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# Motion trajectories of over-height vehicles for warning drivers

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**Abstract**

Collision of over-height vehicles with low bridges and tunnels occur with high frequency in the UK as many structures were built at a time when there was less moving traffic on the roadway. These older bridges are now considered at risk of vehicular strikes due to its low clearance height (less than 16 feet 6 inches or 5.03 metres). While previous methods have used vision-based systems to address the over-height warning problem, such methods are sensitive to wind. In this paper, we proposed an extension of the work done to minimise false detections due to wind by using a constraint-based method to track motion trajectories to improve the overall performance of the system. The dataset consists of 102 over-height vehicles recorded at 25 fps. The paper compares feature detectors to optimally track vehicle trajectories and analyses its motion to accurately classify positive detections. The final validation yields a performance of 94.5% recall and 91.1% precision.

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

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## 1. Introduction

A bridge or tunnel strike is an incident in which a vehicle, typically a lorry or double-decker bus, tries to pass under a bridge or tunnel that is lower than its height, subsequently colliding with the structure (Nguyen, Brilakis & Vela, 2017). Network Rail (2016a) reports on average a strike every 4.5 hours on bridges over roads in the United Kingdom (UK). Bridge strikes have caused rail passengers more than 12,000 minutes of delays and cost the taxpayer-funded organisation more than £800,000 in compensation since data has been recorded (Network Rail, 2016b). Bridge and tunnel strikes are still a reoccurring event in the UK costing asset owners thousands of pounds in repairs, maintenance and inspection costs. The average bridge strike cost £25,000 per event (Nguyen & Brilakis, 2016). Other disruptions caused by bridge and tunnel strikes are the traffic congestion and delays across road and rail networks. These strikes lead to an increased cost of bridge repairs, clogged up roadways and increased potential for catastrophic events: hazardous spillage and/or total collapse. When a strike occurs, the event can affect five key communities: road, rail, and bridge/tunnel users, as well as both vehicle drivers and the wider public. There are several reasons why strikes occur, and why drivers of heavy goods vehicle sometimes fail to recognise the warning signs, consequently striking the bridge or tunnel. At first glance, it may seem like the problem is an easy one to solve; however, no matter how well planned the road system, human error is an ever-present risk.

Current state of practice falls into three categories: passive systems including signage's and alarms (quick fix, least effective), sacrificial systems including crash beams and portal frames (mitigation tool, varies on effectiveness) and active systems including early warning and reporting (costly, most effective). The most effective readily available system is the laser-beam active system that detects over-height vehicles (OHV) using a transmitter and receiver approach, however, for the common low bridge, asset owners have chosen to opt out due to the high upfront costs. Asset owners are seeking a more feasible option to address the low bridge problem.

To address this problem, the research is an extension of the work published by Nguyen and Brilakis (2017) for bridge and tunnel strike prevention. The extension continues to minimise the false positive detections of OHV due to wind. In this paper, an additional constraint is added to track motion trajectories of vehicles to accurately warn drivers. The following paper is organised as follows: Section 2 describing the current state of research, gaps in knowledge and research problem. The proposed approach in Section 3 stepping through the details of the method with experimental setup and results in Section 4. Section 5 concludes with discussions, conclusions and recommended future work.

## 2. Background

Computer vision-based methods for vehicle detection is an affordable and reliable approach for asset management however, in windy weather conditions the approach may prove to be challenging. Prior vision-based approaches for OHV detection uses vanishing lines to estimate the vehicle heights (Dai, Park, Sandidge, & Brilakis, 2015; Shao, Zhou, & Chellappa, 2010) however, this method is problematic in cases of occlusions (the vehicle not fully visible) causing the method to miscalculate or entirely miss the vehicle (false negative detection). The methods have not been tested under real-time conditions therefore, the true challenges of the system are not evident.

