будуть розглянуті питання компенсації температурних впливів для телевізійних систем наведення з більш складними схемами об’єктивів.

Ключові слова: телевізійні системи наведення, температурні впливи, розрахунок термокомпенсаторів.

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YOLO AI MODELS TRAINING FOR OBJECT DETECTION IMPROVEMENT

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Object detection is a groundwork for object recognition and plays crucial role for efficiency of computer vision based automated and unmanned systems. YOLO (You Only Look Once) model is one of the most used AI models for utilizing this task. It need to be trained before applying. For this purpose transfer learning is used. One promising technique during transfer learning is layers freezing.

Modern versions of the YOLO series such as YOLOv11 and YOLO26 training methods were discovered.

YOLO26 has many improvements:

- replacement of C2f block with C3k2 and adding C2PSA block after SPPF;

- SPPF block includes a shortcut connection, which improves gradient flow and stabilizes optimization;
- replacement of C2f block with C3k2 and adding C2PSA block after SPPF;
- box regression is used directly instead of Distributed Focal Loss (DFL) block that simplifies training and enables more confident predictions;
- new optimizer MuSGD is used for better convergence and training stability. YOLO26 uses score-based prediction selection instead of IoU-based filtering.

These improvements suggest a significant increase in the performance. Training was made on two datasets: medium-size (1000 mages) and small-size (200 images), - in terms of such metrics as precision, recall, mAP@50 and mAP@50-95. Computational productivity was estimated through per-image inference latency, training time and GFLOPs.

Training was held for 50 epochs with an early stopping mechanism (patience 20), batch size 16, learning rate 0.01, optimizer MuSGD for YOLO26 and SGD for YOLOv11 and optimizer AdamW for both models.

Beneficial is freezing layers of the backbone or SPPF layer than freezing higher layers of the neck.The best freezing strategy is to freeze layers of the backbone and stop freezing on C3k2 layer for both models with all optimizers.

YOLO11 demonstrates better overall performance, lower training time and per image inference latency, higher improvement in precision, recall, mAP@50 and mAP@50-95 then YOLO26 on both datasets.

The main VOLO26 advantage is computational efficiency, which is 21% better than in VOLO11.

Training on medium-size dataset.

Productivity with AdamW optimizer without freezing is better in VOLO11. Per-image inference latency relative VOLO26 is 56%. Specialized optimizers SGD for YOLO11 and MuSGD for YOLO26 changes productivity. In VOLO11 per-image inference latency is decreasing on 30%, in VOLO26 is increasing on 6%.

Freezing with AdamW optimizer in VOLO11 decreases per-image inference latency on 30%, with SGD optimizer do not change per-image inference latency.

Freezing with AdamW optimizer in VOLO26 changes per-image inference latency from -7% to +40%, with MuSGD optimizer from 0% to +50%.

Best results for YOLOv11 with optimizer AdamW gives freezing of 6th layer, for YOLO26 with optimizer MuSGD – 8th layer.

Highest metrics' values provides for precision with and without per-image inference latency limit – YOLO11 nano with freezing of 9th layer and optimizer SGD, for recall with per-image inference latency limit – YOLO11 with freezing of 6th layer and optimizer AdamW, for mAP@50 with per-image inference latency limit – YOLO11 with freezing of 6th layer and optimizer AdamW, for mAP@50-95 with and without per-image inference latency limit – YOLO11 with freezing of 6th layer and optimizer AdamW.

Highest metrics' values without per-image inference latency limit provides for recall – YOLO11 with freezing of 7th layer and optimizer SGD, for mAP@50 – YOLO26 nano with freezing of 10th layer/without freezing and optimizer AdamW.

Freezing first six layers for YOLO11 with optimizer AdamW gives the best overall results on medium-size dataset.

Training on small-size dataset,

Best results for YOLO11 with optimizer AdamW gives freezing of 6th or 8th layer and for YOLO11 with optimizer SGD – 6th layer.

Productivity with AdamW optimizer without freezing is better in VOLO11. Per-image inference latency relative VOLO26 is 75%. Specialized optimizers SGD for YOLO11 and MuSGD for YOLO26 do not changes productivity.

Freezing with AdamW optimizer in VOLO11 increases per-image inference latency up to 30%, with SGD optimizer up to 10%.

Freezing with AdamW and MuSGD optimizers in VOLO26 decreases per-image inference latency to 10%.

Highest metrics' values provides for precision with and without per-image inference latency limit – YOLO11 with freezing of 8th layer and optimizer AdamW/ YOLO11 nano with freezing of 13th layer and optimizer SGD/ YOLO26 nano with freezing of 16th layer and optimizer MuSGD, for recall and mAP@50 with and without per-image inference latency limit – YOLO11 with freezing of 6th layer and optimizer AdamW or SGD/ YOLO11 nano with freezing of 10th layer and optimizer AdamW or SGD, for mAP@50-95 with and without per-image inference latency limit – YOLO11 with freezing of 6th layer and optimizer SGD.

Keywords: YOLO, object detection, transfer learning, freezing, computer vision.

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GLOBAL OPTIMIZATION TESTER: A COMPUTER PROGRAM FOR AUTOMATED STATISTICAL ANALYSIS OF CONTINUOUS GLOBAL OPTIMIZATION ALGORITHMS

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Introduction

Continuous global optimization (GO) problems often play a decisive role in modern applied mathematics, various fields of engineering, machine learning and physical