Dam Deformation Monitoring via Dam Segmentation and Fast and Slow Change Detection

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Abstract. Dam banks deformation monitoring enables the early detection of potential hazards and the way based on video surveillance provides a simple, convenient, low-cost, and non-contact monitoring manner compared with the other contact-type monitoring devices. While, it faces many challenges: large background changes, the coexistence of fast and slow changes, and the lack of a dam dataset. To emphasis these issues, we build a dam segmentation dataset (DamSeg) and a lightweight dam semantic segmentation network (Dam-YOLO), so that the change detection can efficiently focus on dam bank regions. Then, we adopt Flow-CDNet to simultaneously detect fast and slow changes. Finally, Dam-CDNet is presented, which integrates the Dam-YOLO trained on DamSeg and Flow-CDNet, to achieve accurate dam deformation detection. Experiments show Dam-YOLO achieves the best overall speed-accuracy balance, and quantitative tests on the self-built DamChange dataset show Dam-CDNet further improves dam deformation monitoring compared to Flow-CDNet.

Keywords: Semantic segmentation · Dam deformation monitoring · Change detection · Optical flow estimation

1 Introduction

Dam bank deformation and damage represent high-risk scenarios that pose significant threats to the life and property safety of people on both sides of the river. Dam bank play a crucial role in regulating water flow and stabilizing the river channel. Dam monitoring enables the early detection of potential hazards and provides vital supporting information for the decision of disaster response and

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rescue. Currently, the mainstream method for dam monitoring involves manually using displacement detectors, break-line sensors and other devices to monitor changes in the dam bank. However, the monitoring methods have drawbacks such as high installation and maintenance costs. With the popularization of video surveillance, monitoring networks along dam bank of river basins have been gradually established. However, due to the limitations of human visual observation and the suddenness of dam breaches, emergency work can only be carried out when significant changes occur in the dam bank. This often results in a waste of financial resources and substantial damage to the dam bank. Therefore, utilizing existing video surveillance resources for visual monitoring of dam deformations, analyzing potential risks through monitoring slight changes in the dam bank, and promptly dispatching manpower for reinforcement can help prevent further enlargement of dam deformations and mitigate potential risks.

Recent advances in artificial intelligence and deep learning have demonstrated significant potential for infrastructure monitoring applications [1,2]. The integration of advanced sensor, communication, and unmanned aerial system technologies with deep learning has enabled intelligent structural health monitoring systems that facilitate automated defect detection and real-time condition assessment for civil infrastructure [3]. Motivated by these technological developments, we seek to leverage deep learning approaches for automated dam monitoring to address the critical need for continuous and reliable assessment of dam structural integrity.

To overcome the above issues, we build a dam semantic segmentation dataset considering dams with different typical forms and scenes with different weathers and seasons, then adapt semantic segmentation technology to extract dam bank so as to only focus on the changes in the dam bank. Furthermore, a novel change detection framework taking both slow and fast changes into consideration is adopted, named as Flow-CDNet. It can fuse multi-scale displacement change features and simultaneously detect fast change and slow change features to obtain a better detection effect. To adapt to this adopted change detection framework, the existing change detection datasets DamChange containing both kinds of changes are also utilized.

The main contributions can be summarized as follows:

- We construct a lightweight dam semantic segmentation network (Dam-YOLO) and a dam semantic segmentation dataset (DamSeg). Experimental results on the Dam-Seg dataset indicate that Dam-YOLO achieves an mIoU of 89.25 and 90.91 FPS on a single NVIDIA Tesla V100, achieving the best balance in terms of speed and accuracy.
- We adopted a detection network capable of simultaneously detecting slow changes and fast changes (Flow-CDNet). The network includes an optical flow detection branch and a fast change detection branch.
- We combine the above two networks to form a dam-bank change detection network (Dam-CDNet). The dam-bank regions produced by Dam-YOLO are used as masks, overlaid with the regions detected by Flow-CDNet. Experi-

mental results, on the DamChange dataset, indicate that Dam-CDNet can effectively address the issue of early warning for the dam-bank hazards.

2 Related Work

2.1 Dam Segmentation

Semantic segmentation, as a means of foreground segmentation, significantly enhances the effectiveness of dam deformation detection. In most cases, the dam bank in images vary in size and have irregular shapes, requiring segmentation models to possess the ability to extract multi-scale features. Additionally, segmentation models are often deployed to hydrological stations with limited computational resources, necessitating the establishment of time-efficient and accurate models. There are no available dam semantic segmentation models. To meet the above realistic requirements, we focus on semantic segmentation methods based on deep learning.