In the work of Nguyen & Brilakis (2017), the researchers deployed a real-time system in London UK which tests the threshold line approach to tackle the problem of windy weather conditions. The method uses an imaginary 3D plane which calibrates to a line in the 2D camera view. This line is calibrated to the exact height of the low bridge. Any motion above this line is analysed within a region of interest and passes through a set of 'checks' to determine whether it is in fact an OHV. By adding these 'checks', the researchers are able to minimise the misclassifications of OHV due to wind. Although the threshold line approach performs ideally in sunny weather conditions, the performance drops by nearly 31.0% in windy weather due to camera shake. The approach to solve this problem was by adding a further constraint which increased the precision by 14.3% to 83.3% and a false positive rate of 8.3%. Although the precision of the system has improved, the false positive rate remains high. Other related methods to handle this problem of windy camera frames can be explored using video stabilisation methods.

### *2.1. Video Stabilization*

Computer vision image enhancement techniques for video stabilisation is the process of identifying and removing undesired image motion from video data. Shaky and blurry video data due to wind movements suffer from significant amounts of unexpected image motion caused by external weather conditions. The initial step in video stabilisation is global motion estimation followed by feature and intensity-based methods.

Global motion estimation is a vital step in the process of video stabilisation for OHV detection. By understanding what is happening and what motions are evident, the motions can be separated into two categories: 1) intentional motion (what we are trying to analyse) and 2) unwanted motion (camera jitteriness, jerkiness, background noise and wind motions). By removing the unwanted motion, we are then left with a stabilised frame. The use of video stabilisation techniques as part of a pre-processing stage can be used to bridge this concept to minimise the number of false positive detections invoked by the system. Methods for video stabilisation fall under two categories: 2D and 3D methods. Although 3D methods are more accurate, the method is more computationally complex and 2D methods are sufficiently robust to solve the problem of windy camera frames. A general survey of approaches to address this challenge of feature and intensity-based methods are presented.

### *2.2. Feature-Based Methods*

This section covers the current feature-based extraction methods. Feature based methods has become an increasingly used method for detecting objects in a scene, ideal for OHV detection which includes distinctive attributes such as edges and corners. The edge detection is one of the most practical and commonly used algorithms which treats edge detection as a signal processing problem that maximises the signal to noise ratio to provide good detection (Hocenski & Vasili, 2006). However, corners are mathematically the best features to track due to its difference in intensity values (Shi & Tomasi, 1994).

Corners are common features to track, due to their distinctive edges (as a sub-attributes of a corner) and distinguishable changes in intensity values at all vertexes. Corners are rotation-invariant, which means that if an image is rotated, the same corners can be found despite its orientation. Detected corners are often referred to as keypoints, otherwise as ‘points of interest’.

In computer vision, the concept of keypoints have been used to address many problems in visual tracking, object recognition and 3D reconstruction. The method relies on the idea of focusing on a region of interest in the image to select interesting points known as feature points and to perform a local analysis around the points. An advantage of using the keypoints is that they permit matching even in the presence of clutter and occlusions and large scale and orientation changes (Sadeghi-Tehran, Clarke, & Angelov, 2014).

The common leaders in keypoints are *Scale Invariant Feature Transform* (SIFT) and *Speeded up Robust Feature* (SURF); however, SURF outperforms the SIFT feature detector by computational speed (Dawood, Cappelle, El Najjar *et al.*, 2012; Valgren & Lilienthal, 2010). SURF is similar to SIFT, however the results of the SURF detector and descriptor outperforms other feature detectors (SIFT, Harris) significantly and most importantly, the use of integral images improving the speed of detection. Other techniques include *Accelerated Segment Test* (FAST), *Binary Robust Invariant Scalable Keypoints* (BRISK) and Harris corner detector (Harris & Stephens, 1988).

