

RGB-ONLY WORK-AREA RECOGNITION FOR FIREPROOFING SPRAY ROBOT

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Abstract

Deep learning-based segmentation is widely used for construction work-area recognition. But it may lead to mask boundary misalignment, degrading work quality in processes requiring precise work-area recognition, such as fireproofing spray. To address this limitation, we present a pipeline for accurate work-area recognition of steel structures. It uses deep learning for segmentation and edge detection, followed by computer vision for line extraction and work-area segmentation. Experiments show mean Intersection over Union (mIoU) gains of 4.47 pp before spraying and 4.51 pp during spraying over the segmentation model. These results indicate our pipeline enables more accurate work-area segmentation.

Introduction

Fireproofing spray is essential for delaying the loss of load-bearing capacity of steel structural members under fire exposure. However, it is still performed manually at height on many construction sites, posing substantial risks due to airborne dust and fall hazards. Accordingly, interest in fireproofing spray robots has increased (Ikeda et al., 2020). For reliable operation, the robot typically needs to know where to spray, which requires accurate work-area recognition. In construction robotics, work-area recognition is often treated as a deep learning-based segmentation task in which predicted masks are used directly for localization and downstream processing (Dung et al., 2019; Wu et al., 2024). However, in fireproofing spray, small boundary misalignment in these masks can degrade work quality. To improve boundary reliability, some approaches combine depth sensing and

3D processing. However, these pipelines typically require additional sensors such as RGB-D or LiDAR, increasing hardware cost (Schmidt et al., 2024). Moreover, a fireproofing spray robot must recognize each surface separately because the spray position and robot pose differ across surfaces such as the web and flanges. Therefore, this study proposes an RGB-only work-area recognition pipeline for a fireproofing spray robot in construction robotics, enabling separate work-area segmentation for each surface of steel structures.

Methodology

Figure 1 illustrates the overall framework of the proposed RGB-only work-area recognition pipeline. First, an instance segmentation model based on YOLOv11m-seg segments a steel structure into surface classes and outputs binary masks (Khanam et al., 2024). Next, for each class, we generate an edge map using a Lightweight Dense CNN for Edge Detection (LDC) model (Soria et al., 2022). Since the extracted edge map is produced in grayscale, we eliminate noise through binarization and contour-length-based filtering. From the refined edge maps, boundary lines are extracted through Random Sample Consensus (RANSAC) based line detection. Because the edge detector responds on both sides of the same physical boundary, RANSAC-based line detection produces a pair of nearby lines for one internal boundary. Therefore, we apply midpoint correction by averaging the endpoints of the neighboring line pair to obtain a single representative boundary line. Finally, the outer boundary lines and the corrected internal boundary lines are used to segment the

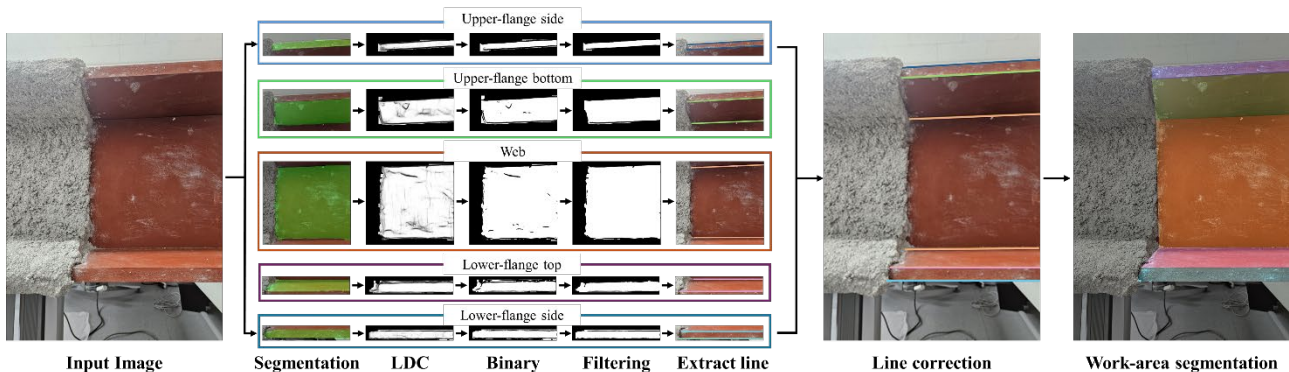


Figure 1: Framework

steel structures into surface work areas. An example of the final work-area segmentation results is shown in Figure 2.

