Detection of level crossing barriers using the histogram of oriented gradients method and support vector machine

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Abstract. Railroad crossing is a place where the railroad lines intersect with other roads, such as a highway. Referring to the Regulation of Minister of Transportation No. 36/2011, level crossing must be equipped with signs, markers and traffic signaling devices and crossing gate guards. However, 4600 of the 5800 level crossing points are without railroad keeper so that they are prone to traffic accidents. In addition, hazard information (danger signs) from the railroad keeper to the PUSDALOP and machinists sometimes cannot be seen at night and in a foggy situation. Therefore, this research aims to detect obstacles (cars) at a railroad crossing using the Histogram of Oriented gradient (HOG) method and the Support Vector Machine (SVM) classifier. HOG functions to extract object features (cars), while SVM is responsible for classifying car objects whether they fit the criteria of car features or not. The results show that an accuracy rate of car objects was 85%, 73% for empty train tracks and 91% for detection of passing trains.

1. Introduction
Level crossing is a place where the railroad lines intersect with other roads, such as a highway. Based on the security system aspects of level crossing applied in Indonesia, level crossings must have technical completeness in the form of a gate that fully closes the width of the road equipped with service panels and indicators of the direction of train arrival [1]. Referring to the Regulation of Minister of Transportation No. 36/2011, level crossing must be equipped with signs, markers and traffic signaling devices and crossing gate keepers. However, 4600 of the 5800 level crossing points are without the keepers so that they are prone to traffic accidents [2]. In addition, hazard information (danger signs) from the keepers to the PUSDALOP and machinists sometimes cannot be seen at night and in a foggy situation. Therefore, it is necessary to do obstacle detection method that serves to minimize fatal human error.

The first obstacle detection system was studied to help blind people avoid obstacles in the environment by various technological methods such as WiFi, RFID, laser, ultrasound, or camera [3-5]. After a while, some researchers began to develop obstacle detection to prevent collisions between trains at railway level crossings. Transponders are used to communicate between onboard train devices and trackside devices with infrared sensors [6-10], which has not been implemented in Indonesia due to the high cost. Thus, it is necessary to optimize the railroad obstacle detection method with a simple method and cheap enough to be implemented.

This study aims to detect obstacles (cars) at a level crossing using the HOG-SVM method. Histogram of Oriented gradient (HOG) method and Support Vector Machine (SVM) classifier are used for vehicle
object detection at level crossings. HOG functions to extract object features (cars), while SVM is responsible for classifying car objects whether they fit the criteria of car features or not. If a car object is detected in the point of view of the level crossing meeting area when the train gate is closed, the system will detect a danger situation.

2. Systems design

2.1. Object detection design

Start

Input frame of picture

Vector histogram production and input contours

Match object to dataset

The output is a registered or unregistered object

End

Figure 1. Flowchart of object detection by HOG.

In general, the working principle of HOG will match the input criteria captured with the dataset stored earlier. By implementing this method, the system can be trained to classify various types of unconventional objects apart from cars, trucks, and objects other than motorized vehicles which might be barriers.

3. Results and discussion

3.1. Features of extraction testing

The dataset consists of three database subsets. First, it contains a training dataset with vehicle images. Second, it contains a training dataset with an empty crossing path image. The last, it contains a training dataset with a train image.

The training process of the first subset begins by taking a video sample of conditions based on the angle and height of the installation of the detection system at crossing number 163. From the video, the test sample is cut to 320x180 pixels for sample.
The number of dataset sample of car are 522 items with 79 false positive samples.

The results of the training dataset show the precision of 0.99 recall 0.98 and the average precision of 0.98. The second subset is a dataset of safe crossing image.

The number of dataset sample of safe level crossing image are 45 items with 12 false positive samples.
Figure 6. The result of training dataset of safe level crossing.

The third subset is a dataset of passing train images.

Figure 7. Dataset of passing train.

Figure 8. The result of training dataset of passing train.

The number of dataset sample of safe crossing image are 45 items with 4 positive false samples. Those all subsets produce HOG image characteristic data as shown in Figure 9.
As shown in Figure 9, the left window shows the features of car objects; the middle window shows the safe crossing area; while the right window shows the features of passing train. These three features are then used in the classification machine.

3.2. Testing of sensitivity classification
The classification machine is tested by installing a system in the crossing testing area 163. To limit the classification of the wrong object, the lower threshold of the object classification confidence is determined. The lower threshold for this test is at confidence 0.1, 0.2 and 0.3. The test was carried out every 30 minutes with the assumption that traffic was the same and the passing train was twice.

Table 1. The result of sensitivity classification testing.

| Threshold | Detector | False Detection | Total Frame |
|-----------|----------|-----------------|-------------|
| thre 0.1  | detector 0 | 200             | 1092        |
|           | detector 1 | 5               | 913         |
|           | detector 2 | 1               | 34          |
|           | detector 0 | 70              | 1936        |
| thre 0.2  | detector 1 | 2               | 738         |
|           | detector 2 | 1               | 23          |
|           | detector 0 | 164             | 1020        |
| thre 0.3  | detector 1 | 0               | 656         |
|           | detector 2 | 0               | 23          |

The following is a graph of the total error detection from 3 thresholds with the same time span.
Based on Table 1 and Figure 10, the threshold level and false detection rate show that the machine worked well in collecting image data without ignoring image data in the minimum confidence threshold range of 0.2. However, the data of detector 1 graph shows that the classification engine experienced overfit and sloping confidence in point 0.6. Therefore, the C value from the detector 1 training dataset must be recalibrated by lowering the C value from 5 to 2.

4. Conclusion
The Histogram of Oriented gradient (HOG) method and the Support Vector Machine (SVM) classifier can be used to detect vehicle objects at level crossings. The first subset test contains a training dataset with 522 object images of car vehicles and an accuracy of 85%. The second subset contains the training dataset with object 45 safe empty crossing path images and an accuracy of 73%. The third subset has a higher accuracy of 91% for the training dataset with 45 object images of the train.

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