Enhancing Railway Obstacle Detection System Based on Incremental Learning

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Abstract: Obstacle detection systems face challenges related to the Catastrophic forgetting problem, where old obstacles may be misclassified when training new unseen obstacles. Re-training a model from scratch for every new obstacle is often impractical. In this work, we propose a continual learning-based approach to efficiently update the model without repeatedly retraining on previous data, while simultaneously mitigating catastrophic forgetting. Experimental results demonstrate the effectiveness of our proposed method.

1 INTRODUCTION

With the advancement of high-speed rail systems, their safety and reliability have garnered significant public attention in recent years. Obstacles within railway zones represent a major threat to railway safety. Potential obstacles encompass a wide variety of categories, including rocks, animals, pedestrians, and tree branches. A core challenge in railway obstacle detection is the inherent difficulty of predefining all possible obstacles. Furthermore, the dynamic environmental conditions(Guo, 2024) surrounding railway areas add additional complexity to this task.

Deep learning-based approaches have achieved significant success in domains such as mobile payment(Guo et al., 2023), disaster detection(Sazara et al., 2019), and remote sensing(Bischke et al., 2019). Obstacle detection in railway areas can be framed as an Out-of-Distribution (OOD) problem (Yang et al., 2024). In real-world scenarios, obstacles may not be encountered during training, presenting a significant challenge. Traditional deep learning-based approaches struggle with this issue, as models trained on specific datasets can only detect objects represented within the training data. One potential solution is to update existing models when new obstacle categories emerge. For example, consider an obstacle detection model at stage T that is trained to detect pedestrians. At stage T+1, the model must be updated to detect new obstacles, such as rocks. Consequently, the training dataset must also be expanded to include both categories—pedestrians and rocks.

However, this approach presents several challenges. First, model updating is time-consuming and costly, as it requires retraining the model. Second, training a model necessitates a large volume of data, and storing previous object images becomes increasingly burdensome over time. Finally, when a model is fine-tuned on new data, it often experiences a loss of performance on previously learned tasks, a phenomenon known as catastrophic forgetting, which can be detrimental in our scenario. As illustrated in fig. 1, obstacles such as pedestrians and rocks may be misclassified during later stages, underscoring the critical nature of mitigating catastrophic forgetting(Kirkpatrick et al., 2017) in obstacle detection tasks.

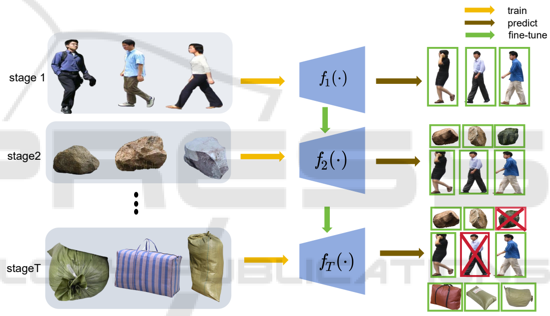

Figure 1: Demonstration of the Catastrophic Forgetting Problem: In the early stages, both previous and current obstacle categories are accurately predicted (denoted by the green box). However, as time progresses, the likelihood of misprediction for objects from previous stages increases, leading to a higher probability of incorrect classifications (denoted by the red box).

In this work, we propose a incremental learning-

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based approach to address the aforementioned challenges. To alleviate storage pressure, we introduce an object-level memory bank that retains information about obstacles and their corresponding priority indices. The obstacle information represents previously encountered objects, which can be fused with current images, while the priority index determines the likelihood of an object being selected for inclusion in the model. The selected objects are then overlaid onto the current image, which incorporates both previous and new obstacles into a single frame.

To identify previous objects that are more likely to be misclassified, we employ two strategies. First, we design a policy to update the memory bank. At the end of each training stage, the priority index is updated based on the sum of the absolute gradient values of the pasted images. Second, we update the shallow layers of our model at the beginning of each stage. This targeted modification is based on the premise that shallow layers capture shape-related features(Geirhos et al., 2018), which are critical to the accuracy of our task. The details of our methods are provided in Section 3.