BRISK performs similarly to the state-of-the-art methods while dramatically more computationally efficient. A comprehensive evaluation comparing SIFT, SURF and BRISK reveals that BRISK’s performance overall trumps the other feature detectors with a lower computational cost and at an order of magnitude faster than SURF in cases (Leutenegger, Chli, & Siegwart, 2011). The timing analysis compares the three state-of-art feature descriptors SIFT, SURF and BRISK showing a faster BRISK computation time per point (ms) by 99.4% from SIFT and 91.3% from SURF. The time comparison compares BRISK to SIFT by 69.4% faster and BRISK to SURF by 69.0% faster. The key to the speed lies in the application of FAST-based detector in combination with the assembly of a bit-string descriptor of each keypoint neighbourhood. In the next section, optical flow is discussed as it uses the feature detectors to track useful points for OHV detection.

### *2.3. Intensity-Based Methods*

Optical flow is a widely used intensity-based method, which estimates the motion of image objects or discrete image displacements between two image frames at frames, $I$ and $I_{i+1}$, often paired with the Lucas-Kanade method for optical flow estimation. The method assumes that the flow is essentially constant in a local neighbourhood of the pixel examined and using the least squares criterion, solves the basic optical flow equations for all pixels in that neighbourhood.

Feature-based methods are generally more accurate but less robust than intensity-based methods due to its ability to adapt to illumination changes and invariant qualities to scale and rotation. Khorramshahi, Behrad & Kanhere (2008) uses KLT (Kanade-Lucas-Tomasi) feature detection algorithm to detection OHV yielding favourable results. However, the study did not test in variable weather conditions. KLT can be paired with any of the feature-based methods and tracked using the optical flow methods to determine the direction of OHV to minimise false positive detections. KLT feature tracking assumes that small spatial and temporal changes of motion across an image sequence (Sadeghi-Tehran et al., 2014); therefore, this method works well for static cameras in windy weather conditions.

*2.4. Gaps in Knowledge, Objectives and Research Questions*

Previous computer vision approaches to OHV detection have proven sensitive to wind therefore, more constraints need to be in place to minimise the misclassifications of OHV. The gaps reveal that although these feature detectors have performed well for other vehicle detection scenarios, it has yet to be compared for the OHV detection scenario. In this paper, a comparison of the current state-of-art feature descriptors are explored: 1) SURF (instead of SIFT as it underperforms), 2) BRISK (faster results than SURF and SIFT), 3) EIGEN (Shi and Tomasi's method), 4) HARRIS (classic corner detection algorithm yet robust) and 5) FAST (fast as the name suggests). The best performing feature detector will be used as part of the final validation process of the system. These objectives hope to answer the research question: *Does tracking vehicle trajectories improve the overall performance of the system in windy weather conditions?* In the next section, the extension of the work of Nguyen & Brilakis (2017) is proposed.

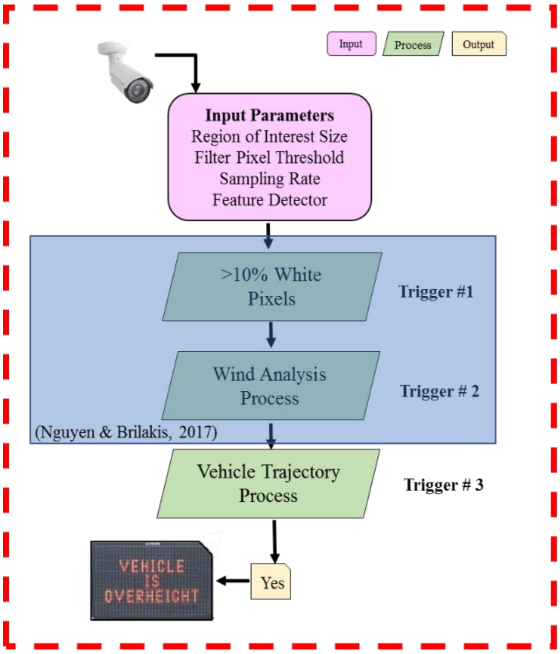



Fig. 1 Extension of proposed approach for OHV detection using a trigger based approach