Many excellent semantic segmentation algorithms based on deep convolutional neural networks have been proposed, such as AlexNet [4], VGG [5], NiN[6], DenseNet [7], and UNet [8]. These networks employ an encoder-decoder architecture, significantly improving the accuracy of feature extraction across different scales, but running at a slow speed.

BiSeNet [9] and BiSeNetV2 [10] collect shallow features through the spatial branches, capture deep features through contextual branches, and merge the mentioned features. EDANet [11] introduces an efficient module using asymmetric convolutions, achieving real-time semantic segmentation. FastSCNN [12] adopts skip connections from deep convolutional neural networks and proposes a shallow learning module for rapid and effective multi-branch low-level feature extraction. These networks achieve a balance between performance and accuracy.

However, existing real-time semantic segmentation networks show suboptimal performance in the field of dam semantic segmentation, with both accuracy and speed needing improvement. To enhance the effectiveness of dam semantic segmentation, we design a new semantic segmentation network based on YOLOv11 [13], called Dam-YOLO, significantly improves both speed and accuracy.

2.2 Change Detection for Fast and Slow Changes

We have the following definition: when an object is in motion in the bitemporal images, it is classified as slow change if a certain part of the object exists in both images; it is classified as fast change if the target only appears in one of the bitemporal images.

Extensive research has been conducted on the challenge of detecting either slow or fast changes. For slow changes, researchers commonly employ optical flow detection, that is because it aims to determine the pixel-wise correspondences between source and target images in the form of a 2D displacement field, allowing it to capture minor variations effectively. Traditional methods, such as EpicFlow [14], DeepFlow [15], MirrorFlow [16] and so on, propose numerous strategies to improve the accuracy of optical flow estimation. However, all of them face challenges in achieving real-time performance. SpyNet [17] employs a coarse-to-fine approach that combines traditional methods with deep learning techniques. AccFlow [18] accumulates frame-to-frame optical flow to obtain long-distance cross-frame optical flow, adapting to optical flow estimation algorithms for arbitrary frame pairs. VideoFlow [19] can thoroughly explore and utilize multi-frame data, significantly enhancing the performance of optical flow estimation. SAMFlow [20] proposes a solution that embeds a frozen SAM image encoder into FlowFormer to enhance object perception. RAPIDFlow [21] combines NeXt1D convolutional blocks with a fully recursive structure based on feature pyramids. This not only reduces computational costs but also does not significantly affect estimation accuracy. For fast changes, researchers commonly employ change detection with deep neural networks. PSPNet [22] is the first to introduce the concept of pyramid pooling modules and integrate global contextual information. Due to its ability to leverage global contextual information through context aggregation from different regions, it has become a baseline method in the deep change detection. Liu [23] uses semantic segmentation as an auxiliary task to aid change detection. This approach helps to learn more distinctive object-level features, thereby enhancing the quality of change detection results.

However, to detect both slow and fast changes simultaneously remains unsolved. On one hand, optical flow estimation can not capture situations where objects suddenly appear or disappear due to rapid motion; on the other hand, the currently proposed change detection network architectures struggle to address the issue of slow changes. Flow-CDNet [24] effectively addresses this challenge by providing a unified framework for detecting both types of changes simultaneously. Therefore, we adopt Flow-CDNet [24] as our change detection framework.

3 Proposed Method

In this section, we first illustrate our proposed Dam Change Detection Network (Dam-CDNet), which is shown in Fig. 1, with Dam-YOLO and the adopted Flow-CDNet [24] in detail. Furthermore, we elaborate on the effectiveness of these two networks correspondingly. Finally, we demonstrate how to combine these two networks and the whole architecture of our Dam-CDNet.

3.1 Structure of Dam-YOLO

The proposed dam semantic segmentation network, Dam-YOLO, is built upon the YOLOv11 [13] architecture, which integrates an enhanced backbone, neck, and segmentation head within a unified framework, as shown in Fig. 2. The backbone adopts Cross-Stage Partial connections with kernel-size-2 convolutions

