Improving Vision Clarity and Object Detection Accuracy in Heavy Rain Base on Neural Network

Chi Han Chen, Chien Hung Wu, Cheng Jun Wu, and Rung Shiang Cheng(✉)

Overseas Chinese University, Taichung, Taiwan
rscheng@ocu.edu.tw

Abstract. In heavy rain situation, clarity of both human vision and computer vision are significantly reduced. Rain removal GAN network is developed to resolve this problem. However, we find that this kind of network causes the decreasing of detection accuracy. In this work, we analysis the performance and the propose a detection network to get higher accuracy. Through the comparison of experimental results, our method can improve the IOU accuracy and detect confidence.

Keywords: Generative Adversarial Network(GAN) · Intersection over U ion(IoU) · Non-Maximum suppression · Object detection · Self-driving car

1 Introduction

With the rapid development of technology, Artificial Intelligence (AI), Computer Vision (CV) have many applications in industry, medical treatment, and road driving, Under the response of different industries, the combined technology of the two gradually replaced a lot of manpower consume, have begun to popularize the use of artificial intelligence in many industrial chains or daily life applications.

With technology gradually replacing manpower, many technologies have begun to pursue convenience and safety. Under related topics, various problems of self-driving cars have been raised one by one, especially safety issues. It is safer for humans to judge the road conditions by human eyes compared to automatic assisted driving vehicles. In the accident record [1], the cause of the failure of the self-driving car may occur in a complex or the poor sight environment, but self-driving cars can operate well on road planning with systematic structure, it can be seen that in an environment where the route is not planned, autonomous driving is not completely reliable. The "human eye" is the most important factor of judgment when people are under normal conditions.

By [2] the author expressed the widely used rainfall image formation model as a rainfall. It is extended to convert the visible rain streaks (R) into a binary mask, use 0 and 1 to judge the presence or absence of rainfall area, keep good background details. In the real world, however, the accumulation of rainwater caused by heavy rain (rain

Y.-B. Lin et al. (Eds.): SGIoT 2021, LNICST 447, pp. 111–116, 2022.
https://doi.org/10.1007/978-3-031-20398-5_9

pattern overlap) is ignored. Taking atmospheric light factors into consideration, bring in the neural network to restore the image to a clean image. Although the rain can be removed by this method, but the output fake image make object detection sometimes failed.

In this work, we apply object detection with and without rain removal network respectively. Then, analysis the cause of miss detection and false detection of object detection cases. Base on the analysis, we implement an approach to combine rain removal network and object detection network into an assemble that can both output a clear image for human vision and higher accurate detection result base on object detection.

2 Related Works

2.1 Object Detection

1. With the development of neural networks, CNN is not purely for application in label classification applications. Therefore, [3] aims to make R-CNN perform better in terms of speed and accuracy by modifying the operation sequence and structural is-sues, simplifying the model design, and increasing the calculation speed. A picture only needs to be convolved once, saving a lot of computing and hardware resources, and using a multi-objective loss function, so that the original R-CNN multi-layer training becomes a simple backpropagation. After experimenting, Fast R-CNN mAP is also slightly higher than R-CNN the speed of training has also increased by nearly 9 times.

2. Use a two stage approach in the technique of [3]. Due to them all need to get regional suggestions first to locate the object, and then identify. In the [4] technique, the object recognition is regarded as the network structure of the regression problem. Based on one stage network architecture. After the image is input to the network, the corresponding object position and category will be directly output.

2.2 Image Restoration

3. In [5], it is introduced that the light reaches the video equipment, will be scattered by the atmosphere, resulting in poor image contrast. In bad weather, even if the image contrast is restored, but the image will still be blocked by natural factors such as fog and rain, there are still occlusion factors in the image. A physical model based on blurred images [6], propose an adaptive enhancement of a single image, to suppress the halo phenomenon caused by aerial removal, through the concept of adjacent pixel depth information, the concept of effective edge strength is given based on the perceived difference, a method to calculate the dephasing rate due to the entire image using the effective edge strength is proposed. Research [7] explains that time will not be covered by rain. Since rain removal model based on the morphological component analysis is been published [8], the image is decomposed into high and low frequencies [9], performs sparse coding and dictionary learning, restores the rain image to a clean image.

