DDConv: Dilated Depthwise Convolution with YOLOv5 for Drone Imagery*

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Abstract. Unmanned Aerial Vehicles (UAVs) with Convolutional Neural Network (CNN)-based artificial intelligence technologies have recently received high attention for various applications. In this paper, our focus is on object detection network research for real-time drone systems. Thus, we propose the DDConv block, considering the unique characteristics of drones, such as a wide shooting range, objects of various types and scales, and high resolution. The DDConv block analyzes images using dilated convolution and depth-wise convolution, and replaces the C3 module of the YOLOv5 backbone. The experimental results showed that the number of parameters and the GFLOPS value decreased by about 20%. The object detection time was recorded at 6.5 ms per image, which is almost twice as fast as the original network. Although accuracy slightly decreased, the detection results still found most of the objects well. In the future, we plan to apply this network for traffic analysis and surveillance systems.

Keywords: Object detection · drone dataset · dilated convolution · depth-wise convolution.

1 Introduction

Recently, drones combined with computer vision-based artificial intelligence technology have been utilized in various fields, such as autonomous flight, unmanned delivery, and missing person searches. The most crucial part of these technologies is object recognition, as the camera mounted on the drone must be capable of analyzing its surroundings and detecting and avoiding obstacles in its path. Therefore, many researchers are focusing on real-time object detection technology in drone images. The modification of Convolutional Neural Networks (CNNs), the

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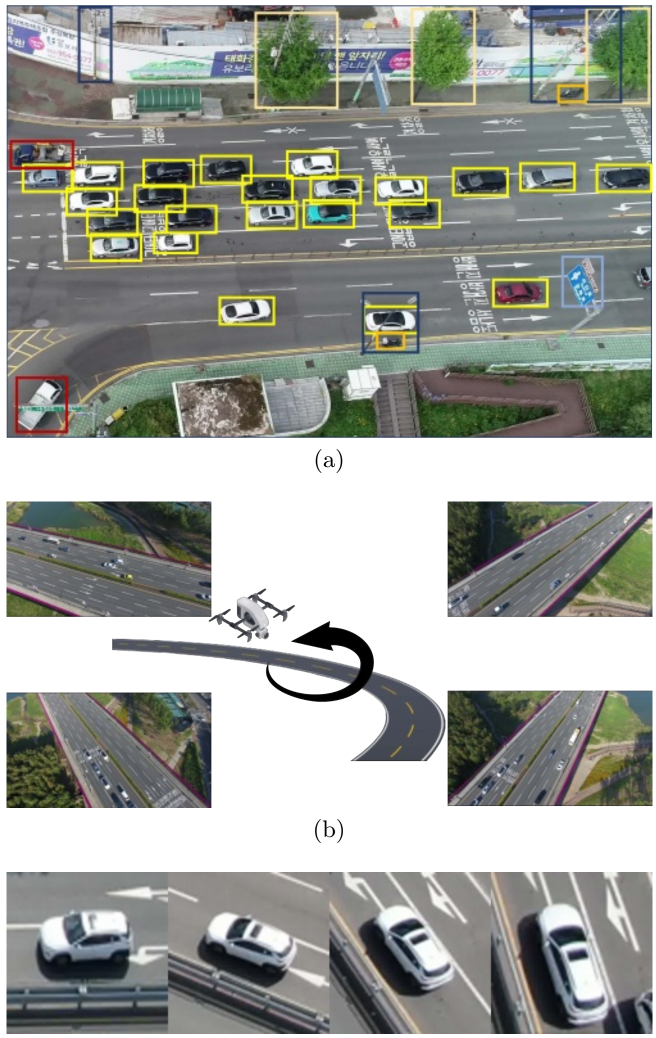
development of new algorithms, and modification methods for real-time object detection in drone images have been introduced in previous studies [1–3]. In addition, multi-object detection methods [4–7] and strategies for detecting small objects [8–11] are also attracting attention from many researchers. In this paper, we conduct a study focused on a real-time object detection network for drone images, which is the first step towards drone traffic analysis and surveillance systems. In addition, multi-object detection methods and small object detection strategies are also hot topics for many researchers. In this paper, we conduct a study focused on a drone image real-time object detection network which is the first step for drone traffic analysis and surveillance system.
First, we introduce the data analysis performed to create a suitable network for real-time object detection in drone images. The drone captures Bird's-Eye View (BEV) videos from a high altitude, which presents three challenges, as shown in Figure 1. Firstly, the types of objects captured are very diverse as a wide area is filmed, as depicted in Figure 1(a) with six types of objects and a large number of objects. Secondly, the shape of objects is irregular even within the same area, as the drone is moving while filming, as shown in Figure 1(b). Thirdly, the diversity of object forms is a distinct challenge, as objects may change their form due to differences in altitude, angle, and field of view, as seen in Figure 1(c).