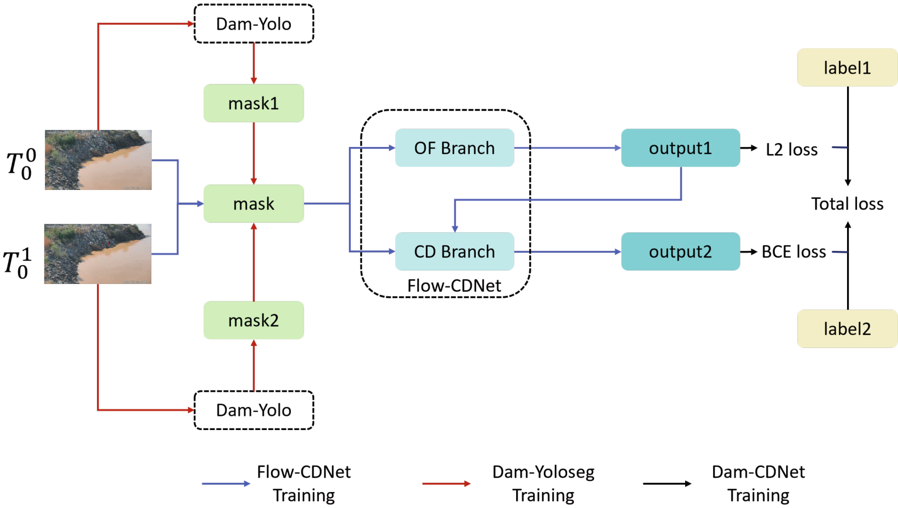

Fig. 1. An overview of the Dam-CDNet.

(C3k2 modules) to efficiently extract multi-scale features while reducing computational redundancy. The neck incorporates a fast spatial pyramid pooling (SPPF) module and a lightweight feature aggregation structure, enabling effective fusion of multi-resolution features. For the segmentation task, YOLOv11 [13] extends its detection head by introducing a mask prediction branch that generates precise instance masks concurrently with bounding box regression and classification. Furthermore, the incorporation of parallel spatial attention (C2PSA) strengthens the network's ability to focus on salient regions, significantly improving segmentation performance, especially for small and occluded objects. This architecture achieves a favorable balance between accuracy and inference speed, making it suitable for real-time instance segmentation applications.

We first input the two consecutive images T_0^0 and T_0^1 into Dam-YOLO to obtain the corresponding segmentation masks, denoted as $mask_1$ and $mask_2$. To address the issue that certain riverbank regions might not be segmented due to local variations or deformations between frames, we apply a logical OR operation on the two masks to generate the final mask:

$$mask = mask_1 \cup mask_2 \tag{1}$$

This strategy ensures that any area identified as riverbank in either T_0^0 or T_0^1 is retained, thereby improving the robustness of segmentation results under change scenarios and reducing the likelihood of missing riverbank regions caused by transient or localized changes.

3.2 Structure of Flow-CDNet

In this section, we adopt a framework named Flow-CDNet [24] for simultaneously detecting slow and fast changes in bitemporal images. It consists of two complementary branches: an optical flow detection branch (OFbranch) and a classical change detection branch (CDbranch). The OFbranch leverages the recurrent correlation-based architecture proposed in RAFT [25] to estimate dense flow fields that characterize gradual temporal changes. Specifically, it extracts multi-scale features and integrates contextual information through iterative refinement to achieve accurate and spatially consistent motion estimation.

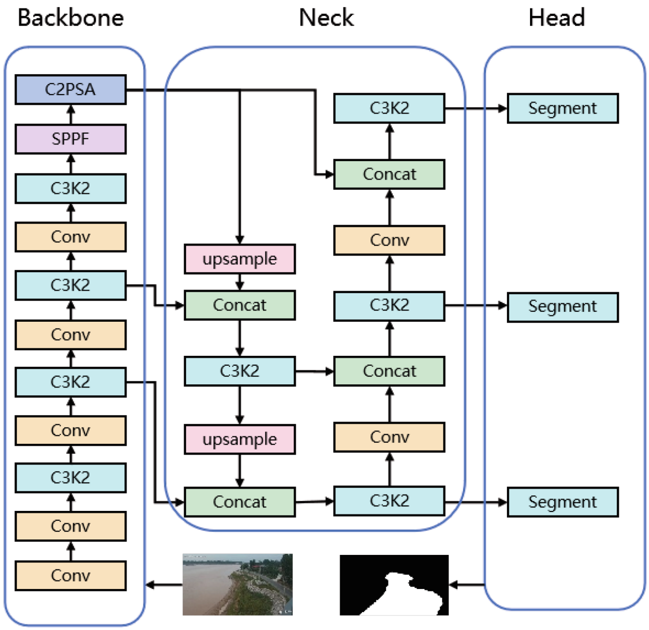

Fig. 2. Architecture of Dam-YOLO based on YOLOv11.

In parallel, the CDbranch focuses on capturing fast or abrupt changes. It utilizes a convolutional neural network combined with spatial pyramid pooling to generate binary change maps efficiently. The two branches are designed to complement each other: the OFbranch emphasizes smooth, continuous variations, while the CDbranch highlights significant local differences. By integrating both branches, Flow-CDNet effectively addresses complex change scenarios and achieves robust performance without requiring handcrafted operations or additional post-processing.

