Automated Detection of Roadway Obstructions Using UAVs and Reference Images

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ABSTRACT

Natural disasters such as wildfires, landslides, and earthquakes result in obstructions on roads due to fallen trees, landslides, and rocks. Such obstructions can cause significant mobility problems for both evacuees and first responders, especially in the immediate aftermath of disasters. Unmanned Aerial Vehicles (UAVs) provide an opportunity to perform rapid and remote reconnaissance of planned routes and thus provide decision-makers with information relating to a route's feasibility. However, detecting obstacles on roads manually is a laborious and error-prone task, especially when attention is diverted to needs that are more urgent during disaster scenarios. This paper thus proposes a computer vision and machine-learning framework to detect obstacles on a road automatically to ensure its possibility in the aftermath of disasters. The framework implements the YOLO algorithm to detect and segment roads on images from UAVs and reference images from publicly available datasets. The images retrieved from UAVs and reference images are segmented and counted pixels of the roadway for comparison of the difference in pixels to identify the obstruction on the road. In addition, the method is proposed to automatically detect obstructions found in the region of interest (ROI) only on a roadway with images and videos from UAVs. Preliminary results from test runs are presented along with the future steps for implementing a real-time UAV-based road obstruction system.

INTRODUCTION

Disasters can severely impact the regions by causing various types of damage to the built and natural environment, which can in turn damage and block roads in the surrounding area. This can adversely impact the safety of motorists and limit the mobility of people to and from the disaster area. Promptness in locating available routes is very crucial as it can help evacuees and first responders access the disaster area. However, it is difficult to know ahead of time as to which routes are passable and free from obstructions in the immediate aftermath of disasters.

Thus, detecting obstacles or objects on the roadway is very helpful for responders to plan routes for evacuation and rescue operations. Recently, there have been some sensing methods developed for detecting obstacles or objects which could be applied to this area. For example, Li and Guzman (2020) used lidar to detect surrounding obstacles, vehicles, and people for purposes of autonomous vehicle operation. Paulet et al. (2016) proposed the use of ultrasonic sensors to detect objects, the range of this sensor is from 2 centimeters to 4 meters. Dunai et al. (2012) presented an acoustic object detection sensor for unsighted people and this model operated precisely for a distance between a user and an object of fewer than 5 meters. While these methods are related to the topic of obstruction detection on roadways, these sensing methods are mounted on resources that need to be on the ground due to the limitations of these sensors. This

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is a very risky as well as time-consuming task for ground vehicles to access such areas in the aftermath of disasters.

Alternatively, there are some vehicles that people utilize for inspecting roads after disaster situations other than the ground vehicles such as helicopters, and unmanned aerial vehicles (UAVs). Although helicopters are effective in manually inspecting the overall areas, it is very costly and requires experienced pilots and inspection teams to search for inspecting post-disaster areas (Yan and Shih 2009). Therefore, UAVs can be considered as an attractive option to inspect routes after a disaster. While UAVs can collect video footage autonomously, detecting obstructions on the road from that footage is still a very involved manual task, that can be laborious, time-consuming, and prone to human error. This situation can be overcome using computer vision-based methods, which have been successfully used on UAVs footage to automatically detect damaged buildings in post-disaster areas (Hu et al. 2023) and UAVs with computer vision-based also proposed for detection and segmentation of damaged assessment of building and flooding area from a post-disaster (Pi et al. 2021). Review of current literature indicated that computer vision-based methods for roadway obstacle detection are typically not generalizable to consider the various types of obstructions that can be expected after a disaster. Therefore, the goal of this research is to automatically detect obstructions on roads from UAVs footage by comparing collected image data with reference images of roadway segments collected during its normal operations. Computer vision-based segmentation is applied to images of roads after disasters from UAVs and compared to the same segments identified from satellite images of the same road portion. This enables a comparison between roadway pixels in both cases, which can then be used to infer the presence of significant obstructions on the road. This detection framework is novel due to its use of publicly available satellite data for comparison with drone footage, which can increase the accuracy of obstruction identification.

The rest of this paper is organized as follows: First, a review of common types of obstructions on roads after disasters and state-of-the-art automated techniques for their detection is provided. Next, the authors' approach is thoroughly described in the methodology section, after which its implementation is demonstrated using a case study. Finally, the preliminary results from test runs are presented along with the future steps for implementing a real-time UAV-based road obstruction system.

