Weather Eye: Object Detection in Adverse Weather Conditions

Y. Mistica Dhas
Assistant professor
misticajimson.@gmail.com

K. Rohith
Final Year Student
221401075@rajalakshmi.edu.in

* T. Gnanesh Reddy
Final Year Student
221401103@rajalakshmi.edu.in

Computer Science and Business Systems
Rajalakshmi Engineering College
(Affiliated to Anna University) Chennai, India

Abstract. Object detection systems used in outdoor settings are often degraded by adverse weather conditions, such as fog, haze and low illumination. Reduced visibility results in weak feature representation and unstable prediction and missed detections. This paper introduces Weather Eye, a weather aware object detection system to combine the image dehazing algorithm and real time deep learning object detection model. The proposed system works in two modes direct detection under clear conditions and enhancement assisted detection in case of degraded visibility. Classical and learning based dehazing methods which include Dark Channel Prior (DCP), CLAHE, DehazeNet, AOD-Net are applied prior to inference using a YOLO based detector. Experimental evaluation on real world outdoor data goes to show improvements in detection confidence, bounding box stability, as well as overall accuracy in comparison to direct detections on degradation images. The results prove that synchronization of visibility enhancement with object detection makes the system robust and reliable in dynamic outdoor lighting environments, which leads to diverse use cases for surveillance and traffic monitoring, and for safety playgrounds and safety critical applications.

Keywords: Object Detection, Image Dehazing, Adverse Weather Vision, Deep Learning, YOLO, Visibility Enhancement.

1 INTRODUCTION

Object detection is in the center stage of intelligent surveillance, autonomous driving, and smart traffic monitoring systems. The most recent deep learning systems, especially the detectors of the YOLO model, exhibit great accuracy and can run in real time when the surroundings are clear. Nevertheless, they are not very reliable when there is poor weather conditions like fog and haze, low light, and even snow. Reduced visibility results in a decrease in edge contrast, texture information and color consistency which may make bounding boxes unstable and reduce confidence for detection.

Recent studies have tried to overcome this weakness with domain adaptive object detection, image adaptive YOLO models and weather specific robust architectures. Domain adaptation techniques try to minimize the distribution gap from clear to degraded environment, and image adaptive detector is a technique of detecting dynamically adjusting feature representation to account for the distribution difference of visibility. Simultaneously, there has been an important advancement in single image dehazing and visibility enhancement using both classical but also deep learning methods of analysis: Dark Channel Prior and AOD-Net, FFA-Net and GAN-based enhancement networks. These methods result in better perceptual image quality and recovery of structure that is degraded by scattering off the atmosphere.

In spite of these developments, a large number of current studies consider the enhancement of visibility and the detection of objects as different tasks. There are only a few fully integrated pipelines that combine adaptive enhancement and real time detection, and are still computationally feasible to be deployed in practice. In addition, there are few studies that examine the stability of detection with respect to quantifiable characteristics of visibility including haze density, contrast change and edge curvature across time.

To fill in these gaps, the paper will suggest an integrated object detection system that can be used in adverse weather conditions and which integrates adaptive image dehazing and a YOLO based real time detector. The major contributions of this work are:

1. A dual mode detection pipeline that performs direct inference under clear visibility and enhancement assisted inference under degraded conditions.
2. Integration of both classical and deep learning based dehazing techniques prior to detection to improve feature clarity and stability.
3. Visibility aware performance analysis using quantitative attributes such as haze density, contrast level, and edge sharpness.
4. Experimental validation demonstrating improved detection confidence and bounding box stability in real world outdoor scenarios.

The proposed framework enhances reliability in safety critical outdoor applications where environmental conditions are dynamic and uncontrollable.

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2 RELATED WORK

In [2], the authors proposed the single-stage object detection system known as YOLO that is able to achieve real-time detection speed with competitive accuracy. Subsequent enhancements like YOLOv4 [1] only improved the detection performance with architectural and training optimization. Real-time deployment was also more available with the implementation of YOLO-based models in PyTorch [3]. Nonetheless, such detectors exhibit a loss of performance when subjected to unfavorable climatic conditions like fog and haze.

