International Journal of Engineering Research And Management (IJERM)
ISSN: 2349- 2058, Volume-11, Issue-01, January 2024

A Video-Based Dust Detection Method for Bulk Yards using Dynamic and Static Features

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Abstract— **Industrial and urban development has resulted in significant dust emissions in dry bulk cargo yards at ports, leading to environmental and health concerns. Timely and accurate detection of dust generation is essential for pollution prevention and control. However, current video-based dust detection methods encounter challenges with false alarms in complex environments. This study introduces a novel method that combines dynamic and static features to address this issue. The proposed method uses object detection techniques and introduces a new classifier based on Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, augmented with an Adaptive Epsilon neighborhood (AE-DBSCAN), for extracting both static and dynamic dust features. Experimental results show that the proposed method high accuracy and real-time performance, making it suitable for complex open-air cargo yards.**

Index Terms— **Dry Bulk Cargo Yards; Fugitive Dust; Fusion of Dynamic and Static Features; Video Dust Detection**

I. Introduction

The operation of dry bulk cargo yards can emit a large amount of fugitive dust with an aerodynamic diameter ≤10μm (PM10), including emissions during loading, wind erosion, equipment transportation, and unloading processes[1]-[2]. Fugitive dust not only causes significant loss of coal materials but also may lead to serious air pollution problems in surrounding and other areas through long-distance dispersion[3]. Therefore, continuous and real-time monitoring of fugitive dust in dry bulk cargo yards are essential. Equipment such as oscillating microbalances, beta attenuation analyzers, and light scattering monitors are used to measure fugitive dust concentration and particle counts in open environments[4]. However, they are inevitably affected by distance, wind direction, and obstacles. Notably, visible dust plays a crucial role as an indicator of fugitive dust presence and some studies also suggest visual inspection of dust[5]-[6].Thus, practical dust visual detection can complement traditional concentration detection and to some extent improve the aforementioned problems.

Much progress has been made in the field of dust detection in open environments based on video. Albatayneh *et al.*[7] developed a pre-trained Inception-v3 model to classify and evaluate road dust with a predictive accuracy of 72%. However, its applicability is limited as it can only categorize specific images as road dust. Li *et al.* [8]proposed a four-category dust detection method based on the improved YOLOv4-tiny network for hopper unloading, but images of visible dust in dry bulk cargo yards are more complex than hopper coal dust images, leading to higher false alarm rates. Wang *et al.* [9] proposed a multi-object detection method for construction dust using DCN and Wise-IoU, which improves performance based on visible dust's non-rigid characteristics. However, there still exists a problem of false detection of targets with common features like water mist. In the field of video smoke detection similar to video dust detection, researchers have proposed methods that incorporate visual features like smoke motion, color, and texture to improve accuracy by reducing background interference. For instance, Zhang *et al.* [10] introduced a method based on changes in the smoke target area across multiple frames. However, this method does not account for changing dust shapes or simultaneous dust changes in multiple locations. Existing video dust detection methods suffer from frequent false alarms in practical applications due to diverse dust states in different environments and the difficulty in extracting dust visual features.

In this regard, we developed a dataset of visible dust images with multi-angle information and proposed a method that fuses dynamic and static features to more comprehensively extract dust features from video, thereby improving the detection performance of visible dust.