4. In [10] according to the framework proposed by [2]. The extension of the rain image is divided into high frequency images and low frequency images, input the rain image to the recursive ResNet [11], through the Guided Filtering Layer structure proposed

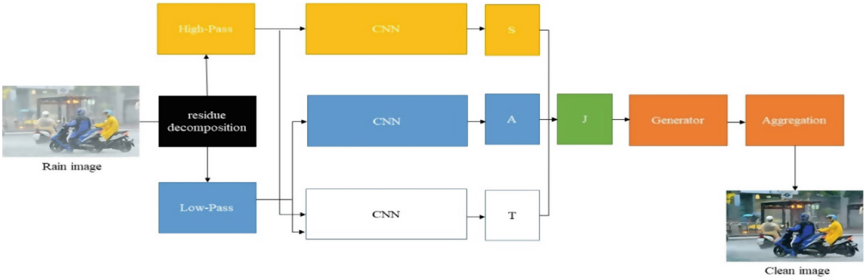

Fig. 1. Schematic diagram of rain removal network architecture

Table 1. Comparison of the accuracy of object etection in HeavyRainRemoval image

	Rain removal image	Rain image
Recognition rate is reduced, recognition error		
Increased recognition rate		

by [12], the exported high and low frequency images are brought into neural network training (Fig. 1). Finally, output the rain restoration image.

Even through technologies such as image restoration and restoration, but the photo has a gap with the real scene. Because this is a fake photo produced by repairing and restoring technology, may be different from the original image features, the object that causes the accuracy of object detection to decrease or to identify the wrong object (Table 1).

3 Methods

3.1 Networks

We experimented with System structure and Our method inference (Fig. 2). Tried to improve rain removal IOU accuracy.

3.2 Obtaining Rain and Restoring Street Images

Based on the collected rain image dataset. For image filtering that is not a street or pure natural scenery. Then filter the images that do not match object to be identified, speed

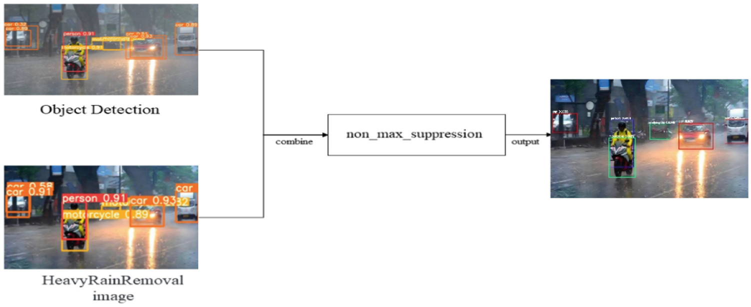

Fig. 2. Our method inference

up the next step of object annotation. Input the image into the rain removal model. Get the rain removal image.

3.3 Tracking Object Recognition Accuracy

Bring the rain image and rain removal image into object detection to predictions first. Through observing the result whether as expected. But even after rain removal. The human eye can improve the image recognition of the object. For computer vision feel it's not good. The result is not as good as expected (Table 1) as shown.

4 Result

There we can filter low confidence bounding boxes with Non-Maximum Suppression algorithm to reduce error detections to improve accuracy (Fig. 3) (Fig. 4).