In order to address the problems mentioned, this paper applies a convolution technique that can effectively analyze drone images in an object detection network. Firstly, using a large filter to calculate an image of a large area increases the probability of high-accuracy results but also significantly increases the computational load. Therefore, we apply a dilated convolution technique that provides a similar effect to using a large filter while maintaining a lower computational load. In addition, we apply a depth-wise convolution technique that has a similar effect to normal convolution but with a reduced computational load to ensure real-time object detection. This reduction in computation leads to a reduction in object detection time. Secondly, the number of detection heads is increased from three to four based on the scale of the objects in the drone image. As shown in Figure 2, objects in drone images can be divided into four scales, so the detection head must be configured accordingly to detect objects of various scales.

2 Related work

2.1 CNN-based object detection

Object detection is a computer technology that relates to computer vision and video processing to identify the presence of objects. It often uses the method of pre-extracting object features and detecting them within an image. In computer vision, there is a CNN technique for object detection. This method can preserve the spatial information of an image and identify features through convolution. YOLOv5 [12] is a popular real-time object detection method among the YOLO series, known for its fast computational speed. The YOLOv5 series includes versions such as nano, small, medium, large, and x-large. These versions differ in



(a)

(b)

(c)

Fig. 1: Challenged of drone image object detection, (a) Existence of many types and number of objects in one image, (b) Difficulty in analyzing same-area information due to the irregular movement path of the drone, (c) the diversity according to the taking altitude, angle, and field of view in the same object

Fig. 2: Illustration of object scale comparison in drone images.

terms of accuracy and computational speed, achieved by adjusting the number of convolutions in the backbone. Performance can also be influenced by changing the convolution method, such as Transpose convolution, Separable convolution, Dilated convolution, Depth-wise Separable convolution, etc. Dilated convolution was selected as a method for efficiently learning wide-pixel photos. Dilated convolution is the main idea in the DilatedNet [13] that increases the reception file by adding zero padding inside the convolution filter, allowing the same number of input pixels while accommodating a wide range of inputs. This paper [14] also improves performance by making the CFEM(Context Feature Enhancement Module) a multi-path dilated convolutional layer.

2.2 High speed CNN method

There are two key evaluation indicators for CNN. The first is accuracy, and the second is speed. The topic of this paper is real-time object detection in drone images, and it focuses on speed because it is a priority to detect many objects quickly. The Depth-wise Separable Convolution used as a method for improving CNN speed performance. The paper MobileNets [15] presents the Depth-wise Separable Convolution method. This paper is a representative paper that speeds up CNN by changing the calculation method without focusing on reducing the amount of calculation by increasing the filter size as 5x5 and 7x7. Therefore, Our paper applied the Depth-wise Separable Convolution method to speed up the CNN computation.