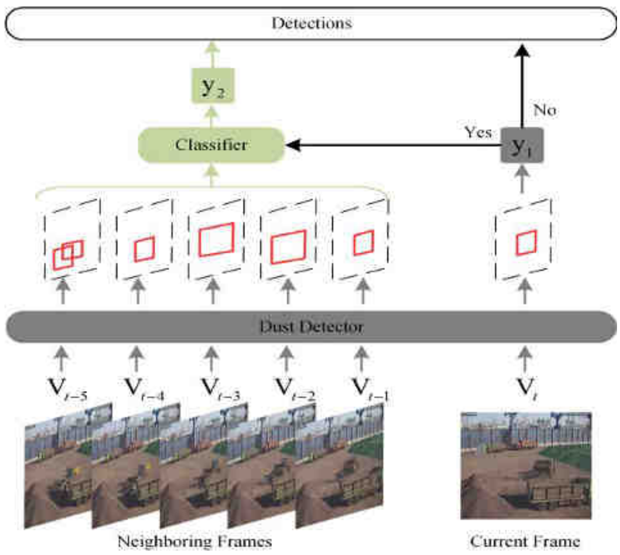

Fig. 1 Overall framework of the proposed method

II. Methods

The proposed visible dust detection model in dry bulk cargo yards consists of two cascaded parts: a dust detector and a classifier based on the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [11] algorithm,

Manuscript received January 11, 2024

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enhanced with an adaptive epsilon neighborhood (AE-DBSCAN), as illustrated in Fig. 1. The dust detector initially processes the video input to extract static features for the first step of dust detection. However, false alarms may occur due to interference from dust-like objects such as clouds, sprays and shadows. Therefore, if a dust target is detected in the current frame (y1 = Yes), the output from the dust detector is utilized as input for the second-level classifier. The classifier analyzes the spatiotemporal dynamic characteristics of the current frame to reduce false alarms. If y2 = Yes, dust is detected, otherwise it is a false alarm.

A. Dust Detector

The YOLOv8[12] model is a state-of-the-art object detection algorithm that utilizes a deep neural network to efficiently identify and classify objects in images. We specifically adapted this model for the detection and localization of dust in dry bulk cargo yards. Among the five versions available (YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x), we selected YOLOv8s considering factors such as computational speed, real-time performance, and accuracy.

The YOLO algorithm is a single-stage object detection method consisting of three main components: a feature extraction network (Backbone), a feature fusion network (Neck), and an output detection head (Head). The Backbone employs convolution operations to extract features of various scales from RGB images in a bottom-up manner. The Neck incorporates feature fusion techniques like PAN (bottom-up path aggregation) and FPN (Feature pyramid networks) to enable effective fusion and utilization of feature layer information at different scales. The Head separates the classification and detection processes, generating classification and regression branches to obtain bounding box size and category confidence information.

For each video frame V_t, YOLOv8s generates a set of detection results, including bounding box information denoted as: $bb_t^i = \{x, y, w, h\}$. Here, t represents the video frame V_t, i represents the i-th bounding box in the current frame, and x, y, w, and h represent the normalized coordinates of the bounding box's center point, representing the horizontal coordinate, vertical coordinate, width, and height respectively.

B. Classifier based on the AE-DBSCAN Clustering Algorithm

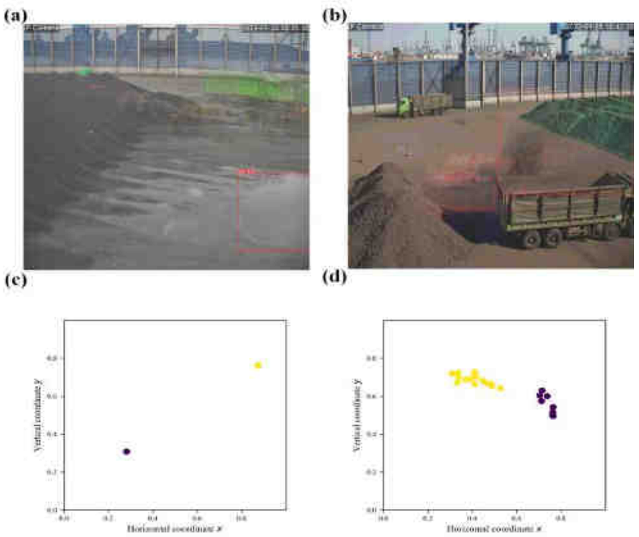

Fig. 2 Analysis of clustering of bounding box center points in consecutive frames using the AE-DBSCAN Clustering Algorithm. (a) illustrates the "weighted sum" results of consecutive frames with misclassified objects, while (b) displays the same results with dust. The clustering results of the centroids corresponding to the bounding boxes in (a) and (b) are visually represented in (c) and (d), respectively. Different colored dots in (c) and (d) indicate distinct classes.