BACKGROUND AND RELATED WORK

Generally, road obstacle detection methods have been studied and developed to detect obstacles that cause safety hazards to motorists on roadways. An example of previous work in this domain is the application of stereo vision for obstacle detection to find safe routes (Broggi et al. 2005) using cameras mounted on ground vehicles. The integration of radar and vision sensors has also been used for automated vehicles to detect surrounding objects (Kim et al. 2018). Another technique is the use of LiDAR for pavement cracks and objects on roads using mobile systems (Ravi et al. 2021). Li et al. (2018) used an ultrasonic sensor to detect several types of objects for ground vehicles within 5 meters of the vehicles. While these methods provide sufficient accuracy in detecting obstructions on roads, their limitation is their requirement to be mounted on ground vehicles, which would be difficult to implement in post-disaster scenarios.

To overcome this limitation, researchers have been studying the use of types of vehicles that can access such areas, which is unmanned aerial vehicles (UAVs). There are several common types of UAVs, which are used in the construction industry including fixed-wing, multi-rotor,

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single-rotor drones, and fixed-wing hybrid VTOL (Tkáč and Mésároš 2019). The desired characteristics of a UAV that enable it to be used in road inspection are a long range of control, long battery life and flight duration, cameras attached, GPS software installed, and stable flight (Massaro et al. 2021).

Besides the UAVs to access post-disaster areas, road obstacle detection also required tools for detecting objects which usually apply with computer vision-based methods. For example, the images from UAVs and computer vision-based are used to automatically detect cracks on roadways (Li et al. 2022), (Dadrasjavan et al. 2019). UAVs and CNNs are applied to detect objects from an aerial perspective for post-disaster areas(Pi et al. 2020). (Pi et al. 2021) proposed UAVs, CNN, and pyramid pooling modules for detecting damaged residential, vehicles, vegetation, and road in after-disaster areas.

There is another tool for detecting objects with computer vision-based methods, which uses satellite images along with the You Only Look Twice (YOLT) detection algorithm to detect vehicles such as cars, planes, boats, and buildings (Van Etten 2018). The method of using satellite images and convolution neural networks (CNNs) was implemented to detect several types of objects including vehicles and sports stadiums or courts (Guo et al. 2018). Lee et al. (2020) applied satellite images and a semi-supervised learning model for damage assessment of post-disaster areas.

According to the methods above, UAVs and computer vision-based to detect obstructions on roads with satellite images as reference images are proposed in this study. UAVs are utilized instead of ground vehicles to be able for accessing such areas, and the combination of computer vision-based methods and machine learning are integrated to automatically detect obstacles on roads with long-range detection. In order to detect obstructions on roads, images of post-disaster situations collected from UAVs and satellite images of normal situations, used as reference images, at the same location are utilized to compare the difference in the conditions of roads to identify the obstruction on roads. Furthermore, the combination of these methods can provide accurate locations of roads blocked in the real world.

METHODOLOGY

The goal of this study is to automatically detect obstructions on roads compared between footage from UAVs and reference images, which are satellite images. Figure 1 shows the methodology for training a custom dataset of roads to identify the existence of obstructions on roads.

As shown in Figure 1, there are five steps involved, which are described in detail below.

a. Data Collection: To achieve the goal of this study, several types of images are required including satellite images of roads from Google Maps, UAVs obstructions on roads images, and obstructions images.

b. Annotation: In this step, the annotation is used to locate the roads with polygon lines to the precise shape of the roads. Following this, data augmentation is applied to create more images and this is used to increase the performance and improve results of machine learning in the training section. During the annotation step, training, validation, and testing sets are generated by using automatically generates polygon lines and manually drawing polygon lines of all the road images.

c. Training: After finishing the annotation, the You Only Look Once (YOLO) is used, which is an object detection model providing bounding boxes and classification names of the objects