## 3. Proposed Solution

Figure 1 schematises the approach to minimise the number of false positive detections. The input parameters for the camera are the region of interest (ROI) size, filter pixel threshold (background subtraction), sampling rate and the feature detector. The OHV detection is processed using a trigger-based approach. The first trigger quantifies the number of white pixels within the ROI. If the number of white pixels exceeds 10%, this passes the frame to Trigger #2. Trigger #2 inputs the sampling rate and uses the KLT feature tracker to determine whether the flow is constant and moving in a positive direction. The need for this check is due to windy weather conditions. If the flow is not constant, the assumption is that the movement is caused by noise, which in this case caused by windy weather conditions. To minimise the number of false detections, Trigger #2 is required. The final check (Trigger #3) tracks motion trajectories in the image. This trigger uses the feature detectors to analyse its capabilities to reliably track vehicle displacements over a set number of consecutive frames. If the image passes the three triggers, this will trigger a warning to the driver and flag the image as a positive OH instance. Each step is explained more in detail.

**Camera calibration and setup**: The camera is calibrated and set up on the side of the roadway with sufficient clearance from the side of the roadway upstream of the low bridge. This distance should allow sufficient time for the vehicle to be detected, for the warning to be issued and the driver to react, stop or brake. For existing deployments, 1 km was our benchmark.

**Input Parameters**: Based on the optimised parameters in the work of Nguyen, Brilakis & Vela (2017), the same input parameters are used in this experiment. The first parameter is the ROI with a vertical height of 70 pixels tall by 1920 pixels wide and the filter pixel response value set to 142-pixel intensity. The sampling and frame rate are set at every 10 frames using the dataset of 25 fps. The optimised feature detector is used to detect any corners in the moving objects in the ROI. The input frame passes through the following three trigger points, otherwise known as checks in the validation process to verify that the detected object behaves as that of a vehicle.

**Trigger 1**: The first trigger point checks whether the motion within the region exceeds a white pixel intensity difference of 10% or more. If this check is true, 1 is assigned to the image and the image passes onto the next validation trigger. If this is false, the input frame is discarded and the next frame is analysed.

**Trigger 2**: The Wind Analysis Process uses a control variable to analyse the direction of movement of features. This check is based on the characteristics and behaviours of OHV. The tracking of flow and positive directional movement of objects through frames eliminates the false detections of wind. Sampling rate information is used as an input to activate the KLT feature-tracker detection algorithm. Any motion passing through the ROI is detected and tracked. Each point is tracked over a number of consecutive frames and analysed with reference to its neighbours to determine whether the flow is constant and moving in a positive direction. If the flow is constant, *i.e.* monotonically increasing along the x-axis, then a warning is displayed on the OH sign. If the motion is oscillating, the instances are classified as noise and the process starts over.

**Trigger 3**: The Vehicle Trajectory Process evaluates the averages of the positive displacement vectors, $M$ to account for camera motion due to wind. For example, let's set the threshold, $h$ to a displacement of 5+ positive pixels. This means, if the flow vectors within the ROI is moving in a positive direction at an average of 5 pixels or more, this will increase the counter to c+1. If this occurs consecutively for 5 frames or more, this passes the wind analysis #2 and vehicle trajectory checks #3 therefore triggering the warning. If the displacement is less than the threshold (meaning less than a displacement of 5 pixels), the counter resets itself to 0.

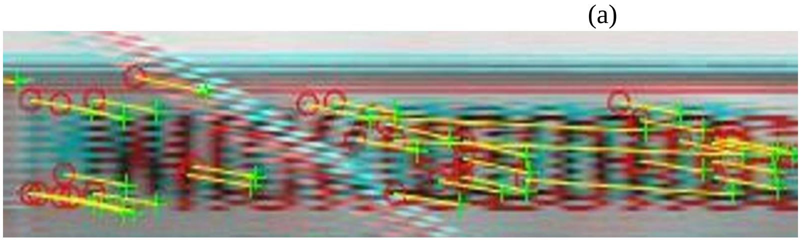
## 4. Research Experiments & Results

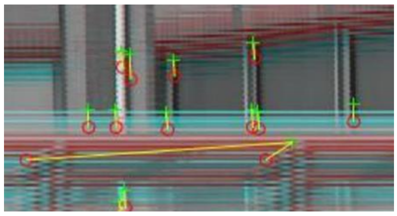
The experiment compares five feature detectors to determine the optimal detector to track motion trajectories of OHV to accurately detect and warn the driver. The optimal detector is used in the final validation of the system to determine its overall performance using recall and precision metrics. Recall is the percentage of the positive instances triggered by the system. Of the positive instances, precision is the percentage of how accurately it could classify the instances into positive (1, OHV is present) and negative (0, noise) cases.

