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A modified YOLOv4 detection method for a vision-based underwater garbage cleaning robot

Key words: Object detection; Aquatic environment; Garbage cleaning robot; Modified YOLOv4

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Motivation

1. The water resource reserves are limited and the loss is serious. What is worse, it is still facing serious pollution, which affects people's life and production activities. It also brings huge challenges to many industries such as tourism and fishery.

2. The numerous non-degradable garbage mixed in the water poses a serious threat to the diversity of aquatic organisms. Moreover, plastic garbage in the water environment has been almost everywhere. The sudden COVID-19 epidemic has caused a large number of masks to be abandoned in the sea. These masks provide a breeding bed for bacteria and pose a huge safety hazard to human beings.

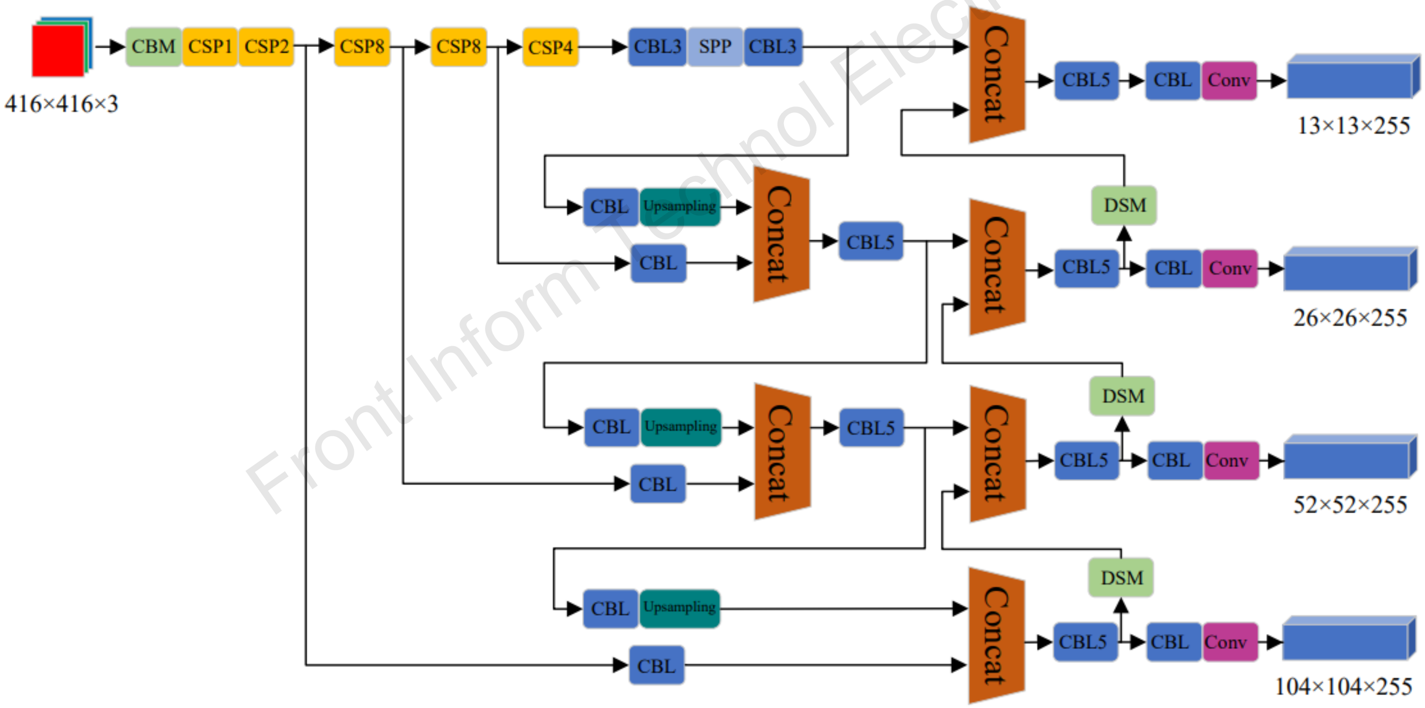
Main idea

1. To better achieve high-precision target detection, YOLOv4 is converted into a four-scale detection network, from 13, 26, and 52 to 13, 26, 52, and 104. Thanks to this improvement, targets of various sizes can be better considered.