In this work, our contributions can be summarized as follow:

- We propose a data-efficiency approach to fuse previous obstacles with current new emerging obstacles without increasing the number of total training images.
- We propose a memory bank and corresponding update policy. The memory bank is updated based on the sum of absolute gradient of fused images.
- We update the shallow layer of current network with previous one to retain previous learned features.

2 RELATED WORKS

2.1 Railway Obstacles Detection

In recent years, several approaches have been applied in obstacle detection in railway areas. Rahman et.al. (Rahman et al., 2022) propose a classification based method which leverage MobileNetV2 to classify the obstacled images. They claim that proposed model outperforms other approaches; Brucker et.al. (Brucker et al., 2023) propose utilizing a shallow network to learn railway segmentation from normal railway images, besides they explore the controlled inclusion of global information by learning to hallucinate obstacle-free images; Zhang et. al. (Zhang et al., 2023)propose an intelligent obstacle detection system based on deep learning to improve the safety of train operation. To further improve the robustness and reliability of the system, signals of other modal signals are introduced, LiDAR, for instance. Bai et al .(Bai et al., 2024) fuse visual and Lidar data in real time railway obstacle detection task. However, LiDAR is expensive compared to camera and is easily affected by temperature, which is impractical to be widely deployed in practical scenarios. Wen et. al.(Wen et al., 2024) propose a multi-contrastive learning strategy to improve point cloud segmentation in complex weather for rail-obstacle detection.

2.2 Incremental Learning

Incremental learning, also known as lifelong learning or continual learning, has been applied across various computer vision tasks (Douillard et al., 2021; Si et al., 2025). The primary objective of incremental learning is to address catastrophic forgetting (Robins, 1995), wherein a model gradually loses its ability to recognize objects from earlier stages. Some approaches retain a limited number of previous data samples or features for integration with current data (Zhu et al., 2023). Other methods focus on modifying network structures to accommodate new tasks (Frankle and Carbin, 2018), designing effective sample selection policies for task adaptation (Prabhu et al., 2020), or generating pseudo-labels and synthetic images to mitigate class imbalance (Douillard et al., 2021). To the best of our knowledge, incremental learning has not yet been applied to railway obstacle detection. We believe that a well-designed incremental learning system could improve efficiency while simultaneously addressing catastrophic forgetting.

3 METHODS

In this section, we describe the components of our system in detail. As illustrated in fig. 2, our system comprises the following key components: an Object-based Memory Bank, an Absolute Gradient Value Update Policy, and Shallow Layer Replacement. These components work together to integrate past information with current images, effectively addressing the catastrophic forgetting problem.

3.1 Reformulation

Railway Obstacle Detection

Given an Image $I \in \mathbb{R}^{C\times H\times W}$, a sub-area $\mathcal{M} \subset I$, which indicates that there exists a railway area