In order to solve the issue of detection robustness in low visibility, [9] research work suggested DSNet, which is joint semantic learning of object detection during poor weather. Likewise, in the previous based domain adaptive detection schemes were presented in [10] to minimize the gap in distributions between clear and degraded images. This method is also extended in [11] by the use of domain adaptive YOLO models that match features representation across various environmental conditions. Even though these approaches enhance cross domain robustness they usually necessitate a lot of retraining and more elaborate architectures.

Similar studies on visibility enhancement have been conducted on single image dehazing methods. The Dark Channel Prior (DCP) technique suggested in [4] makes an approximation of atmospheric light and transmission maps in order to recover image clarity. DehazeNet [5] and AOD-Net [6] offer end to end frameworks of haze removal as deep learning based approaches. More sophisticated designs such as the FFA-Net [7] and Gated Fusion Networks [8] enhance the feature conservation with the attention and multi-scale fusion schemes. Although such techniques play a large role in improving the quality of perceptual image, they are frequently discussed without considering the performance in object detection.

The recent researches have addressed image adaptive detection frameworks, which adaptively change the detection behaviour when the conditions are degraded [12]. These methods are aimed at altering the layers of detection as per the environment. Most of such approaches however tend to emphasize more on architectural adaptation as opposed to detection stability being analyzed in relation to attributes of measurable visibility that include density of haze, contrast degradation and edge attenuation.

Regardless of these developments, there is scant literature that combines adaptive visibility enhancement as an integral part of an object detection pipeline in real time and at the same time imploring detection confidence trends with given measurable environmental changes. This void is a driving force behind the creation of the suggested improvement-aided detection model.

3 METHODOLOGY

The suggested object detection system is expected to improve the detection strength in unfavourable weather conditions through visibility enhancement and real time detection. The methodology consists of four key elements, which are data collection, an analysis of the visibility feature, an analysis of the temporal stability, and analysis of the feature importance. The framework analyzes the influence of the environmental degradation in a systematic way in terms of the confidence of detection and stability of the bounding box. The approach enables the use of adaptive preprocessing to enhance the deployment in dynamic outdoor environments and more robust deployment through incorporation of quantitative visibility measures with model performance analysis.

3.1 Data Collection and Preprocessing

The data employed in this experiment is the real life images of the outdoors that were taken in varying weather conditions like fog, haze, low light, and moderate snow. Two major sources of data were used:

- Continuous live frames from web cam obtained by using OpenCV.
- Pictures posted by users as outdoor that showed lower visibility.

All frames were also resized, normalized and transformed into a comparable format for dehazing algorithms and the YOLO masks detection model. Preprocessing steps were used to normalise the resolution and color distribution in order to make sure that the various capture conditions are uniform. The reduction of noise and contrast normalization was also added where necessary to reduce sensor related distortions. In order to measure the extent of environmental degradation, visibility related attributes were derived on individual frame which include the intensity of haze, level of contrast, sharpness of edges, and the level of brightness variation. The data set was grouped in the categories of Clear, Light Haze, Dense Fog, and Low Light conditions to allow organized evaluation of the performance and compare its performance under the conditions of different visibility degree.

3.2 Correlation Analysis of Visibility Features

In order to analyze the impact of environmental degradation on detection performance, correlation was done between visibility related attributes and YOLOv11 detection metrics. The numerical measures like haze density, contrast level, and edge sharpness were used together with scores of detection confidence and bounding box consistency. The strength magnitude and direction relationship between the environmental variables and the output of detection were calculated by Pearson correlation coefficients to understand the direction and strength of the relationship.