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(Redmon et al. 2015). The reason for choosing the YOLO algorithm is because Gupta and Verma (2022) illustrates the results from the F1 score and YOLO have higher accuracy compared to Faster R-CNN and SSD. Therefore, the RCNN, Fast RCNN, and Faster RCNN are increased computing expenses associated with this sort of method as well as the longer processing duration (Lalak and Wierzbicki 2022). Yolov4 also performs better in precision and speed for many road conditions than R-FCN, Mask R-CNN, SDD, and RetinaNet, in which Yolov4 have the highest accuracy in most weather conditions(Haris and Glowacz 2021). The convolutional neural network of YOLOv8 architecture is used to search patterns to identify and classify objects in images. The network of the YOLOv8 model is shown in Figure 2 with four main parts for detection including the input images or videos, backbone, neck, and head. The input images are used with the trained weights from the training process in the previous step. Then, the input images are processed through the YOLOv8 network of the backbone, neck, and head, which contains convolution neural networks (CNNs), C2f module, ConvModule, DarknetBottleneck, and SPPF (Ju and Cai 2023).

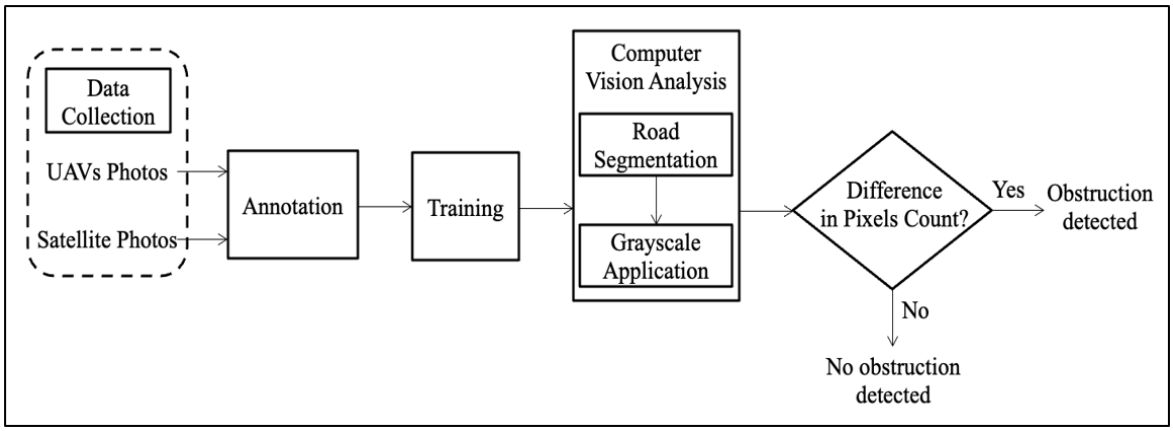

Figure 1. Methodology for detecting obstructions

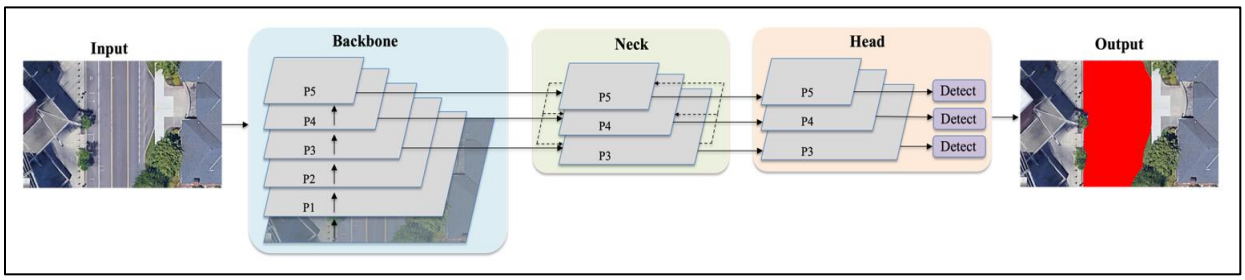

Figure 2. The network model of YOLOv8 architecture

d. Computer Vision Analysis: After training the custom dataset for the YOLOv8 model, the objective of this step is to detect and segment with images of roads for after-disaster areas from UAVs and reference images of satellite images from Google Maps. As an output of this technique, these images are detected and segmented for roads.

e. Pixels Comparison: In this section, the segmented images of images from UAVs and satellite images are applied into grayscale to have a binary color with the segmentation of roads

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in white color and others in black color. Following this, the grayscale images are counted with the white color pixels of the segmented area in the images. Then, the comparison of pixels count is used to identify the number of pixels in both cases between the post-disaster images and satellite images at the same location. Finally, the pixel areas of both cases are utilized to compare and predict that fewer pixels counted in the post-disaster images than in the satellite images are predicted as the existence of obstructions on roads.