3.3 Structure of Dam-CDNet

The network architecture of Dam-CDNet is shown in Fig. 1. This network combines semantic segmentation network Dam-YOLO with the change detection network Flow-CDNet. we first utilize the dam region semantic segmentation result obtained by the aforementioned Dam-YOLO, and subsequently apply it to constrain the change detection outputs. Then, the bitemporal images T_0^0 and T_0^1 are input into the pre-trained Flow-CDNet to obtain the *mask* from the optical flow branch and from the change detection branch.

Finally, we use *mask* as a mask to overlay it onto $output_1$ and $output_2$ separately, making the detected change areas more focused on the dam region and achieving better change detection results.

4 Experiments

4.1 Dataset and Experimental Settings

Dataset for Dam Segmentation. We extract images of typical dam bank from the management platform of the Yellow River application system and construct the dam-bank Semantic Segmentation Dataset (Dam-Seg dataset). The dataset covers 85 monitoring sites in the Henan and Shandong sections of the Yellow River, including dam-bank images with different morphological features and at different times (seasons and light intensities). We collect 666 images to form the dataset. Subsequently, they are divided into training, and validation sets in a ratio of 8:2. These labeled image data focus on the dam bank, providing significant support for the subsequent training of supervised semantic segmentation models.

Dataset for Dam Deformation. To provide sufficient training data for our change detection framework, we adopt the datasets from Flow-CDNet [24], which include two parts: **FlowChange** and **DamChange**, each serving different purposes. To further enhance the training data diversity and quantity, we performed data augmentation and expansion on these datasets.

Experiment Settings. The experiments are carried out on 4 NVIDIA RTX 4090 GPUs. As for the Dam-YOLO, we employ the Adam optimizer for optimization. The initial training rate is set to 8×10^{-3}, the batch size is 16, each model is trained 500 epochs. As for the Flow-CDNet, we set the initial learning rate for optical flow branch to 1×10^{-5}, while the change detection branch employs 1×10^{-4}. We configure the optimization framework with AdamW and train for 1,000 epochs using batch size 4.

4.2 Training and Optimization

First, we train Dam-YOLO using the cross-entropy loss function to obtain the *mask*. The *mask* serves as the foreground image of the dam bank, eliminating the influence of significant background changes (such as flowing river water and constantly changing clouds) around the dams on dam change detection. Subsequently, we apply the adopted Flow-CDNet with its original training approach to obtain $output_1$ of the optical flow branch and $output_2$ of change branch, achieving simultaneous detection of fast and slow changes. Finally, by utilizing the trained Dam-YOLO and Flow-CDNet and using the improved loss function of Flow-CDNet, we train Dam-CDNet to obtain the corresponding $mask$, $output_1$ and $output_2$.

In the training phase of Dam-YOLO, we use the original YOLOv11 loss function, which combines classification, bounding box regression, and segmentation losses for effective training.

In the training phase of the adopted Flow-CDNet, we use the original loss function designed for simultaneous detection of fast and slow changes.

In the training phase of Dam-CDNet, the network's loss function has been improved from that of Flow-CDNet. In this case, the is used as a mask and multiplied separately with the $output_1$ and $output_2$. By considering the distinct magnitudes of the two losses, we also assign the weight ψ ($\psi = 100$, the same as the $loss_{total}$). This modification results in a loss function specifically tailored for Dam-CDNet, as presented in Eqs. 2, 3 and 4, respectively.

$$loss^*_{l2} = ||output_1 \cdot mask - label_1||_2 \cdot (1 - label_2) \tag{2}$$

$$loss^*_{BCE} = -(label_2 \log(output_2 \cdot mask) + (1 - label_2) \log(1 - output_2 \cdot mask)) \tag{3}$$

$$loss^*_{total} = loss_{l2} + \psi \cdot loss_{BCE} \tag{4}$$

4.3 Evaluation Criteria

To evaluate the Dam-YOLO and the other comparison methods, mIoU and FPS are adopted as the evaluation criteria for the semantic segmentation. mIoU is mean intersection over union, which represents the accuracy of segmentation. FPS represents frames per second, which indicates the segmentation speed, and is evaluated on a single NVIDIA Tesla V100 GPU.

4.4 Results and Evaluation

Experiments On Dam-YOLO. We validate the comparison results between Dam-YOLO and advanced methods on the Dam-Seg dataset and visualize Dam-YOLO's test results in some specific scenarios.

