights was taken from

383   the videos and tested separately for this purpose. Information regarding the heights of these trucks that

384   serve as ground truth are obtained by referring to the truck manufacturers or moving equipment and

385   storage rental companies such as U-Haul. These business companies' official websites provide

386   specifications that clearly indicate the dimensions of their trucks. The tested trucks are categorized into

387   two classes – semi-trucks with standard trailers and box trucks. Total 120 trucks, 60 for each category,

388   were tested to measure the performance of the proposed method.

389

390   **4.2 Results**

391   The measurements of the three metric parameters are statistically analyzed, which are summarized in

392   Table 2. Table 2 indicates the overall effectiveness of the proposed method. For the experiment at the

393   bridge in Atlanta, the heights 58 trucks out of 60 were successfully measured. There were two instances

394   of failure in measuring truck heights, which results in 3.3% of detection error rate. The detected 2D image

395   height when compared to the actual 2D image height boasts a 97.52% accuracy rate for the 58 measured

396   trucks. This accuracy rate for estimated 3D truck height when compared to the actual 3D truck height

397   drops slightly to 96.59%. The experiment at the PRT bridge in Morgantown had a result that 57 truck

398   heights out of 60 were successfully measured, leading to a detection error rate of 5%. Fig. 15 shows a

399   snapshot of processing the PRT bridge video with Gygax. The detected 2D image height and 3D physical

400   height of trucks yielded an accuracy rate of 96.23% and 94.96% respectively. It can be observed that the

401   results of the two experiments are comparable to each other. The accuracy rate of the physical truck

402   height is lower than that of the image truck height. This can be attributed to the inaccuracy of the

403   vanishing line and point detection. The average accuracy record, which is around 96%, signifies that the

404   proposed method is highly accurate in measuring the height of trucks from streaming videos. The fact that

405   the method missed two/three trucks out of 60 calls for further enhancement, particularly in the

406   performance of truck detection.

407   Insert Table 2 here

408   Insert Figure 15 here

409

410   **4.3 Limitations and Considerations for Field Implementation**

411   This method is developed for low-clearance roadways, and uses cameras installed on the overpass/tunnels.

412   The premise of the proposed technique is that the roadways are straight and flat, trucks are fully covered

413   in the camera view, and sufficient illumination such as daytime light is available. The experiments carried

414   out herein were geared toward demonstrating that on-road truck heights are able to be measured with

415   sufficient level of accuracy using the described methodology. As such, the proposed vision-based

416   technique has the promise for field implementation. However, it should be noted that the proposed

417   method described here was exercised in a relatively simple way, which may not fully represent the

418   complexity of truck measurement in the field; namely that roadways present particular characteristics

419   (e.g., curved pathways, sloped surfaces, and multiple intersections) and that trucks have irregular tops

420   (e.g., a flatbed carrying a tarped load). Furthermore, depending on the road geometry and camera angles,

421   trucks may be occluded in the field of view. As such, the proposed method may suffer false positive

422   detection issues and that over-height trucks are therefore missed. To avoid the occlusion cases, it is

423   recommended to use one camera for each lane. This is possible because roads with low clearance

424   overpasses usually involve only one or two lanes per direction. By doing so, it prevents the occlusion of

425   one truck by another in the other lane. In addition, the capability of the method to detect and measure a

426   truck height in situation where the truck is changing its driving lane needs further validation.

427   Several research hurdles must be addressed before the proposed vision-based technique can be

428   implemented into a field-deployable system readily for use in over-height collision prevention. Further

429   studies are needed to determine required levels of brightness and proper types of cameras for night time

430   applications. The authors have noticed that the most popular and well known method of performing low

431   light vision is based on the use of image intensifiers. An image intensifier is a vacuum tube device that

432   enables imaging to possess high sensitivity in ultra-low-light conditions. Recent research in low light

433   imaging techniques primarily focuses on the military and crime surveillance. These applications have

434   demonstrated the promise. A tangible extension that can be explored is the use of image intensifiers

435   incorporated into the charge-coupled-device (CCD) cameras followed by the study of advanced image

436   processing that allows for nighttime measurement.

437   Another hurdle that needs to be addressed is the influence of vehicle shadows on the performance of

438   the height detection. A vehicle shadow is an area where sunlight cannot reach due to obstruction of the

439   vehicle. The accuracy of measurement on truck heights implemented at the image pixel level may be

440   severely affected by truck shadows. As such, the impact of truck shadows on the measurement accuracy

441   should be carefully measured and controlled. Removal of truck shadows could be a feasible solution

442   which has been presented in several research papers [44,45,46]. However, validation and customization

443   are desirable to enable the techniques in these papers amenable to EDWS field implementation.

444

445   **5. Conclusions**

446   This paper evaluated a vision-based EDWS which can be a cost-efficient alternative to the laser- or

447   infrared-based systems. The system is comprised of four main processes – field of view calibration,

448   detection, truck height measurement, and warning notice. Having the same warning system as the laser-

449   or infrared-based systems, it can substitute cameras and embedded processor units for expensive

450   equipment and infrastructure such as mounted poles, transmitters, receivers, and detect loops. As the core

451   of the vision-based EDWS, this paper proposed a novel method to measure truck heights using a camera

452   installed on an overpass. Given the detected region of a truck, the method locates top and bottom

453   boundaries of the truck by using line detection and blob detection, respectively. The height is determined

454   by measuring the distance between the boundaries and converting it to the real world length units. The

455   method is implemented in C#, and tested on videos taken at two local roads in Atlanta and Morgantown.

456   The experiment results demonstrated the promise of the proposed method for use in on-road over-height

457   truck warning. The merit of this research was the creation of an automatic video based method which can

458   provide height determination of trucks and is a low cost alternative to the current expensive laser and

459   infrared detection systems. As described in the preceding section, several critical technical issues must be

460   tackled before the proposed technique is deployable in the field. Further efforts, given the demonstrated

461   capabilities, will be to detail cost comparisons and potential savings between the proposed video based

462   approach and other height detection systems, in various operating environments, given that cost-

18

463   efficiency is a primary driving force for the present study. Being able to project estimate savings in

464   dollars may help further understanding of benefits and limits of the vision techniques versus other

465   techniques. This proposed method could be the valid option for the budget limited DOTs that needs state-

466   wide implementation of EWDS to protect state infrastructure such as bridges and tunnels. Nevertheless,

467   the technical issues are more critical and urgent than the cost comparisons for the future work to address.

468   Though this paper presented experiments on local and highway roads, its wide use can be expected in

469   controlled conditions in terms of occlusion and illumination. For instance, the proposed system can be

470   easily applied for prohibition of over-height vehicle at parking decks and luggage handling in airports.

471

472   **6. Acknowledgement**

477

478   **7. References**

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