CASE STUDY

The framework of this study was implemented on specific aerial images of post-disaster roads from UAVs with obstructions on them that were collected from the internet. These were compared to reference satellite images of the same location that was obtained from publicly available datasets (Google Maps in this case). This section describes how the various steps from the methodology were applied to these case-study images.

a. Dataset collection and preparation: First, an image dataset for training, testing, and validation of the methodology was created using aerial images of obstructions and their corresponding satellite images from Google Maps based on the location of the original image. In order to improve the performance of the detection model, cut-and-paste and image augmentation techniques were utilized to improve the precision, recall, and F-measure of the model (Bang et al. 2020). Therefore, the cut-and-paste technique was used to cut the obstructions images and paste them into the satellite road images. Then, the Roboflow website was utilized to annotate the images with a smart polygon function, which automatically generates polygon lines and increases the accuracy of polygon lines to precise the shape of roads (Dwyer and Nelson 2022). This annotated step for polygon lines of roads was utilized for every image. The image augmentation technique was also applied with adjusting the brightness, exposure, and noise of the images in Roboflow. In this study, the dataset of 600 images was separated into 70% for training, 20% for testing, and 10% for validation, as shown in Table 1.

Table 1. Training, testing, and validation of dataset statistics

Object Class	Training Images (70%)	Testing Images (20%)	Validation Images (10%)
Roads	420	120	60

b. Training: The YOLO version 8 (YOLOv8) was trained on Google Collab that provides free GPU services online to train a detection model with 16 batch sizes, 100 epochs, and 640 pixels image size. The weights from the training were reserved for the next step.

c. Classification: In this process, the training weights from the previous step have been applied with the YOLOv8 model to test additional post-disaster road images as well as the reference images from satellite images to classify roads and identify obstructions on roads.

RESULTS

As demonstrated in Table 2, presents the confusion matrix for the attained custom dataset of road performance. This custom dataset of roads has been classified with 100% of precision, 93% of recall, and 93% accuracy based on the confusion matrix. Figure 3 illustrates the landslide that happened on Oregon 138 West captured by a UAV on November 12, 2021. Figure 4 presents the

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satellite images from Google Maps at the same location as Figure 3. Therefore, Figure 5 and Figure 6 show the segmentation result from the YOLOv8 custom dataset for the road from Figure 3 and Figure 4, respectively. Figure 7 and Figure 8 illustrate the grayscale images with the white pixel count of roads from the detected roads in Figure 5 and Figure 6, respectively.

Table 2. Custom dataset of the roads confusion matrix

	Road	Background
Road	0.93	0.07
Background	0	0

Figure 3. The landslide occurred on Oregon 138 West captured by a UAV (Source: ODOT 2021)

Figure 4. The satellite images at the same location as Figure 3 (Source: Google Maps)

Figure 5. The segmentation from YOLOv8 custom dataset model for road in Figure 3

Figure 6. The segmentation from YOLOv8 custom dataset model for road in Figure 4

As shown in Table 3, the mean square error (MSE) is proposed to determine obstructions on roads from the difference in the percentage of pixel count of normal situations and obstructions on roads. Based on the testing set with various sizes of obstructions, there are 3 main categories including neglect situation, minor obstruction, and major obstruction.

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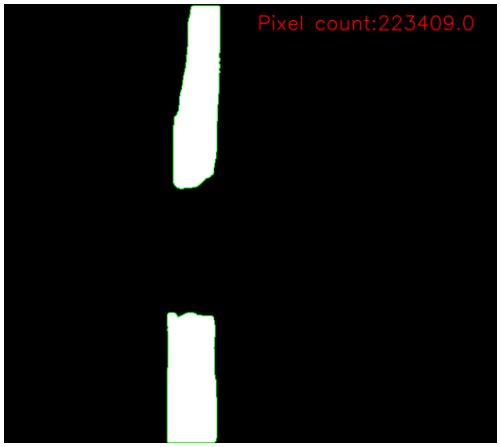