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$$

Where:

- X_i = visibility feature (e.g, haze intensity)
- Y_i = detection confidence
- r = correlation coefficient

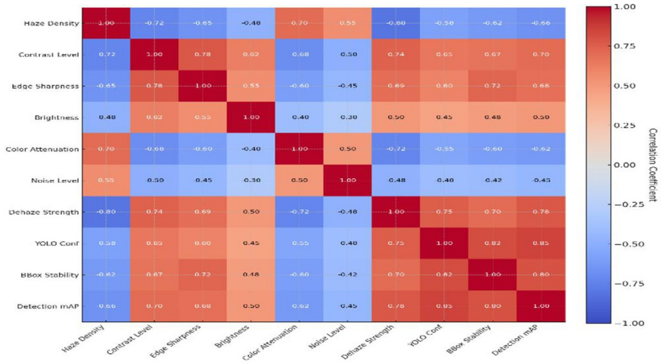

Fig. 1. Correlation of visibility and detection measures

Fig. 1 shows the relationships between visibility features and detection performance metrics. Correlation heatmaps were created to assess the relationships such as:

- Increased haze density correlating with reduced detection confidence.
- Higher contrast associated with improved bounding box precision.
- Greater edge sharpness leading to enhanced recognition stability.

The results of this analysis further showed that contrast and edge sharpness have stronger positive correlations with confidence stability than brightness variation does. In contrast, haze intensity showed a uniform negative correlation with detection confidence and localization accuracy. These results suggest that structural clarity is more important than overall illumination to the reliability of object detection. This analysis reveals critical environmental factors that affect detection accuracy and helps in tuning preprocessing parameters to improve system reliability and adaptive behaviour in real-world conditions.

3.3 Temporal Stability and Stationarity Analysis

The dynamics of outdoor conditions are characterized by changes in visibility because of weather variations, changes in light and atmospheric disturbances. These variations bring about time instability in the performance of detection. Temporal analysis of visibility attributes was performed to determine the impacts of environmental drift on detection reliability to make the system behaviour stable.

Time series (intensity and detection confidence) of haze were also analyzed to find non stationary trends. The measure of statistical stationarity was used to evaluate the changes in the mean and the variance between sequential frames. Techniques of differencing were used to decrease the long term variation and isolate short term variation due to sudden patches of fog or changes in the illumination. Moving average smoothing was also used in order to see the bigger trends of performance without short term noise interference.

To examine the correlation between level of haze and level of detection, contrast verses confidence behaviour, scatter plots have been created. It was found that sudden rises in the strength of the haze are accompanied by a rapid reduction in confidence, and the slow changes in the visibility lead to a more gradual worsening of the performance. This time dependent evaluation allows testing the robustness of the detection in real-time conditions of constant environmental uncertainty, and designs the adaptive preprocessing strategies to be deployed in real-time.

3.4 Feature Importance and Environmental Pattern Analysis

Long term feature behaviour was examined to comprehend the effects of the environment on an aspect of detection stability. The ranking of feature importance was obtained through the measurement of the variance in detection confidence in terms of visibility related variables. The results of the analysis suggest that edge sharpness and contrast level are the most impactful variables influencing the detection performance whereas the density of the haze has a negative correlation with the stability of the confidence. Luminance difference was relatively moderately affected and this may imply that structural clarity is a more pivotal element compared to illumination.

In order to further analyze the performance dynamics, performance time series data was decomposed into seasonal and trend using seasonal and trend decomposition methods on detection confidence time series data. The component that is observed is indicative of performance change when weather conditions vary. The trend component embodies long-term environmental effects, including the long haze seasons, and the seasonal component represents the repetitive patterns of visibility, which are connected with changes of the light daily or periodically. The abrupt environmental disturbances such as sudden increase in the intensity of fog or glare are isolated by the residual analysis.

This is a multi level analytical framework that gives a more detailed analysis of the effect of environmental variability on the reliability of detection. The results can be used to develop an adaptive and weather resilient object detection pipeline, which can be sustained in the dynamic real-world conditions.

4 EXPERIMENTS

4.1 Dataset

The experimental data comprises of real-world outdoor photographs taken in different weather conditions such as clear visibility, light haze, heavy haze, low visibility and gentle snow. The data was gathered on the basis of continuous live webcam feeds and user uploaded outdoor pictures showing exemplification of degraded visibility.

The dataset has variations in object scale, camera angle, complexity of scene and intensity of light so as to guarantee representative evaluation. There were frames filled with levels of visibility to compare the level of performance in an organized manner (Clear, Light Haze, Dense Fog, Low-Light). Such a classification allows comparing detection stability in increasingly degraded environmental conditions, which can be analyzed in a quantitative way.