The dataset used for this experiment is the same as Nguyen & Brilakis (2017) collected in sunny, windy, cloudy and rainy weather conditions in the UK and USA. A total of 102 OHV is used consisting of 3661 positive frames with an average of 35.9 positive frames per every over-height occurrence. The data is processed using MATLAB R2016a Computer Vision Toolbox on an Intel Core i7-4790. The camera is a Sony aR2 II mounted on a fixed tripod pole where the rotational angle: θyaw is at 90° and $\theta$pitch at 10° at a height between 2.5m and 3.2m.

Optical flow was used to detect and track the motion features evaluating the feature detectors: SURF, BRISK, EIGEN, HARRIS and FAST paired with KLT feature-tracker algorithm. A confidence score is assigned to each point to assess validity. Figure 2 shows the algorithm implemented on MATLAB using the feature matching technique using local neighbourhoods and the Harris algorithm to show the motion of the vehicle. The red indicates the initial frame indicating the starting position and the cyan as the sampled frame showing its finishing position; the total motion of the vehicle is shown sampled at every 10 frames at 25 fps. Figure 3 visually compares the number of detected and tracked feature points for each feature detector. A visual comparison can be obtained for the number of displacement vectors calculated for each frame comparison.


(a)





(b) (c)

Fig. 2 (a) shows the over-height vehicle passing through the region of interest with KLT feature vectors detected on the image. The red circles represent the starting pixel location and the green cross represents the ending pixel location. The yellow line represents the length of the pixel movement sampled at every 10 frames; (b) zoomed in capture of the KLT vehicle displacements; (c) shows the KLT vehicle displacements in windy weather conditions; voiding the assumptions of the algorithm




(a) SURF (b) BRISK (c) EIGEN



(d) HARRIS (e) FAST

Fig. 3 a frame comparison sampled at 10 frames @ 25 fps (frames 0148 and 0158 respectively) showing the difference in features detected and tracked for the five feature detectors: SURF, BRISK, EIGEN, HARRIS and FAST

### *4.1. Results*

Table 1 shows the overall performance of each feature detector under all scenarios. The best performing feature detector is SURF, with a recall value of 0.941 and precision value of 0.879. This metric results show that the algorithm can detect 94.1% of all OHV while being able to accurately classify 87.9% of the detected OHV. The total number of OHV is 102 however, the algorithm detected 5% more vehicles therefore contributing to the decrease in performance. The false positive rate is 0.3%, while the warning accuracy is 95.8% based on the sampling and frame rate parameters.

Table 1. Performance of each feature detector for all scenarios.

| SUMMARY | SURF | BRISK | EIGEN | HARRIS | FAST |
|---|---|---|---|---|---|
| False Positive | 520 | 316 | 1140 | 1305 | 482 |
| True Positive | 3482 | 3497 | 3126 | 2872 | 3152 |
| False Negative | 204 | 357 | 857 | 805 | 812 |
| True Negative | 189672 | 189658 | 188870 | 188912 | 189342 |
| Total Frames | 193878 | 193828 | 193993 | 193894 | 193788 |
| Total OHV | 102 | 102 | 102 | 102 | 102 |
| OHV Detected | 107 | 107 | 127 | 160 | 110 |
| Precision | 0.879 | 0.920 | 0.747 | 0.734 | 0.859 |
| Recall | 0.941 | 0.921 | 0.838 | 0.806 | 0.802 |
| False Positive | 0.003 | 0.002 | 0.008 | 0.009 | 0.003 |
| Warning Accuracy | 0.958 | 0.945 | 0.783 | 0.633 | 0.909 |

*****Eigen – Shi and Tomasi (1994) method

### *4.2. Final validation*

This section provides details shown in Table 2 of the validation using SURF as the optimal detector to determine the overall performance of the OHV detection and warning system using the three-trigger approach strategy. The validation results show the system could recall 94.5% of all OHV while accurately classifying each recall frame by 91.1%. The system achieved a low false positive rate at 0.2% while achieving a warning accuracy of 96.6% based on the input sampling and frame rate parameters.