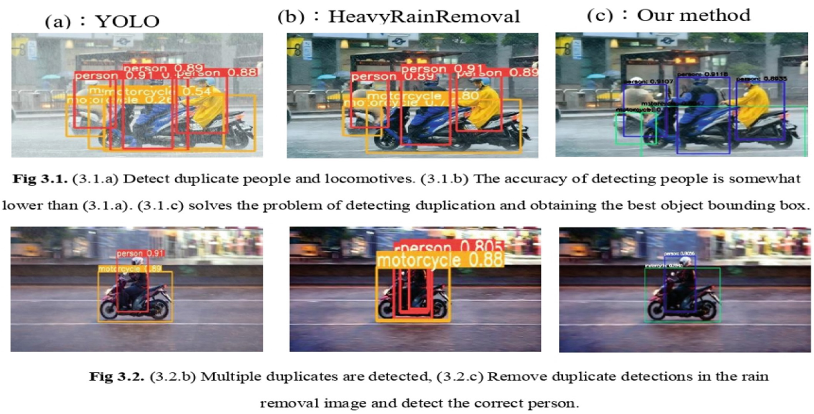

Fig. 3. YOLO, HeavyRainRemoval, our method Compare

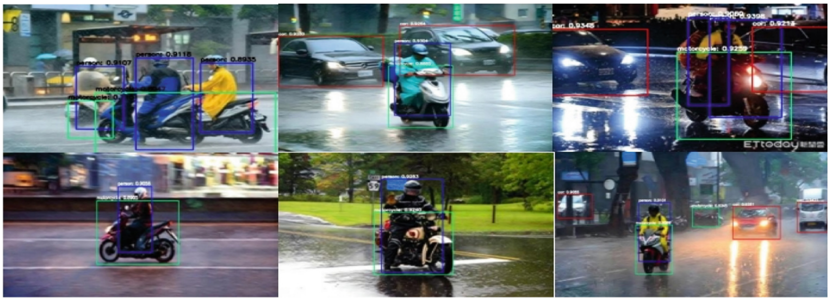

Fig. 4. Ours method result: combine the images of the two methods through our proposed method. After Non-Maximum Suppression, the resulting images are more accurate

5 Conclusions

According to the experimental results, the accuracy of the image after rain removal in the object recognition not entirely better than images with rain. Extract the bounding box of the two images through Non-Maximum Suppression. The best recognized bounding box and confidence can be obtained between the two images. Make up for the identification error between the two. This method can effectively reduce misjudgments. Improve the accuracy of object recognition.

Acknowledgements. The authors would like to thank the National Science Council, Taiwan, R.O.C. for financially supporting this research under Contract No. NSC MOST 109-2221-E-240 -002 -MY3, MOST 110-2622-E-240 -002, 110-2813-C-240 -004 -E.

References

1. Tian, Y., Pei, K., Jana, S., Ray, B.: Deeptest: automated testing of deep-neural-network-driven autonomous cars (2017). arXiv preprint arXiv:1708.08559
2. Yang, W., Tan, R., Feng, J., Liu, J., Guo, Z., Yan, S.: Oint Rain Detection and Removal via Iterative Region Dependent Multi-Task Learning
3. Girshick, R.: Fast R-CNN. IEEE International Conference on Computer Vision (ICCV) **2015**, 1440–1448 (2015). https://doi.org/10.1109/ICCV.2015.169
4. Redmon, J., Divvala, S., Girshick, R., Farhadi, A.: You only look once: unified, real-time object detection. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, pp. 779–788 (2016). https://doi.org/10.1109/CVPR.2016.91
5. Narasimhan, S.G., Nayar, S.K.: Contrast restoration of weather degraded images. IEEE Trans. Pattern Anal. Mach. Intell. **25**(6), 713–724 (2003). https://doi.org/10.1109/TPAMI.2003.1201821. June
6. Yao, B., Huang, L., Liu, C.: Adaptive defogging of a single image second international symposium on computational intelligence and design. Changsha **2009**, 56–59 (2009). https://doi.org/10.1109/ISCID.2009.21
7. Zhang, X., Li, H., Qi, Y., Leow, W.K., Ng, T.K.: Rain removal in video by combining temporal and chromatic properties. In: 2006 IEEE International Conference on Multimedia and Expo, Toronto, Ont., pp. 461–464 (2006). https://doi.org/10.1109/ICME.2006.262572

8. Kang, L.W., Lin, C.W., Fu, Y.H.: Automatic singleimage-based rain streaks removal via image decomposition. IEEE Trans. Image Process. **21**(4), 1742–1755 (2012). April
9. Bobin, J., Starck, J.L., Fadili, J.M., Moudden, Y., Donoho, D.L.: Morphological component analysis: an adaptive thresholding strategy. IEEE Trans Image Process. **16**(11), 2675–2681 (2007). Nov.
10. Li, R., Cheong, L., Tan, R.T.: Heavy rain image restoration: integrating physics model and conditional adversarial learning. In: 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, pp. 1633–1642 (2019). https://doi.org/10.1109/CVPR.2019.00173
11. Yang, W., et al.: Deep edge guided recurrent residual learning for image super-resolution. IEEE Trans. Image Process. **26**(12), 5895–5907 (2017). https://doi.org/10.1109/TIP.2017.2750403. Dec.
12. Kingma, D.P., Ba, J.: Adam: a method for stochastic optimization. CoRR, abs/1412.6980 (2014)