2.3 Object detection using drone image

When using drone dataset, the background occupies a large portion because it was shoted at a high altitude, and the size of objects to be detected is small. As a way to increase the accuracy of small object detection, there is a method of constructing a dataset using OBB(Object Bounding Box) in the paper [16], as shown in Fig1. In other ways, it's easier to find large objects in small images, and it's easier to find small objects in large images. For example, YOLOv1 [17] is fast but has a low ability to detect small things, and YOLOv3 [18] has increased its ability to catch small objects by performing prediction on three scales. This paper got the idea from this method and used the dilated convolution to YOLOv5's backbone to obtain a wide range of values, which would help detect small objects. In fact, it worked in a paper [19] that used dilated convolution to detect small objects.

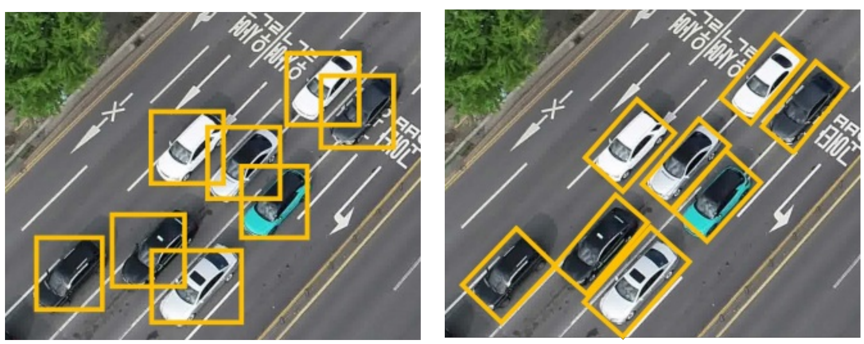


Fig. 3: Visualization of original annotation method(left) and proposed annotation method of DOTA(right)

3 Proposed method

The base-line network of proposed method in this paper is YOLOv5 [12] model. We propose the Dilated Depth-wise block for more efficient calculation and to get result faster instead of C3 module.

3.1 Detection strategy

As mentioned, there are three challenges in object detection tasks with drone imagery, which are all related to high resolution. High resolution means a large

image size and the ability to observe a wide area at once. However, this also increases the amount of computation and slows down learning and result derivation due to the wide area of convolution operations. In this paper, we aim to speed up learning and result derivation by reducing computation without sacrificing performance. Another characteristic of high resolution is the presence of various types and a large number of objects in the image. To address this, the detection head at the end of the network is increased to detect more objects in the high-resolution drone image.
Therefore, the detection strategy in this paper focuses on two aspects. Firstly, the proposed network aims to speed up computation without sacrificing detection accuracy in high-resolution images. This is achieved by using dilated convolution and depth-wise convolution. Dilated convolution maintains the same number of pixels as regular convolution but has a wider receptive field, and depth-wise convolution reduces the number of calculation parameters by performing calculations on each channel. Secondly, the detection head is increased from three scales to four scales to improve object detection in drone images. Drone images contain various objects of different sizes, such as small objects like people, medium-sized objects like cars and trucks, large objects like trees and streetlamps, and extra-large objects like apartments and buildings, as shown in Figure 2. Thus, a detection head with at least four scales is necessary to increase the probability of detecting multiple objects of different sizes.

3.2 Proposed module

The proposed network in this paper focuses on speeding up the object detection process in high resolution drone images. It achieves this by reducing the amount of computation without reducing the accuracy of detection. This is achieved by using a combination of dilated convolution and depth-wise convolution. The dilated convolution increases the receptive field while the depth-wise convolution reduces the number of computation parameters. The network uses the Dilated Depth-wise block instead of the c3 module used in the YOLOv5 backbone, which only uses 1x1 convolutions without considering the receptive field. To increase the probability of detecting various sized objects in the drone images, the detection head is increased from three scales to four scales.
The flow of the Dilated Depth-wise block is as follows. When the feature map is input, the feature map channel is divided into 4 parts without any calculation process. This is because there are other methods such as point-wise convolution, but the use of convolution layers directly increases the amount of computation. The feature maps divided into 4 parts pass into different calculation methods like (1) depth-wise convolution with size 1x1, (2) depth-wise convolution with size 3x3, (3) depth-wise convolution with a dilation ratio of 2, (4) depth-wise convolution with a dilation ratio of 3. The sum of the number of channels of the feature map generated through a total of 4 operations (1 to 4) is equal to the number of channels in the output feature map. The four feature maps generated are concatenated and passed to a 1x1 convolutional layer. The reason why the concatenated feature map is subjected to 1x1 convolution operation is