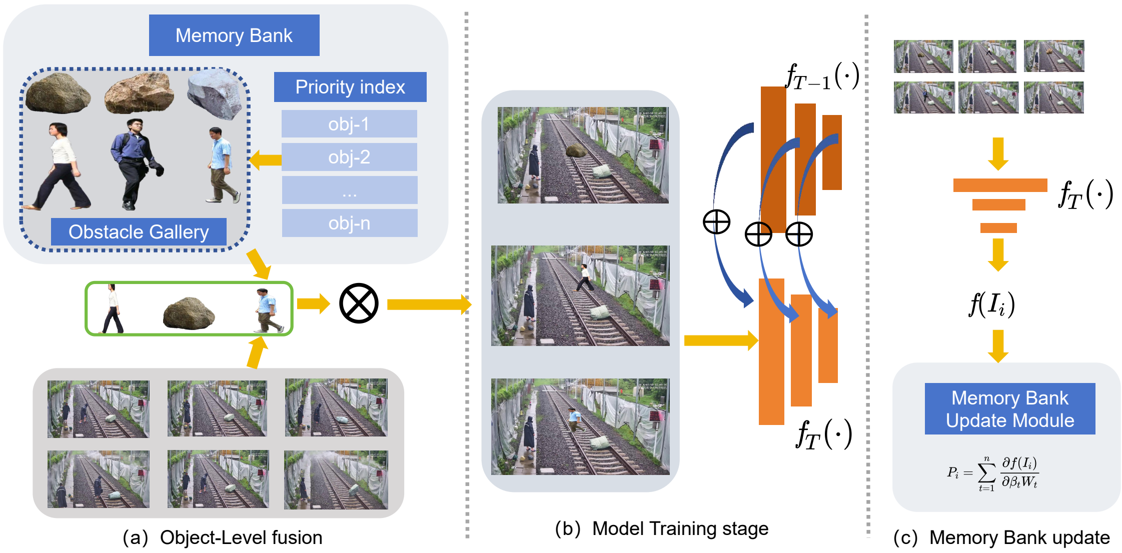


Figure 2: (a) Data Fusion Module: In this step, objects are retrieved from the Object Memory Bank based on their priority index. These objects are then overlaid onto the images in the current stage to integrate both past and present obstacle information. (b) Training Process: During the training phase, the shallow layers of the convolutional neural network (CNN) are replaced with the corresponding layers from the previous stage at the start of each new training cycle. (c) Memory Bank Update: The memory bank is updated at the end of each training stage, with updates determined by the absolute gradient change of each fused image.

in the image; an obstacle set with n classes $O = \{o_1, o_2, ..., o_n\}$, The Railway obstacles detection system aims to obtain a CNN model $\varphi : I \longmapsto \{B_i, p_i, c_i\}_i^n$, where $B_i = \{x_i, y_i, h, w\}$. $p_i \in [0,1]$.

$$y = \begin{cases} 0, & \text{if } p_i > \mathcal{H} \text{ and } \exists i, s.t., B_i \bigcap \mathcal{M} \neq \emptyset \\ 1, & \text{else} \end{cases} \quad (1)$$

where y is the prediction of the system, 1 is obstacles detected and 0 is no obstacles; $\mathcal{H}$ is the threshold of confidence of detected candidates, which can be adjusted based on different scenarios.

Incremental Learning

Assuming we are given a data stream $\mathcal{D} = \{\mathcal{D}_1, \mathcal{D}_2, ...\}$, $\mathcal{D}_i \cap \mathcal{D}_j = \emptyset$. θ_i is the parameters of model $\mathbf{f}_i(\cdot)$, which is updated at stage i. The model is initialized based on $\mathcal{D}_0$

$$f_0(\cdot) = \psi_0(\mathcal{D}_0) \quad (2)$$

where ψ_0 is training strategy in stage 0. At stage T, the model is updated in following way:

$$f_T = \phi_T(\mathcal{D}_T, \mathcal{D}_{bank}, f_{T-1}). \quad (3)$$

Where $\mathcal{D}_{bank}$ is memory bank, which saves information of previous $\mathcal{D}_{i,...,T-1}$. $\phi(\cdot)$ is the update strategy, which takes previous model, memory bank and current data as input. The updated strategies may vary along with the change of stages.

3.2 Memory-Bank Module

Object-Level Memory Bank

Previous continual learning based approach save whole image in Memory-Bank(Qu et al., 2021). With the accumulation of time, the memory bank will suffer from storage burden. To alleviate this issue, we propose a object-level memory bank. We extract target obstacle objects in each stage. The extract object patches are no bigger than the original images. In this way, one training image contain both previous obstacles and current obstacles. To simulate the practical scenarios, the objects need to be re-scaled according to their pasted positions.

$$k = \frac{1}{n} \sum_{1}^{n} \frac{patch_i}{s_i} \quad (4)$$

where s_i is the size of original image. We iterate our dataset, calculate the average k in different categories. as illustrated in 1, object-level can save 90% space

Table 1: Object-image ratios in our scenario.

	Pedestrian	rocks	Branch	board	avg.
k	0.12	0.07	0.09	0.11	0.10

compared to image-level approach.

Extracted patches are then fed into Segment-Anything-Model(SAM) to obtain corresponding mask, which will be used in our copy paste step.

