# A Railway Intrusion Detection Framework Based on Vehicle Front Video


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**Abstract.** Railway intrusion seriously threatens railway safety and may cause serious casualties and huge property losses. With the development of autonomous driving, image processing algorithms based on vehicle front video have developed rapidly. This paper proposes a railway intrusion detection framework based on vehicle front video. The framework mainly consists of two stages: object detection and semantic segmentation. In the first stage, an object detection algorithm is used to detect potential intrusion objects. The second stage uses the semantic segmentation algorithm to obtain the railway perimeter area. If the object is found within the railway perimeter, it is regarded as an intrusion. The railway intrusion detection framework proposed in this paper starts the semantic segmentation algorithm only when the object detection algorithm detects potential intrusion objects. Finally, the proposed framework is tested on railway video and achieves 100% accuracy and 23 FPS (Frames Per Second).



**Keywords:** Vehicle Front Video, Semantic Segmentation, Object Detection, Railway Intrusion.


## 1 Introduction

Railway is one of the main means of long-distance passenger and freight transportation on land, and it occupies an important position in transportation. As of the end of 2020, China's railway mileage has reached 146,000 kilometers, of which high-speed railway mileage is 38,000 kilometers. The long railway lacks adequate monitoring, and railway intrusion accidents emerge in endlessly. Fig.1 shows a variety of common railway intrusions. In 2019, the death toll of railway traffic accidents in China was 788, and railway incursions are still the main cause of casualties caused by railway traffic accidents. In addition, train delays and derailments caused by railway intrusion have brought huge economic losses. Therefore, it is necessary to strengthen the detection of railway intrusion.

**Fig. 1.** Various railway intrusions.

Surveillance video has the advantages of visualization and high real-time, and is a common railway intrusion detection method for railways. The railway department has deployed surveillance cameras at key railway locations such as level crossings to be able to detect railway intrusions. However, fixed-point surveillance cameras cannot cover long railway lines and easily fail to detect railway intrusions. The vehicle front camera is installed in the front of the train, which can monitor the running environment in front of the train in real time, which is a powerful supplement to fixed-point monitoring. With the development of autonomous driving, image processing algorithms based on vehicle front video have developed rapidly. This provides a direction for the research of railway intrusion detection based on vehicle front video.

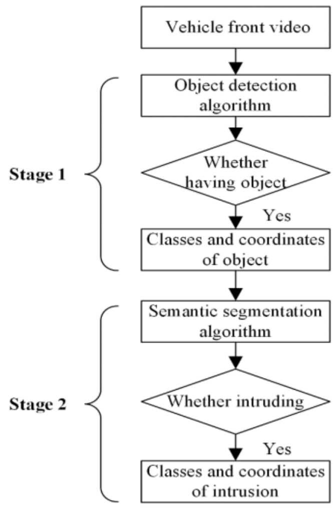


**Fig. 2.** Railway intrusion detection framework based on vehicle front video.

Because the train speed is fast, the intrusion detection algorithm must be fast while ensuring the detection accuracy. This paper proposes a railway intrusion detection framework based on vehicle front video, which can effectively detect the intrusion in front of the train. The framework is shown in Fig.2. The contributions of this paper are as follows:

A railway intrusion detection framework based on vehicle front video is proposed. The framework is composed of object detection algorithm and semantic segmentation algorithm, which is plug and play.

The object detection dataset and semantic segmentation dataset of railway images are produced, and data augmentation is used to solve the problem of small amount of railway images.

The proposed framework is tested using YOLOv5 and BiSeNetv2, achieving 100% accuracy and 23 FPS.

## 2 Related Work

### 2.1 Railway Scene Recognition

In fixed-point surveillance video, since the background is fixed, the perimeter area only needs to be marked once. However, since the background of the vehicle front video is constantly changing, it is necessary to determine the railway perimeter area in real time. In the past, the Hough transform was often used to determine the position of the rail, and then expanded to the perimeter area through expansion. However, the Hough transform is easily affected by the environment. With the development of deep learning, semantic segmentation algorithms have developed rapidly, especially in the field of autonomous driving.

The semantic segmentation algorithm can accurately determine the railway perimeter, and some scholars at home and abroad have carried out related research. [1,2] propose an adaptive railway monitoring image segmentation algorithm. First, the extracted fragmented regions are combined into local regions, and then the convolutional neural network is used to classify and recognize them. [3] proposed a semantic segmentation network called RailNet to directly identify and segment railway track regions.