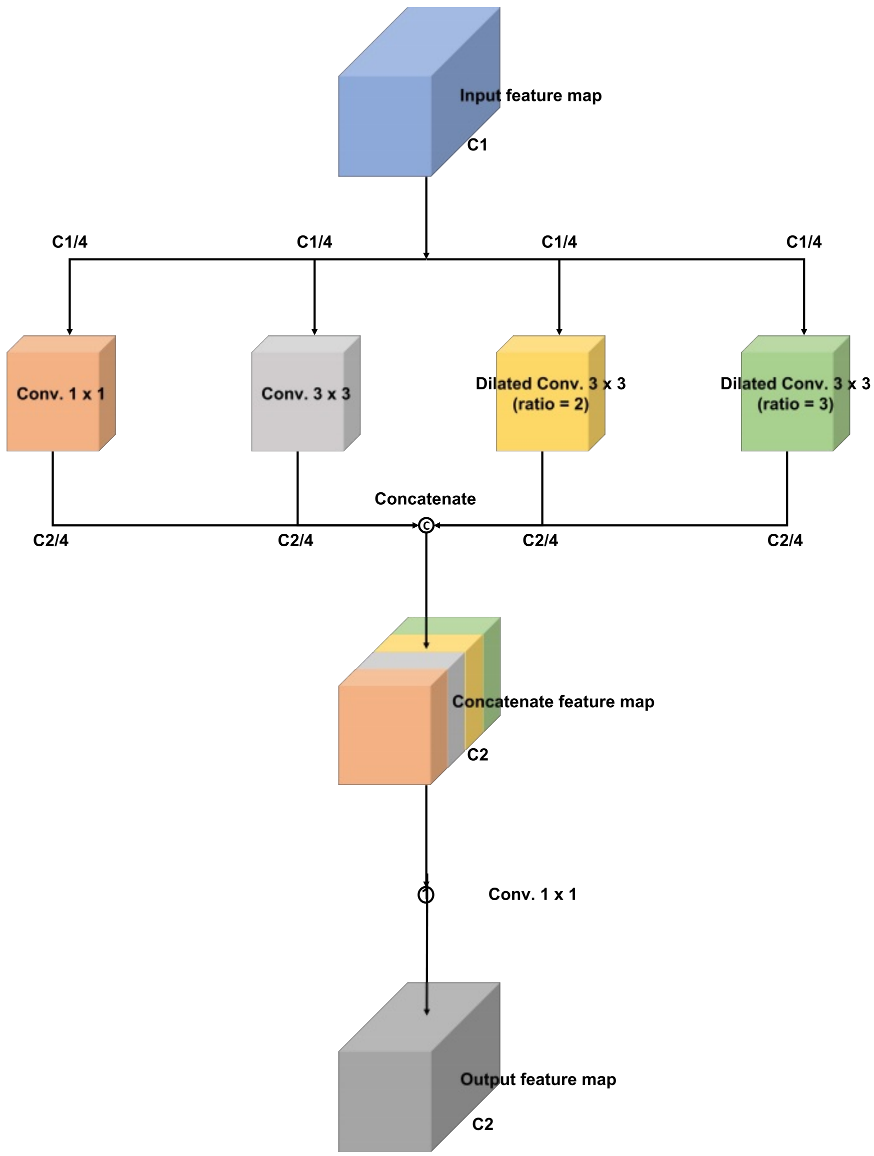


Fig. 4: Illustration of the proposed Dilated Depth-wise module.

that information in a narrow area and information in a wide area exist without sharing each other, so that information is shared using 1x1 convolution with the least amount of computation to obtain higher accuracy.