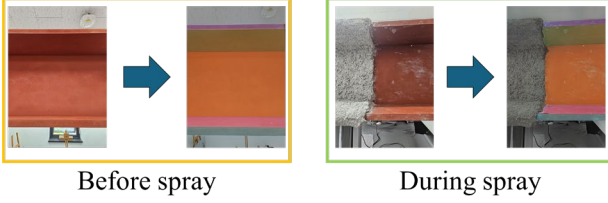


Figure 2: Example of the final outputs

Experiment

Preparing Dataset

To evaluate the proposed pipeline, we fabricated a Medium Density Fiberboard (MDF) H-beam mock-up and collected RGB images from viewpoints relevant to robotic operation. A total of 250 images were used for model development, and an additional 20 images were used for quantitative evaluation. The evaluation set included both before-spraying and during-spraying conditions.

Train Segmentation Model

The YOLOv11m-seg model was trained using a 7:2:1 split for training/validation/test. During training, the segmentation classes were defined as five surfaces: Upper-flange side, Upper-flange bottom, Web, Lower-flange top, and Lower-flange side.

Evaluation metrics

Performance was measured using Intersection over Union (IoU) as in (1) and mean IoU (mIoU) as in (2).

$$IoU = \frac{|Prediction \cap Ground Truth|}{|Prediction \cup Ground Truth|} \quad (1)$$

$$mIoU = \frac{1}{N} \sum_{i=1}^N IoU_i \quad (2)$$

Results and Discussion

Table 1 summarizes the quantitative results by comparing the proposed pipeline with the segmentation model. It reports IoU for each of the five surfaces and mIoU averaged across the five surfaces, both before spraying and during spraying.

Table 1: Quantitative results

	Before spraying		During spraying	
	Proposed	Seg.model	Proposed	Seg.model
Upper-flange top	0.8877	0.9125	0.9509	0.9285
Upper-flange bottom	0.9846	0.8950	0.9718	0.9190
Web	0.9931	0.9210	0.9891	0.9274
Lower-flange top	0.9512	0.8988	0.9609	0.9216
Lower-flange bottom	0.9264	0.8923	0.9694	0.9200
mIoU	0.9486	0.9039	0.9684	0.9233

The quantitative results show that the proposed pipeline improves work-area recognition compared with the segmentation model. Before spraying, mIoU increases from 0.9039 to 0.9486, an improvement of 4.47 percentage points. During spraying, mIoU increases from 0.9233 to 0.9684, an improvement of 4.51 percentage points. These results indicate that the proposed pipeline enables more accurate separation of surface work areas on steel structures. However, the evaluation was conducted

on an MDF H-beam mock-up rather than actual steel structures, and only 20 images were used for evaluation. In addition, the pipeline was sensitive to outdoor shadows, which were sometimes mistaken for structural edges and caused incorrect work-area segmentation.

Conclusions

This study presents an RGB-only work-area recognition pipeline for robotic fireproofing. The proposed pipeline uses deep learning for segmentation and edge detection, followed by line extraction and midpoint-based boundary refinement to derive final surface work areas on H-beams. Experiments on MDF mock-up showed improvements over the segmentation model, achieving mIoU 0.9486 before spraying and 0.9684 during spraying. These results suggest that the proposed method can provide more precise work-area recognition than using the segmentation model alone. Future work will validate the pipeline on actual steel structures under diverse field conditions and improve robustness to edge noise caused by shadows.

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