Copy-Paste Object Fusion

Traditional approaches also suffer from the burden of data accumulating. Assuming we have N stages, in each stages we have M images. Training time of an batch of images(B) is P. The estimated time $\tilde{T}$ is calculated as follow:

$$\tilde{T} = \frac{M \times N \times P}{B} \tag{5}$$

The Training costs become prohibitively expensive as N increases, Not to mention the impact caused by class imbalance.

To alleviate this problem, we introduce a copy-paste approach to fuse history object with current categories. The procedures are as follow: firstly, previous obstacle object are sampled based on priority index in memory bank. As illustrated part a in 2, the sampled objects are pasted on the current stage images according to Mask. In this approach, the training image remain the same in each stage. This approach simultaneously reduces training time and maintains data class balance.

$$\hat{I} = M \otimes P + (1 - M) \otimes I \tag{6}$$

Update Policy

The core component of the Object Memory Bank module is the Update Policy, which serves two main functions. First, it identifies objects or categories that are more likely to be misclassified; second, it refreshes the Memory Bank to prevent excessive growth. In deep neural networks, changes in gradient values can indicate the model's sensitivity to specific input data (Selvaraju et al., 2017). Given a trained model and an input image, gradient values are obtained through an inference process, where higher values indicate greater sensitivity to that object class. Additionally, objects within the same category contribute differently to model training. To assess the priority of objects in the Memory Bank, we introduce the Absolute Gradient Value Update Policy. Given a Model $f(\cdot)$ and fuse image samples $I_{cp} = \{I_1, I_2, ..., I_n\}$. At the end of each stage, the priority index of each image can be calculated as follow:

$$p_i = \sum_{i=1}^{n} \frac{\partial f(I_i)}{\partial \beta W_i} \tag{7}$$

where n is the number of kernels in model, W_i is the corresponding weights in kernels. β_i is a parameter to adjust the importance of each channel, which is between 0.1 to 0.8, shallow layer is with a larger value compared to deeper layer. At stage K, a priority queue L_k is formed based p_i, $1/k$ items in L_k will be replaced randomly by current stage obstacles.

3.3 Shallow-Channels Fusion

Another contributor to catastrophic forgetting is the shift in kernel weights.(Jin et al., 2021) During model fine-tuning, the weights in kernels responsible for recognizing previous objects are overwritten by new weights, leading to an irreversible shift. This weight shift can worsen over time, compounding the issue. To address this, we propose a kernel-level information fusion mechanism.

Previous studies have shown that shallow CNN layers are more effective at capturing shape-based features, while deeper layers tend to capture texture-based features(Hermann et al., 2020). Since shape-based features are robust and crucial for obstacle-related tasks, we enhance our model's resilience against catastrophic forgetting by replacing the shallow CNN layers, enabling better retention of earlier learned features. The target channel k is determined as follow:

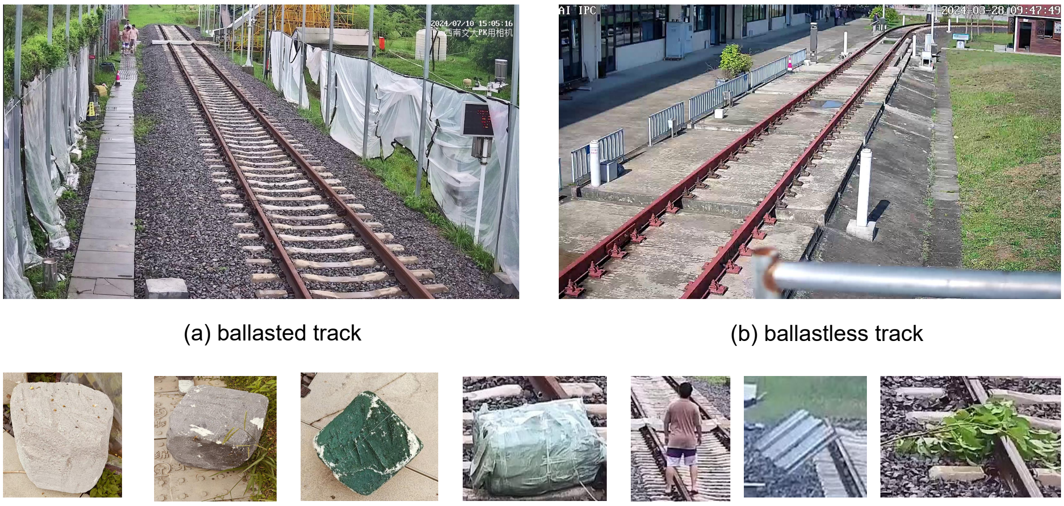
$$k_i = \arg\max_k \frac{\partial f(I_i)}{\partial W_k} \tag{8}$$