Also, the number of detection heads increased from 3 to 4. As mentioned in the detection strategy, object scales in drone images can be divided into four scales (small, medium, large, and extra-large). Therefore, the number of scales of the detection head was modified according to the number of object scales.

4 Experiment

4.1 Dataset

The data used in the experiment are the autonomous drone dataset [20] built by University of Ulsan and the VisDrone dataset [21] built by Tianjin University. The challenge and proposed method of drone object detection presented in this paper are from the analysis of the autonomous drone dataset. After network modification, the experiments of same conditions were applied to the VisDrone dataset to prove that proposed network is not overfitted at autonomous drone dataset built by University of Ulsan.

The autonomous drone dataset provides videos, images, and JSON files taken at various altitudes and angles in tourist areas, city areas, and forest areas. Among them, tourist areas and city areas data were mainly used to build a similar environment for future work as we mentioned above such as traffic analysis and surveillance systems. The information of data used in this paper is shown in Table 1 and Figure 5.

Table 1: The information of data used in the experiment.

Category	Region_Place	Altitude	Angle	The number of image
City	Ulsan_Taehwa-bridge	70m	60°	2,343
City	Ulsan_Samho-bridge	60m	45°	2,291
City	Daegu_Geumho-district	60m	45°	1,854
Tourist	Daegu_Hwawon-amusement-park	80m	45°	1,768

4.2 Evaluation metrics

To evaluate the performance of the proposed network, accuracy and speed were used as evaluation criteria. In the case of accuracy of the network, two indicators are measured: mAP 0.5 and mAP 0.5 to 0.95. mAP (mean average precision) represents the average of the area under the PR curve for each class and is a metric for analyzing object detection accuracy through performance evaluation of precision and recall. The number after mAP means IoU (Intersection over Union) value. It means the value measured when the IoU score is 0.5 and measured when IoU score is gradually increasing the value from 0.5 to 0.95. In the case of network speed, parameters, GFLOPS (GPU FLoating point Operations Per Second), and calculation speed per image were used as indicators for validation.

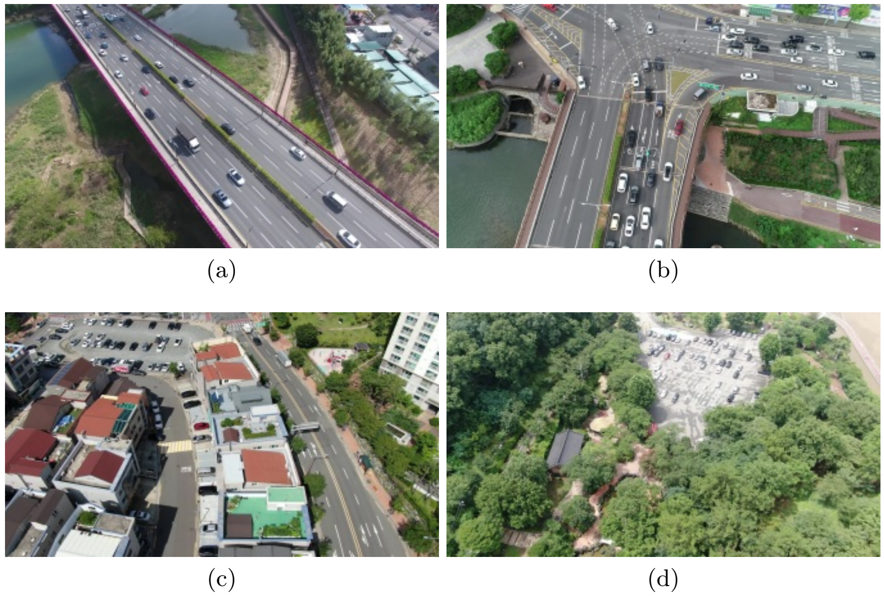


Fig. 5: Example images for each region of the autonomous drone dataset, (a) Ulsan_Samho-bridge, (b) Ulsan_Taehwa-bridge, (c) Daegu_Geumho-district, (d) Daegu_Hwawon-amusement-park.