Images were all checked manually to check the presence of the objects and also to maintain consistency in the annotations in relation to the weather type. To compute accurate values of the accuracy, ground truth binding boxes were transformed into standard object detection formats. The distribution of data was equal, and no clear weather samples were overrepresented so that the degraded conditions were properly represented in the course of evaluation. Also, sequential frame samples were stored to evaluate temporal stability, to enable the evaluation of detection behaviour in the situation of ongoing environmental variation.

The dataset was separated into training and testing subsets so as to prevent data leakage and thereby making the performance evaluation unbiased.

4.2 Experimental Setup

YOLOv11 detection model was trained in a mixture of clear-weather images and visibility degraded images, with foggy and hazy and low-light samples. This combined training method allows the model to acquire strength feature. responses in both favorable and unfavorable environments, enhancing its externalization capacity in the presence of variation of visibility in the real world.

There were two inference settings that were systematically tested to estimate the effect of visibility enhancement:

Direct Detection Mode:

Raw degraded images are directly fed to the YOLOv11 model that has no preprocessing, and it can be evaluated to determine the baseline performance in adverse conditions.

Enhancement Assisted Detection Mode:

Visibility enhancement algorithms, such as Dark Channel Prior (DCP), CLAHE, AOD-Net, and DehazeNet, are used to process images and then are sent to YOLOv11 to localize and classify objects. This arrangement determines the value of preprocessing to detection consistency, and boost of the confidence.

All experiments were written in Python and preprocessing of images was done with OpenCV and model training and inference with PyTorch. Unseen real-world frames were also evaluated in terms of performance to measure the ability to generalize and withstand dynamic outdoor environments.

4.3 Evaluation Metrics

Detection performance was assessed using multiple quantitative indicators to evaluate both spatial accuracy and temporal stability under varying visibility conditions.

Detection Confidence Score:

The mean score of bounding box prediction, which was:

$$Conf_{avg} = \frac{1}{N}\sum_{i=1}^{N} c_i$$

where c_i represents the confidence score of the i^{th} detected object and Nis the total number of detections. This metric reflects the model's certainty under different weather conditions.

Bounding Box Stability:

Measured by analyzing the consistency of predicted bounding box's coordinates for sequential frames. Stable localization means that it can withstand small-scale environment change.

Detection Accuracy:

Computed compared to annotations of ground truth using:

$$Accuracy = \frac{TP}{TP + FP + FN}$$

TP represents true positives, FP false positives and FN false negatives. The measure gauges general correctness of detection.

Missed Detection Rate:

The percentage of the ground truth that the model fails to identify, especially when visibility is poor, which is defined. Besides the spatial indicators, there were temporal stability indicators which were examined to determine the change in the detected confidence over time under varying environmental conditions. This time test helps in knowing how strong the system is in the face of the continuous real-time running.

4.4 Results

The experimental outcomes indicate that YOLOv11 can detect objects with high accuracy when the visibility is on a high level. Performance is however affected negatively with increasing haze content and contrast.

In Direct Detection Mode, there are pronounced degenerations in confidence ratings and higher instability in the bounding box in the dense fog and the poor lighting objects. The process of missed detections increases, especially when catching small items or those covered by part.

Conversely, Enhancement Assisted Detection Mode has better resilience. Images that have gone through the pre-processing stage have the added advantage of having the edges being clearer and the contrast being recovered thus giving the detector a chance to capture more reliable structural features. The false alarms are reduced in an unconscious line with moderate haze conditions, and bounding boxes are much more maintained throughout consecutive frames.

Time series analysis also shows confidence trends that are more smoothly varying following an enhancement meaning that time series is less sensitive to small environmental changes. The integrated preprocessing stage offers a strong counter-measures to the performance degradation even in extreme fog and severe loss of illumination in most of the de-meriting situations.

5 RESULTS AND DISCUSSION

The data of the experiment proves that the degree of haze has a strong negative correlation with the degree of confidence in detection. When visibility is reduced, the structural properties which include edges and texture gradients cannot be distinguished well and this has a direct impact on object localization and classification accuracy. Through the analysis of feature importance it has also been shown that edge sharpness and contrast are more vital in maintaining stability of detection than brightness as a whole, which makes the emphasis on structural clarity rather than mere enhancement of illumination well founded.