Fugitive dust, a continuous and dynamic phenomenon, exhibits significant distributional disparities between dust bounding boxes and false alarm bounding boxes obtained from successive frames using the dust detector. We address this issue by utilizing a "weighted sum" operation that combines N images while preserving pixel proportionality, as shown in Fig. 2(a) and Fig. 2(b). The intra-class distance of clustering serves as a reliable estimator for this distributional difference. Thus, we propose a classifier based on the AE-DBSCAN Clustering Algorithm. It clusters the center coordinates of bounding boxes in consecutive frames with an adaptive neighborhood threshold and computes the intra-class distance.

The DBSCAN clustering algorithm is a density-based spatial clustering algorithm that partitions data points into clusters and identifies noise points (points not belonging to any cluster). It operates on the principle that each point in a cluster must have a minimum number of points within a specified neighborhood radius. Points are classified as core, boundary, or noise based on predefined epsilon neighborhood threshold (Eps) and minimum point requirements (MinPts). Given the distribution of dust bounding boxes is influenced by camera distance in 2D images, we propose an adaptive neighborhood threshold for the DBSCAN algorithm by using the width of the bounding box in the current frame. We set the value of MinPts to equal the number of neighboring frames. In Fig. 2(c) and Fig. 2(d), MinPts was set to 5 and 20, respectively. Additionally, calculate intra-class distances using the Euclidean method to evaluate class density.

Experimental findings indicate that the intra-class distance of dust center points typically exceeds 0.2. Therefore, the flow of the classifier as follows: (1) Derive the Eps from the width of the bounding box in the current frame. (2) Apply AE-DBSCAN clustering to the center coordinates of bounding boxes in the current and neighboring frames. (3) Calculate the intra-class distance. Dust is detected if it exceeds the 0.2 threshold; otherwise, it is classified as a false alarm.

III. Experimental Results and Analysis

a) Datasets and Training Results

The experimental data in this study were collected from the camera system at Tianjin Coking Wharf Limited. The dust detector dataset comprises diverse dust images with a resolution of 2560×1920. A total of 2311 images were collected, with 60% randomly selected for the training set and