4.3 Implementation setup

All experiments were conducted in the same environment, and the configuration environment was Intel Core i9-9960X, NVIDIA RTX 2080 Ti x 4EA, 125.5 GB memory. The training process was 100 epochs in all experiments, and all hyper-parameters such as batch size and learning rate, and depth multiple were set the same.

4.4 Result

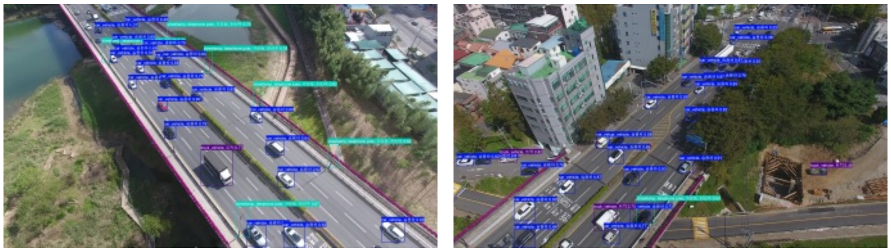
The experimental results are detailed in Tables 2 and 3. The result applied to the autonomous drone dataset is shown in Table 2, and Table 3 is the result applied to the VisDrone dataset. Both results reduced the number of parameters and GFLOPS by about 20%. But, the object detection accuracy was slightly decreased. In the case of autonomous drone dataset, mAP50 decreased by 2.3% and mAP50-95 by 5.5%. Although the accuracy was decreased, as you can see in Figure 6, it can be seen that most objects in the image are well detected. In the case of VisDrone dataset, mAP50 decreased by 0.6%, and mAP50-95 increased by 0.23%. The biggest feature is object detection time. The original network recorded a total of 12.7 ms for pre-processing, inference, and NMS per image. However, the proposed network completed the same process in 6.5 ms per image.

Table 2: The result comparison between DDConv and C3 module using autonomous drone dataset.

Autonomous drone	DDConv		C3		Performance	
mAP(%)	50	50-95	50	50-95	50	50-95
all	60.3	38.8	62.6	44.3	2.3↓	5.5↓
tree	92.8	67.4	94.1	73.1	1.3↓	5.7↓
person	3.6	0.5	0.02	0	**3.58** ↑	**0.5** ↑
house	89.2	70.4	93.1	78.2	3.9↓	7.8↓
apartment	90.4	62	94.5	69.1	4.1↓	7.1↓
traffic sign	63.7	27.2	75.5	36.1	11.8↓	8.9↓
traffic light	15.7	4.3	0	0	**15.7** ↑	**4.3** ↑
streetlamp	78.8	41.1	84.2	51.7	5.4↓	10.6↓
car	92.9	62.3	94	68.3	1.1↓	6.0↓
bus	66.5	50.2	73.5	59.9	7.0↓	9.7↓
truck	69.6	41.4	75.9	51.5	6.3↓	10.1↓
Parameters	1,437,924		1,783,519		**19.38**% ↓	
GFLOPS	3.3		4.2		**21.43**% ↓	

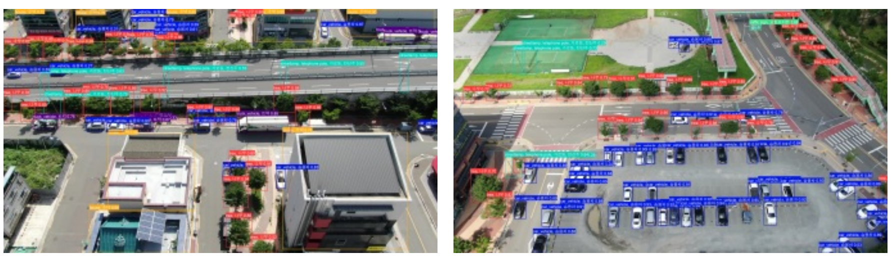
Table 3: The result comparison between DDConv and C3 module using VisDrone dataset.