2. Because the robot has higher requirements for real-time detection, the YOLOv4 model is pruned to reduce a lot of unnecessary calculations. Finally, because the weight file is only 9.499% of the original one, the frame rate can reach 66.67 frames/s and the mean average precision (mAP) is 95.099%.

Method

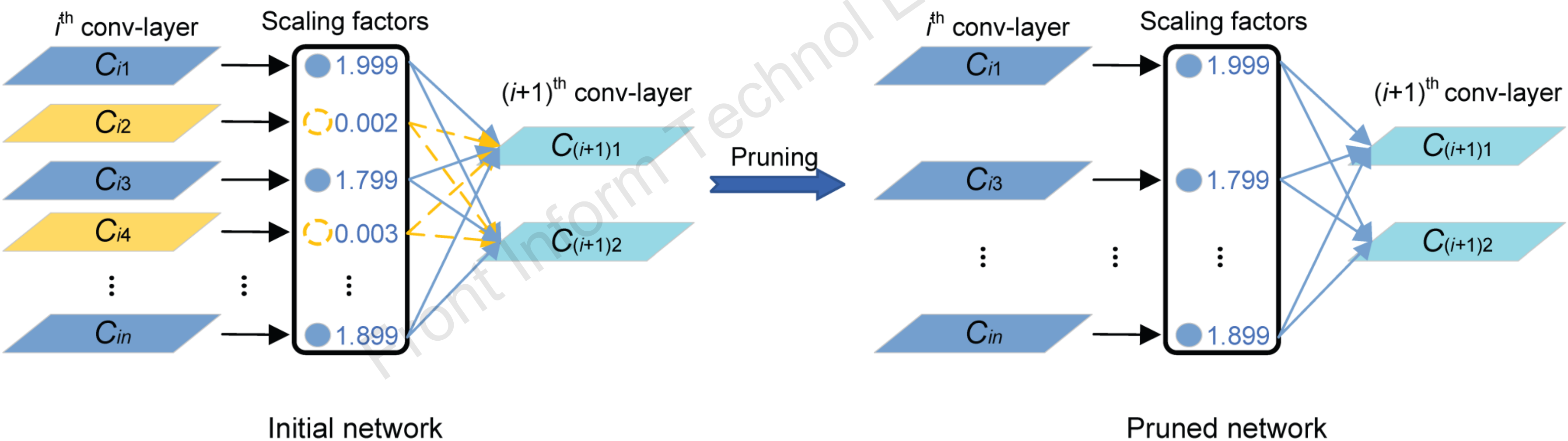
1. To better take into account the target objects of various sizes, the three-scale detection is changed to four-scale detection.



Four-scale detection network

Method (Cont'd)

2. To meet the requirement of high speed, we prune the huge detection network, reduce a large amount of unnecessary calculations, and improve the detection speed.



Channel pruning diagram

Major results

Table 2 Detection results on the dataset

Network	FPS	AP_{net}	AP_{bag}	AP_{stone}	mAP	Size of weight (byte)
4SP-YOLOv4	**66.667**	**0.970**	0.899	0.984	0.951	$\mathbf{2.4323 \times 10^7}$
4S-YOLOv4	36.364	0.966	**0.913**	**0.985**	**0.955**	2.5726×10^8
YOLOv4 (Bochkovskiy et al., 2020)	43.478	0.914	0.908	0.919	0.913	2.5606×10^8
YOLOv3 (Redmon and Farhadi, 2018)	38.030	0.887	0.873	0.897	0.886	2.4635×10^8
Faster R-CNN (Ren et al., 2015)	7.143	0.878	0.857	0.903	0.879	4.8349×10^8
SSD (Liu W et al., 2016)	14.545	0.877	0.870	0.890	0.879	2.1033×10^8

The best results are in bold

Conclusions

First, we convert the original YOLOv4 to four-scale YOLOv4; then we perform model pruning on 4S-YOLOv4. Compared with other detection algorithms, 4SP-YOLOv4 can achieve 0.951 mAP in 15 ms at GTX 1080Ti × 3, and the number of model parameters is only 9.499% of that of the original model, ensuring high-precision and high-speed object detection.

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