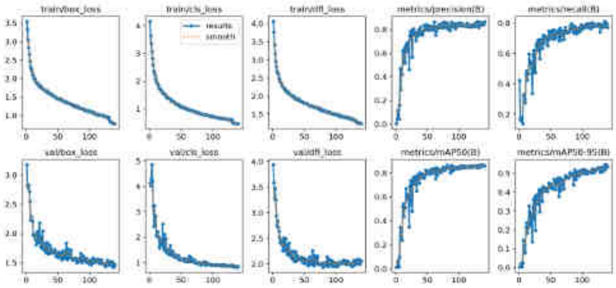

Fig. 3 Training Results of YOLOv8s

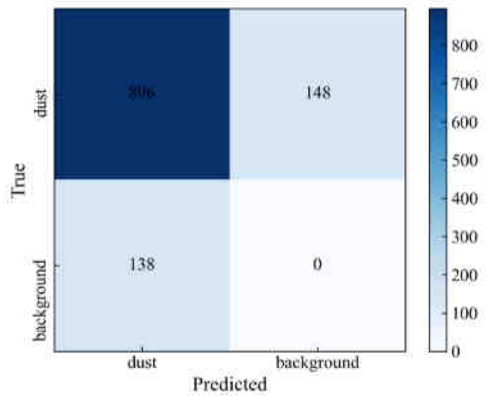

Fig. 4 Confusion Matrix Figure

the remaining 40% used as the test set. The video sequence dataset for the overall model consists of 24 clips with dust and 53 clips without dust. Each clip lasts for 20 seconds at a frame rate of 1.25 fps, and each clip with dust contains at least one dust event. For training, 80% of the dataset was randomly selected for training, while 20% was used for testing. During the training process, YOLOv8s was trained with an input size of 640×640, a batch size of 16, a learning rate of 0.01, weight decay of 0.0005, and 140 epochs. Fig. 3 illustrates the training results of YOLOv8s, presenting the training and validation loss curves, as well as the accuracy, mAP, and recall curves. Additionally, Fig. 4 showcases the confusion matrix, summarizing the classification prediction results. The matrix indicates that 87% of the dust targets in the test set, accounting for 896 dust bounding boxes, were correctly detected.

b) Evaluation Metrics

The evaluation metrics used in the experiment are Accuracy (ACC), True Negative Rate (TNR), and True Positive Rate (TPR). We count the number of incorrectly identified video clips with dust (TP) and without dust (TN), as well as the number of video clips with dust (FP) and without dust (FN). N is the total number of video clips. The formulas for these metrics are:

$$ACC = (TP + TN) / N \quad (1)$$

$$\mathrm{TNR} = TN / (TN + FP) \quad (2)$$

$$\mathrm{TPR} = TP / (TP + FN) \quad (3)$$

ACC measures the proportion of correctly identified video clips out of the total number of video clips, providing an overall measure of the algorithm's performance. TPR measures the algorithm's effectiveness in accurately identifying video clips with dust, while TNR evaluates its ability to accurately identify video clips without dust. These metrics are widely recognized and enable precise evaluation of the algorithm's performance, facilitating meaningful comparisons with other state-of-the-art approaches in the field of Computer Vision.

c) Experimental Results

The experimental results based on the video sequence dataset are shown in Table 1. Compared to the recognition method using the general object detector YOLOv8s, our proposed dust detection method based on the fusion of dynamic and static features achieved a significant improvement in accuracy, reaching 93.5%. The true positive rate increased from 62.5% to 91.3%. This indicates that the dynamic features of dust can effectively complement the static features and solve the problem of high false detection rate in complex backgrounds.

For a detailed comparison of the experimental results, refer to Fig. 5. The first and third rows represent the detection results of the dust detector, while the second and fourth rows represent the detection results of the proposed detection framework. It can be observed that in frame 20, 27, and 33 of control group 1, and frame 5, 7, 8, 9, and 14 of control group 2, the dust detector mistakenly identified rain stains and shadows as dust. However, the proposed framework can timely correct these false detections using dynamic features, resulting in effective detection results. From a subjective visual perspective, the accuracy of video-based detection has been significantly improved.

Table 1 Comparison of the evaluation metric results

Method	TP	FP	TN	FN	ACC	TNR	TPR
YOLOv8s	20	4	41	12	79.2	91.1	62.5
Our	21	3	51	2	**93.5**	**94.4**	**91.3**

Fig. 5 Comparison of two sets of experimental results

IV. Conclusion

Fugitive dust emissions from bulk cargo yards at port terminals pose serious environmental and health risks to residents. Accurate real-time detection of dust is essential for effective control of such emissions. However, existing vision-based dust detection methods are prone to false alarms in practical applications. To address this issue, we propose a video-based dust detection method that combines dynamic and static features. Our model uses the YOLOv8 network, which delivers fast detection speed and high accuracy, while incorporating a classifier and DBSCAN clustering with an adaptive neighborhood threshold to verify detection results using multi-frame information. Experimental results demonstrate that the proposed method effectively complements static features with dynamic features of dust. It ensures real-time dust detection, reduces false detections in non-dust videos, and maintains a high detection rate for dust events in videos containing dust. This method presents new ideas and approaches for developing dust detection technology and contributes to the scientific prevention and control of dust pollution.

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