$$channels = [k_1, k_2, .., k_n] \tag{9}$$

Here, I_i represents a randomly sampled fused image with a high priority index. At the start of each stage, channels from the fine-tuned model in the previous stage randomly replace the corresponding channels in the current model. Through experimentation, we observed that fusing channels from multiple prior models can slightly improve robustness. However, this approach also increases storage requirements and inference time. As a trade-off, we choose to replace channels using only the model from the immediately preceding stage. yellow box), respectively. On the right: after training, intra-class distances become smaller, while inter-class distances become larger. (ViT) (Dosovitskiy, 2020) as its backbone, whereas the light-type employs a modified version of MobileNetV2 (Sandler et al., 2018). To reduce the model size further, we compress the original MobileNetV2 by reducing its width, i.e., decreasing the number of channels. Both ViT and the modified MobileNetV2 replace the final layer with a fully connected layer of size $n \times 128$.

3.4 Pseudo Code

The pseudo code of our update policy is illustrated as algorithm 1.



(a) ballasted track

(b) ballastless track

(c) Obstacles

Figure 3: Experiment sites and obstacles in our work. ballasted track(a) is around 70 meters ling and 8 meters wide; b) ballastless track is around 100 meters long and 6 meters wide. Obstacles from left to right: rocks(20cm), rocks(30cm), rocks(40cm), parcels, pedestrians, steel board and branches.

Algorithm 1: Update policy.

Input: Model $f(\cdot)$, Memory Bank $\mathcal{M}_{T-1}$, image set in stage T $\mathcal{D}_T = \{I_1, I_2, \ldots, I_n\}$
Result: Updated Memory Bank $\mathcal{M}_T$
Data: Priority index P = [...]
foreach I_i **do**
    // copy-paste to generate fused image
    $I_{fuse} = m \otimes P + (1-m) \otimes I_i$;
    // Calculate absolute gradient across layers
    $P_i = \sum_{i=1}^{n} \frac{\partial f(I_{fuse})}{\partial \beta W_i}$;
    $P.append(p_i)$;
end
sort(P);
for i = *0 to n* **do**
    // Replace Memory bank objects according to priority index
    $\mathcal{M}.Patch[i] = ranndom(obj_t, P[i])$
end

4 EXPERIMENTS

4.1 Configuration

Our method is implemented using the PyTorch framework and the model is trained on an RTX 3090Ti, with 24 GB memory. CPU processor is Intel i7-12700F with 20 cores. We select Adam(Kingma, 2014) as the optimizer. Starting learning rate is set to 0.001. The batch size is set to 16 and the number of epochs to 25. Albumentation(Buslaev et al., 2020) is utilized to perform data augmentation. Data transformations include horizontal flip, coarse dropout, and random brightness contrast adjustments.

4.2 Dataset & Policy

Dataset

The images used in this study were captured at our experimental site in Chengdu, China. As shown in fig. 3, the site includes two types of railway scenarios: ballastless track and ballasted track. The obstacles we prepared include rocks of varying sizes (20 cm, 30 cm, and 40 cm), branches, pedestrians, parcels, and steel boards. For each stage, we collected 2,000 images—1,200 on ballastless track and 1,200 on ballasted track. Obstacles were positioned at varying distances between 10 m and 50 m. The dataset was split randomly into training and test sets, with an 80:20 ratio.

Policy

The categories of obstacles—rocks (20 cm, 30 cm, 40 cm), parcels, pedestrians, steel boards, and branches—are designated as A through G, respectively. In each training stage, only data from one

Table 2: Results w/wo our approach across popular detection architectures.