The Comparison Results. Table 1 presents the comparative experimental results on the Dam-Seg dataset. Dam-YOLO demonstrates exceptional performance in accuracy metrics, achieving an mIoU of 89.25%, which surpasses all competing methods. Specifically, Dam-YOLO outperforms BiSeNet [9] by 7.74%, and exceeds FastICENet [26] and CGNet [27] by 9.11% and 9.13%, respectively. In category-specific IoU evaluation, Dam-YOLO exhibits equally superior performance. The proposed method achieves the highest IoU of 87.08% for dam bank regions, representing a 2.17% improvement over the second-ranked BiSeNet [9]. For other area segmentation tasks, Dam-YOLO attains an IoU of 91.41%, significantly outperforming FastICENet's [26] 82.95%. Regarding computational efficiency, Dam-YOLO achieves a processing speed of 90.91 FPS. Although it operates slightly slower than FastICENet [26] and BiSeNet [9], it maintains excellent real-time performance capabilities and processes 26.42 FPS faster than CGNet [27]. Comprehensive evaluation demonstrates that Dam-YOLO successfully achieves an effective balance between precision and speed, maintaining acceptable computational efficiency while obtaining optimal segmentation accuracy. These results fully validate the effectiveness of the proposed method for dam bank semantic segmentation tasks.

Table 1. Comparison experiments on the Dam-Seg dataset. The best is shown in bold.

Methods	IoU(%)		mIoU(%)	Speed (FPS)
	Dam bank	Other areas		
FastSCNN [12]	80.76	73.35	77.06	**129.87**
CGNet [27]	83.03	77.21	80.12	64.49
BiSeNet [9]	84.91	78.13	81.51	101.54
FastICENet [26]	77.32	82.95	80.14	117.58
Dam-YOLO	**87.08**	**91.41**	**89.25**	90.91

Visualization Results. Visualization segmentation results are shown in Fig. 3. Three columns represent the original images, ground truth, and the segmentation result of Dam-YOLO, respectively. The left three rows depict the segmentation results in nighttime scenes, while the right three rows showcase the segmentation results under rainwater occlusion and fog occlusion. It can be seen that Dam-YOLO performs well in different scenarios.

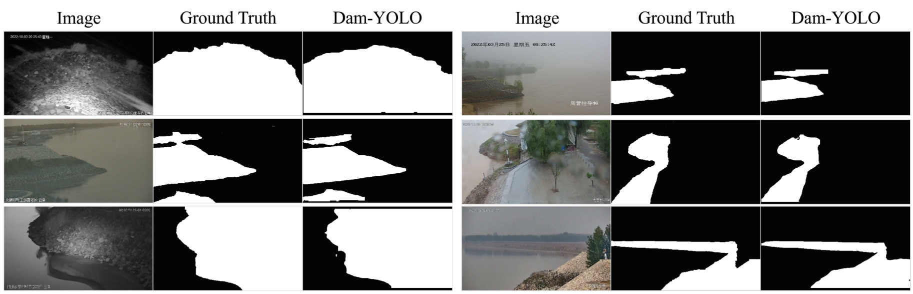

Fig. 3. The typical segmentation results of Dam-YOLO on the Dam-Seg dataset.

Experiments on Dam-CDNet. To validate the benefit of integrating the dam segmentation module, Table 2 presents the F1 Score comparison between Flow-CDNet alone and Flow-CDNet combined with Dam-YOLO. Notably, the models were directly applied to the **DamChange dataset** without additional fine-tuning, after being trained on the FlowChange dataset. As shown, the integration of Dam-YOLO improves the F1 Score from 0.65 to 0.78, clearly demonstrating the effectiveness of dam region segmentation in enhancing the validity and robustness of change detection performance.

Table 2. F1-Score comparison between Flow-CDNet and Flow-CDNet combined with Dam-YOLO on **DamChange dataset**.

Method	F1-score ↑
Flow-CDNet	0.65
Flow-CDNet+Dam-YOLO	**0.78**

5 Conclusion

In this paper, a dam-bank monitoring network called Dam-CDNet is proposed, which can simultaneously monitor fast and slow changes in the dam bank. This network comprises a dam-bank semantic segmentation network Dam-YOLO and a change detection network Flow-CDNet. Dam-YOLO achieves an excellent balance in terms of speed and accuracy. The adopted Flow-CDNet can simultaneously detect fast and slow changes by integrating optical flow detection with fast change detection. Finally, by using the dam bank regions segmented by Dam-YOLO as masks and overlaying them with the regions detected by the adopted Flow-CDNet, Dam-CDNet significantly improves the deformation monitoring effectiveness of the dam bank. Future work will broadly focus on refining the framework and expanding data coverage to enhance generality and practical utility.

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