### 2.2 Railway Intrusion Detection

Object detection algorithms based on deep learning have achieved great success, and some scholars have studied railway intrusion detection based on deep learning. [4] proposed an intrusion detection algorithm based on Mask-RCNN, which can accurately detect intrusion at level crossings. [5] proposed a lightweight railway intrusion detection algorithm, based on feature map clipping, which greatly improves the algorithm calculation speed and reduces the model size. [6] proposed an intrusion detection algorithm based on EfficientNet and SSD, which is fast. [7] proposed an intrusion detection algorithm based on vehicle front video, and the algorithm has achieved very good results. [8] studied the influencing factors of railway catenary nesting and the impact of nesting on railway operations.

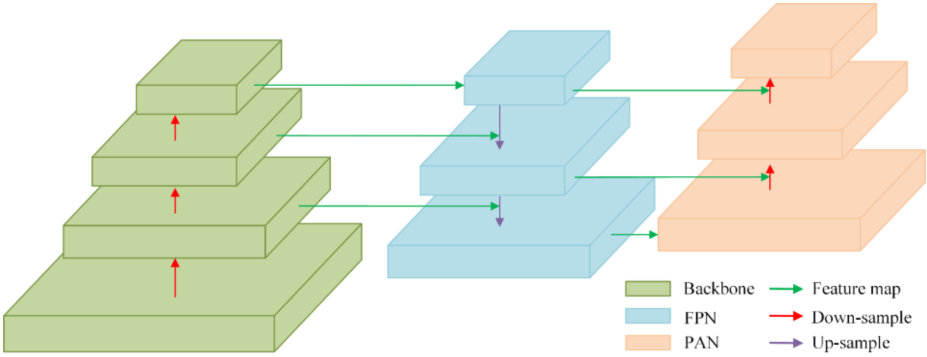


**Fig. 3.** The network structure of YOLOv5.

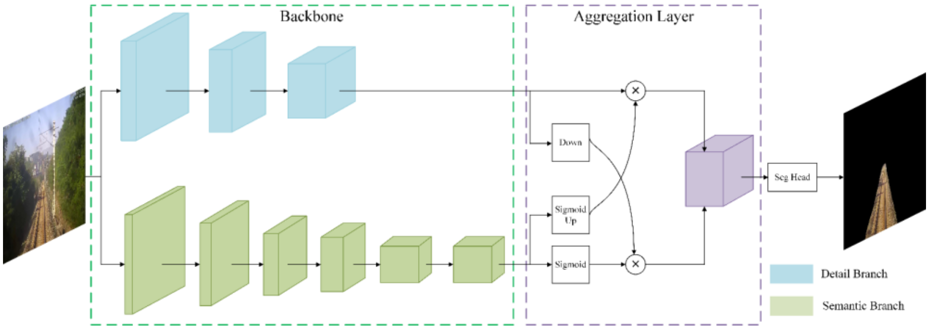


**Fig. 4.** The network structure of BiSeNetv2.

# 3 Methodology

In this section, the object detection and semantic segmentation of the proposed framework choose YOLOv5 [9] and BiSeNetv2 [10] respectively. YOLOv5 is used to detect the vehicle front video. When YOLOv5 detects a potential intrusion object, it starts a semantic segmentation algorithm to determine whether the object location is a railway intrusion.

## 3.1 Object Detection

In the first stage, we use the YOLOv5 algorithm to detect potential intrusion object. The network structure of the YOLOv5 is shown in Fig.3. YOLOv5 is mainly composed of backbone network, feature pyramid network (FPN) and path aggregation network (PAN). The YOLOv5 uses the backbone network to extract image features, then the features are fused in FPN and PAN.

### 3.2 Semantic Segmentation

In the second stage, BiSeNetv2 is used to identify and segment railway scenes. The network structure of BiSeNetv2 is shown in Fig.4. The network consists of two branches. The detail branch is used to capture low-level details and generate high-resolution features, and the semantic branch is used to obtain high-level semantic context. BiSeNetv2 has a guiding aggregation layer to enhance interconnection and fuse two feature information.

## 4 Experiment

### 4.1 Dataset

The railway dataset consists of an object detection dataset and a semantic segmentation dataset. As there are fewer railway image samples, data augmentation methods such as rotation and mirroring are used to increase the number of images. The result of data augmentation is shown in Fig. 5.