	$\mathcal{D}/A \to A$	$\mathcal{D}/B \to B$	$\mathcal{D}/C \to C$	$\mathcal{D}/D \to D$	$\mathcal{D}/E \to E$	$\mathcal{D}/F \to F$	$\mathcal{D}/G \to G$
Yolo v5(Jocher, 2020)	0.824	0.837	0.842	0.791	0.917	0.684	0.635
Yolov5+Ours	0.831	0.849	0.857	0.811	0.934	0.713	0.651
Yolo v10(Wang et al., 2024)	0.819	0.847	0.837	0.811	0.924	0.714	0.672
Yolov10+Ours	0.827	0.853	0.859	0.836	0.928	0.733	0.691
Faster Rcnn(Ren et al., 2016)	0.807	0.825	0.831	0.776	0.909	0.723	0.667
Faster Rcnn+Ours	0.813	0.834	0.844	0.791	0.924	0.737	0.681
nanodet(RangiLyu, 2021)	0.821	0.826	0.847	0.808	0.916	0.696	0.659
nanodet+Ours	0.833	0.829	0.857	0.831	0.931	0.717	0.683
Swin(Liu et al., 2021)	0.827	0.841	0.847	0.822	0.938	0.735	0.649
Swin+Ours	0.839	0.857	0.862	0.831	0.946	0.749	0.661

Table 3: Ablation study on sub-component.

copy-paste	Layer-fusion	GMBU	mIoU
			0.813
✓			0.847
	✓		0.821
		✓	0.871
✓	✓	✓	**0.889**

Table 4: Ablation results on pasted objects fused on images.

# objs	1	2	3	4	5	6
mIoU	0.864	0.875	0.894	0.889	0.896	0.890

category and the corresponding entries in the Object Memory Bank are accessible. The notation $\mathcal{D}/A \to A$ indicates that the current task is to detect category A, where $\mathcal{D}$ represents the union of all categories. We set the training steps to 2, meaning that two categories are trained in each step.

For example, in the stage $\mathcal{D}/A \to A$, the model is fine-tuned using data from category A along with fused data from other categories. The test set consists of all images except those from category A, as our objective is to assess the effectiveness of the method in addressing catastrophic forgetting.

4.3 Results

Quantitative Evaluation

The results of quantitative evaluation is illustrated as below. We deploy our approach on several popular detection architectures(YOLO-V5, YOLO-V10, Faster-RCNN, Swin, nanodet) to verify the effectiveness of it. The results indicates that our proposed methods are effective across all architectures we listed. The improvement of mIoU range from 0.006 to 0.024. Besides, it is noticeable that the effects of Catastrophic Forgetting is different across categories. It is severe in $\mathcal{D}/F \longrightarrow F$ setting, which indicates that the learned features of steel board may overlap the previous ones. The setting $\mathcal{D}/A \longrightarrow A$,$\mathcal{D}/B \longrightarrow B$ and $\mathcal{D}/C \longrightarrow C$ show subtle improvements indicates that cubes share similar features in terms of contours and shapes.

Ablation Study

To verify the effectiveness of each module, we conduct an ablation study in terms of Copy-Paste, Layer fusion and Gradient-Memory-Bank update module. The results are illustrated in table 3. One point that needs to be clarified is, when GMBU is not activated, we adapt a random update policy to update the memory bank. The results indicate that each part contribute to improve the whole system, while GMBU contributes the most.

We also conduct experiments to determine the best number of pasted objects on current images, the results are illustrated as table 4. The results indicate that the performance increase when number of objects range from 1 to 4 and become saturate after that.

5 DISCUSSION

In this work, we have proposed a continual learning-based approach to mitigate the catastrophic forgetting problem in obstacle detection for railway scenarios. The proposed Object-Memory Bank reduces both storage and training burdens simultaneously. The memory bank update policy, along with modifications to the CNN layers, facilitates the retention of previously learned features in later stages. Future work could focus on optimizing the object fusion process, such as incorporating light and shadow information during the image generation stage, which would enhance the realism of the data. Additionally, further research on feature-based methods is needed to compress the memory bank more effectively.

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