VisDrone	DDConv		C3		Performance	
mAP(%)	50	50-95	50	50-95	50	50-95
all	18.9	9.46	19.5	9.23	0.6↓	**0.23** ↑
pedestrian	21.24	7.37	26.2	9.53	4.96↓	2.16↓
people	17.2	5.54	22.9	7.31	5.7↓	1.77↓
bicycle	2.34	0.74	2.22	0.76	**0.12** ↑	0.02↓
car	54.6	32.4	56.6	33.7	2.0↓	1.3↓
van	18.8	12.0	14.1	8.77	**4.7** ↑	**3.23** ↑
truck	14.2	7.75	13.0	6.69	**1.2** ↑	**1.06** ↑
tricycle	9.21	4.42	8.98	4.28	**0.23** ↑	**0.14** ↑
awning-tricycle	4.91	2.85	3.7	2.06	**1.21** ↑	**0.79** ↑
bus	24.7	14.1	20.3	9.85	**4.4** ↑	**9.85** ↑
motor	21.8	7.43	27.5	9.37	5.7↓	1.94↓
Parameters	1,424,004		1,772.695		**19.67**% ↓	
GFLOPS	3.3		4.2		**21.43**% ↓	

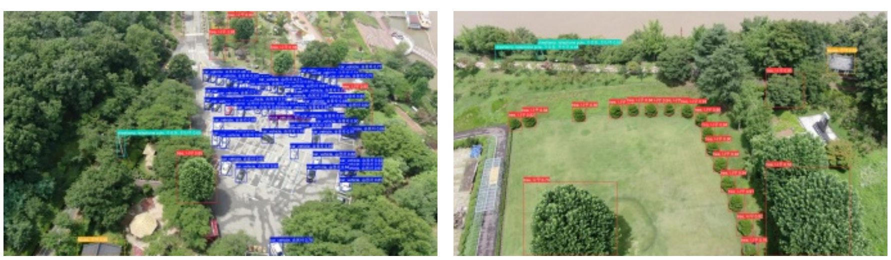


(a) Ulsan_Samho-bridge

(b) Ulsan_Taehwa-bridge



(c) Daegu_Geumho-district



(d) Daegu_Hwawon-amuesment-park

Fig. 6: Visualization of detection results on autonomous drone dataset using YOLOv5 with DDConv block.

5 Conclusion

This paper focused on the object detection work that is the basis of the technologies used in drone-based artificial intelligence systems. So, We proposed a DDConv to reduce the amount of computation of an object detection network for drone systems in which real-time is important. The DDConv includes dilated convolution and depth-wise convolution together to analyze a large area efficiently and to reduce the amount of computation for real-time systems. In addition, a detection head was added at the end of the network to find objects of more diverse scales. As a result of the experiment on the autonomous drone dataset, mAP50 decreased by 2.3% and mAP50-95 by 5.5%. In the case of the VisDrone dataset, mAP50 decreased by 0.6%, and mAP50-95 increased by 0.23%. But, both of two experiments decreased parameters and GFLOPS by about 20%. The object detection speed is almost twice as fast as the original network. The proposed network spends only 6.5 ms per image for inference. Although the accuracy is slightly lower than the original network, the majority of objects are detected as shown in Figure 6. Therefore, the proposed network in this paper is suitable for a drone-based real-time object detection systems.

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