Table 2. Results of the validation using the optimised parameters as inputs for the OHV detection and warning system.

| | Road 1 | Road 2 | Road 3 | Road 4 | Road 5 | Road 6 | Final Validation |
|---|---|---|---|---|---|---|---|
| False Positive | 27 | 12 | 151 | 7 | 182 | 6 | 385 |
| True Positive | 465 | 311 | 387 | 853 | 1107 | 396 | 3519 |
| False Negative | 32 | 18 | 23 | 61 | 69 | 12 | 215 |
| True Negative | 24190 | 16767 | 20330 | 46615 | 59392 | 22378 | 189672 |
| Total Frames | 24714 | 17108 | 20891 | 47536 | 60750 | 22792 | 193791 |
| Total OHV | 13 | 9 | 11 | 25 | 32 | 12 | 102 |
| OHV Detected | 15 | 10 | 10 | 26 | 33 | 12 | 106 |
| Precision | 0.945 | 0.963 | 0.719 | 0.992 | 0.859 | 0.985 | 0.911 |
| Recall | 0.936 | 0.945 | 0.944 | 0.933 | 0.941 | 0.971 | 0.945 |
| False Positive | 0.001 | 0.001 | 0.007 | 0.000 | 0.003 | 0.000 | 0.002 |
| Warning Accuracy | 0.867 | 0.900 | 1.100 | 0.962 | 0.970 | 1.000 | 0.966 |

## 5. Discussion & Conclusions

A comparison of the feature detectors is conducted in this paper to evaluate the performance of the detector to sufficiently track features of OHV over a consecutive number of frames. In Table 1, the results showed that SURF performed best with a recall value of 94.1%. The recall target for the experiment was 95% meaning that only 5% of OHV are to be missed. The best performing feature detector, SURF fell short by 0.9% of the target but despite the margin, is accepted as the ideal feature detector based on the overall results. Ranked second and so forth, BRISK recalled 92.1% of all vehicles while EIGEN, HARRIS and FAST ranking third, fourth and fifth at 83.8%, 80.6% and 80.2% respectively. Overall, the feature detectors performed well yielding a recall disparity of 13.9%; with a precision disparity of less than 2%. The warning accuracies performed well for the feature detectors SURF, BRISK, and FAST. However, EIGEN and HARRIS, the poor warning accuracies was a result of too many false positive OHV detected, 19.7% more OHV detected for EIGEN and 36.3% more detected for HARRIS. This is due to the sensitivity of the corner detection algorithms resulting in too much noise captured by the feature detectors.

### *5.1. Limitations*

The differences in the detected features played a significant role in the precision and recall results. For example, HARRIS and EIGEN feature detectors detected too many of the corners in the background therefore contributing to the increase in false positive and false negative detections. When wind was present, this rate increased as shown in the results in Table 1. While FAST contributed to a high number of false negative detections due to the misclassifications of the positive frames for negative frames. Instances in which the feature detector failed or missed an OHV occurred when:

**1**. A vehicle stopped in the scene,
**2**. Vehicles were moving too slowly or braking in the scene (red light ahead),
**3**. A vehicle was occluded in the scene (either vehicle travelling in opposite direction or two OHV side by side), and
**4**. Insufficient features detected (this occurs when the mid-section of the bus/truck encompasses the entire image frame. There were no detectable corners).