The proposed enhancement assisted framework takes a preprocessing first strategy when compared to domain adaptive detection methods that have been reported recently that seek to learn cross weather feature representations in the network architecture. Domain adaptive model normalizes distribution discrepancies by aligning features via adversarial training or by distributing features via alignment or minimizing difference criteria, although can involve a lot of retraining of weather specific data and addition of architectural complexity. Conversely, the proposed approach enhances input visibility before inference so that the underlying YOLOv11 base detector can work on the feature representations which are clear without changing the structure. This minimizes the amount of computation as well as maintains real-time viability.

Correspondingly, the study aimed the multi task joint learning frameworks optimizing dehazing and detection goals at the same time exhibited greater robustness at the cost of higher training complexity and parameters. The current methodology divides the step of enhancement and detection, which allows it to be integrated in a modular way with the existing object detectors. This modular architecture enhances flexibility in deployment especially when the surveillance system is confined to edges as it is often a system with limited computational capability.

There is a significant improvement in the stability of confidence and the localization of bounding boxes in the enhancement assisted pipeline under low-light and moderate haze conditions in comparison to direct detection on degraded inputs. Nevertheless, the benefits of performance are diminished in cases of very dense fog or a lot of loss of illumination because the important object features can still be partially discerned even following improvement. Such results are consistent with the previous works which show that extreme atmospheric scattering cannot be fully recovered by image-based restoration.

On the whole, the obtained results indicate that the combination of visibility enhancement and YOLOv11 leads to a noticeable increase in detection confidence, decreased miss rates, and temporal stability. The proposed framework provides a computationally efficient and practically implementable solution to outdoor surveillance, traffic monitoring and safety critical implementations running within a dynamic environmental condition as compared to architecture heavy domain adaptation methods.

6 CONCLUSION

This paper shows an extended assisted object detection system that enables an object identification scheme to be more robust to detecting objects in unfavourable weather. The proposed system combines methods of restoring visibility with the YOLOv11 model to enhance structural clarification before inference to achieve a high detection speed, bounding boxes, and fewer false detections in foggy, hazy, and dark conditions.

The experimental evidence indicates that the rate of detection decreases greatly as the level of the haze increases, as well as a quantifiable decrease in the stability of the confidence. Collectively, the addition of preprocessing methods like DCP, CLAHE, AOD-Net, and DehazeNet allows recovering visual accuracy in the detection capability with moderate visibility degradation, which leads to consistency of confidence and localization accuracy in contrast with direct detection on distorted images.

As opposed to domain adaptive or multi task joint optimization methods which imply a structural change and large scale retraining on weather specific datasets, the suggested framework follows a preprocessing first modular strategy. This architecture maintains real time feasibility as well as enhances robustness, thus computationally efficient and practical in deployment to applications in outdoor surveillance and monitoring traffic.

In cases of extreme fog and gross loss of illumination, performance likelihood is minimal despite the significant performance increase in conditions where degradation is light with moderate and heavy conditions. These results reveal that although enhancing visibility is the most effective way of enhancing robustness, when subjected to severe atmospheric scattering, purely image based restoration is limited.

In general, the proposed framework is a practical, scalable, and effective one that would address weather resilient object detection in dynamic real-world conditions.

7 FUTURE WORK

Future studies should therefore focus on increasing adaptability in rapidly changing environmental conditions. One promising direction contains including environmental awareness by means of external indicators such as visibility indices within the atmosphere, such as the time of the day, or by with sensor based weather data. This form of integration may facilitate an active control of preprocessing intensity according to an image of lifestyle losses that are most likely to arise during processing.

Moreover, hybrid models that reach a compromise between image enhancement and image (temporal) models, like ConvLSTM or Transformer-based video models can enhance short-term variations in visibility. Ensemble enhancement strategies could also be investigated in order to better address extreme fog and glare heavy situations.

The additional examination of cases in which failures occur and stills areas of performance fall with the condition of atmospheric scattering will be used to aid in optimization of preprocessing algorithms and scales of training data to new and more diverse weather scenarios.

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