Figure 7. The grayscale of Figure 5 and the white pixel count

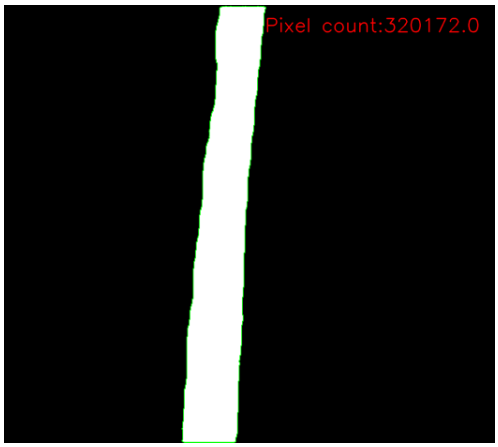

Figure 8. The grayscale of Figure 6 and the white pixel count

For the neglect situation, the situation of small obstructions, less than one-fourth of the road lane, provides a result of the percentage in difference in pixel count ranging from 0 to less than 3%. This neglect situation means that this type of obstruction tends to not harm ground vehicles.

In terms of minor obstructions, more than one-fourth but not greater than one lane, the difference in the percentage of pixel counts ranges from more than 3% but less than 10%. The minor obstruction indicates the obstacles that need to be removed, which have a high potential to harm ground vehicles.

Lastly, the major obstruction identifies as obstructions that are greater than one lane and can cause a severe hazard for both ground vehicles and roads. This major obstruction has a difference in the percentage of pixel count of greater than 10%.

Table 3. Mean Square Error function for identifying obstructions on roads

	Neglect Situation	Minor Obstruction	Major Obstruction
Difference in pixel count (%)	$< 3\%$	$\geq$ 3% but $< 10\%$	$\geq 10\%$

CONCLUSIONS

This paper provides a means of detecting obstructions on roadways after disasters using computer vision methods applied to images obtained from UAVs. The collected image data was segmented and roadways pixels were compared to corresponding image of the road obtained from pre-disaster times using publicly available satellite datasets. Such a methodology is expected to aid first responders and emergency managers plan routes to and from affected regions, which connects to GPS to automatically detect obstructions and report the location of the obstruction on roads. In this study, training process achieved 100% precision, 93% recall, and 93% accuracy for the training set of image data, and it was noted that dataset augmentation is greatly improved the deep learning performance of this framework.

Since most of the obstructions on roads for post-disaster areas are from a natural source, footage from UAVs for such areas usually contains many obstructions from a natural source. It is

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difficult to specifically detect obstructions on roads only because it is visually similar to areas outside of the roads which can result in false positives. Besides the natural source of obstructions on roads, there are many types of obstructions that can block the roads in post-disaster areas. In order to detect specific types of obstructions, each class of obstruction is required to train for a detection model. However, the road detection model in this study can detect obstructions on roads without the requirement for training each class and type of obstruction – which can take very irregular and a broad range shapes and visual appearances. This detection model was applied to detect and segment roads with the comparison of pixel count to reference images from the same location. The location of obstructions on roads can also be obtained based on the reference images from satellite images location, and GPS information obtained from the UAV, although this feature was not implemented in the current demonstration of the methodology.

The following are the limitations of the study, which should be considered for future research. The changes in natural light intensity while collecting images or videos of roads could result in inaccurate detection of the roads, especially at low light intensity. This aspect was not considered in this study. The low quality of images from post-disaster roads may bring about an effect to decrease in the accuracy of the model. Likewise, the quality of some images of roads from satellite images could be low and disturbed which could also affect decreasing the accuracy. The trees aside of the roads in images from satellite images may be different from the UAVs images, leading to an error in the pixel count process. Therefore, some roads in satellite images and post-disaster areas contain trees that cover the major parts of roads. This also results in difficulties detecting the roads. Some of the satellite images could contain vehicles in the images, which can result in some error in the pixel count process. The weather conditions such as fog, heavy rain, and snow also lead to difficulty to collect images and footage from UAVs for post-disaster areas and this also decreases the accuracy of the detection model. Future work will focus on implementing methods to mitigate the impact of the above factors on the accuracy of obstruction detection. Also, efforts should be made to use location coordinates from the UAV's GPS to automatically obtain reference images from satellite images to apply real-time identify obstructions on roads.

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