These events occur in daily traffic and the results of the feature detectors have considered these occurrences and are reflected in the overall algorithm performance results. For example, in Figure 4(a), insufficient points caused the feature detector failed to detect the OHV due to no corners detected. In this instance, the vehicle did not pass triggers #2 (wind analysis) and triggers #3 (vehicle trajectories) therefore was not classified as an OHV vehicle; this was considered as a missed vehicle. Figure 4(b) shows a tractor vehicle moving through the scene. Out of the 5 feature detectors, only SURF could reliably track the vehicle over 5 frames consecutively. The other feature detectors failed due to the average number of positive flow vectors falling below the threshold for detection.


(a) (b)

Fig. 4 (a) shows an instance when insufficient features are tracked on the vehicle to pass triggers #2 and #3; (b) shows a tracker vehicle in the scene. Out of the 5 feature detectors, only SURF could reliable track the vehicle over 5 frames consecutively. The other feature detectors failed in this instance

Figure 4 shows two instances in which the algorithm did not pick up sufficient features to track adequately for five frames or more. In instance Figure 5(a), the vehicle did not pass Trigger #2 where the average displacement of pixels did not pass the threshold limit, resulting in a missed vehicle. In Figure 5(b), the bus is detected in the initial and latter ends of the vehicle. However, when the frame captures only the mid-section of the bus, this causes the feature detector to fail due to no detectable corners in the frame. In Figure 6, there are three instances of vehicles travelling in the opposite direction. The trigger allows the algorithm to disregard objects that are moving in a negative direction and other factors/objects such as birds and wind movement. Although features are detected, the average pixel displacements are not evaluated as the displacement is negative. This allows for better detection and discrimination to minimise the number of false detections.


(a) (b)

Fig. 5 Two instances in which the algorithm did not pick up sufficient features to track adequately for five frames or more. (a) and (b) The vehicle did not pass trigger#2 (average displacement of pixels over threshold limit) and therefore is missed as an OHV


(a) (b)


(c)

Fig. 6 shows three instances of occlusion when an OHV is traveling in the opposite direction blocking the scene for positive detection

*5.2. Conclusions*

The dataset consisted of 102 OHV with a generality of 1.9% (3661 positive, 190303 negative frames) using OHV in the UK and USA on roadways of 25 and 30mph speeds. In this paper, we added a further extension designed to assess camera motion and stabilisation under variable weather conditions and validate the overall system using the optimised parameters; an effort to further minimise false positive detection instances. The experiment analysed the vehicle motion trajectories to determine whether the motion vectors can be tracked to differentiate motion (OHV vs. noise) to provide accurate detection and warning to drivers. Triggers points are used to act as ‘check’ points to evaluate the direction and consistency of the motion. If the trajectories do not behave (or move) as an expected vehicle should, the motion is regarded as noise.

The experiment compares five feature detections: SURF (speeded-up robust features), BRISK (binary robust invariant scalable keypoints), HARRIS, EIGEN (Shi and Tomasi) and FAST (Features from Accelerated Segment Test) feature detectors to evaluate its performance. The feature detector is paired with optical flow to estimate the motion of the image objects using the KLT Feature Detection Algorithm. The experiment evaluated and analysed the best feature detector to track motion within the ROI and determined the false positive and warning accuracy of the algorithm. The experiment reveals SURF feature detector performs best to track vehicle displacement given frame and sampling rates yielding a recall of 0.941 and precision of 0.879. SURF fell short of 0.9% of the target of 95% but is accepted as the ideal feature detector based on the overall results. The experiment achieved a low false positive rate of 0.3% and warning accuracy of 95.8%.

The final validation experiment consisted of using SURF feature detector pair with optical flow showing a performance with a final recall of 94.5% and precision of 91.1%. The recall experienced a slight drop of 0.4% while the precision accuracy increasing by 3.2%. Overall, the results did not differ largely with only Triggers 1 and 2 in place, concluding that Trigger 3 played a minor improvement in precision. Overall, the OHV detection and warning system performs well and can accurately detect potentially offending vehicles while decreasing the false positive rate from 8.3% to 0.2% by controlling the sampling rate resulting in a warning accuracy of 96.6%.

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