The object detection dataset includes 15036 images, including ten categories: person, motorbike, bicycle, train, dog, stone, box, car, truck and bus. The ratio of training set to testing set for object detection is 9:1. The semantic segmentation dataset includes 4500 images, including railway and background two categories, and the ratio of training set and testing set is 9:1.

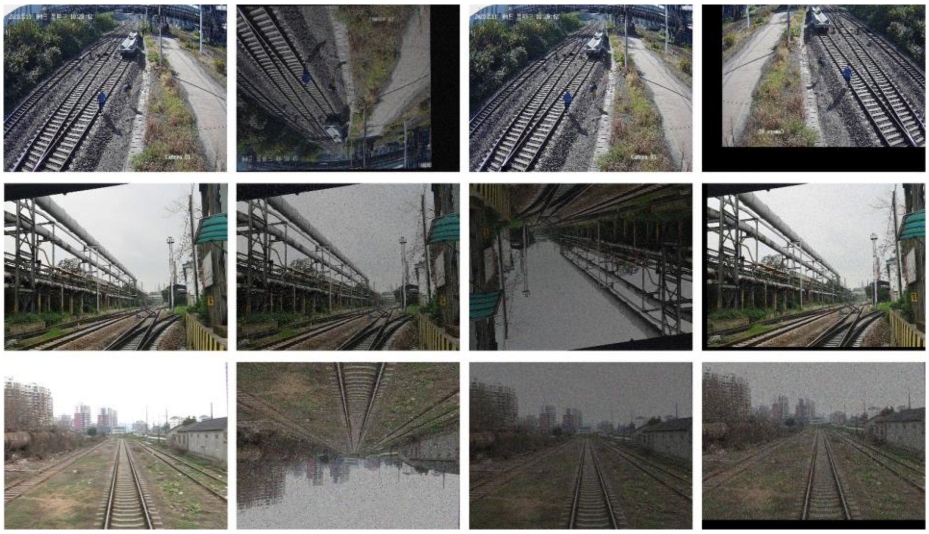

**Fig. 5** The result of data augmentation.

## 4.2 Experimental Parameters

YOLOv5 and BiSeNetv2 are both trained and tested on a CPU (Intel(R)Core(TM) i7-7820x CPU@3.40GHz×16) and GPU NVIDIA 2080Ti. The hyper-parameters of YOLOV5 in training are shown in Table 1. The hyper-parameters of BiSeNetv2 in training are shown in Table 2.

## 4.3 Experimental Results

Several vehicle front videos are used to test the proposed method. The experimental results are shown in Fig.6. The proposed method detects all intrusions and avoids false alarms. The proposed method has a 100% accuracy rate and an operating speed of 23 FPS, which can fully meet the needs of field applications.

As shown in Figure 6, in the first column, the proposed method detects people in the railway area and ignores workers outside the railway area. In the third column, the proposed method detects a very small person in the image. In the fourth column, a rock on the rail is detected. These cases prove the effectiveness and practicality of the proposed method.

**Table 1.** Hyper-parameters of YOLOV5 in training.

| Parameter | Describe | Value |
|---|---|---|
| *F* | Input image size | 640×640 |
| *C* | Input channels | 3 |
| *B* | Batch size | 32 |
| *D_M* | Depth_multiple | 1 |
| *W_M* | Width_multiple | 1 |
| *M* | Momentum | 0.999 |
| *L* | Learn rate | 0.001 |
| *D* | Decay | 0.001 |
| *E* | Epochs | 300 |

**Table 2.** Hyper-parameters of BiSeNetv2 in training.

| Parameter | Describe | Value |
|---|---|---|
| *F* | Input image size | 512×1024 |
| *C* | Input channels | 3 |
| *B* | Batch size | 8 |
| *L* | Learn rate | 0.05 |
| *D* | Decay | 0.0005 |
| *I* | Iteration | 150000 |

**Fig. 6** Experimental results.

## 5 Conclusion

This paper proposes a railway intrusion detection framework based on vehicle front video, which can effectively detect railway intrusion. There are three contributions. First, a railway intrusion detection framework is proposed, and the algorithms in the framework are plug-and-play. Second, there are few railway image samples, so data augmentation is used to increase the amount of data samples. Finally, YOLOv5 and BiSeNetv2 are used to test the proposed framework, and the accuracy rate is 100%, and the running time is 23 FPS.

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