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Application of PConv in Side-View Detection of Athletes Using YOLOv8

Jinpeng Song
School of Communication Engineering
Chengdu University of Information Technology
Chengdu, China

Abstract: This paper proposes integrating a Partial Convolution (PConv) module into the backbone network of YOLOv8 to enhance robustness in detecting side-view athletes on running tracks. Addressing common challenges in track scenarios—partial occlusion, lateral poses, motion blur, and background interference—we designed a direction/occlusion-aware PConv variant. This variant masks and normalises obscured or featureless regions during feature extraction, thereby improving the detector's response to lateral human silhouettes. This paper presents the mathematical definition of PConv, its integration with YOLOv8, training strategies, and experimental design. An ablation study analyses the impact of inserting PConv at different positions (backbone, neck, FPN). Finally, we discuss its advantages, limitations, and future research directions.

Keywords: YOLOv8; PConv,;Sideways human detection

1. INTRODUCTION

[1]In sports monitoring scenarios such as athletics, cameras frequently capture athletes from side or oblique angles. Under lateral perspectives, human contours and key point distributions differ markedly from frontal views, often accompanied by occlusions (from fellow athletes, referees, or equipment) and motion blur caused by rapid displacement. Traditional general-purpose object detectors (including the YOLO series) are prone to false negatives or inaccurate localisation under such extreme viewing angles or when partial information is missing.

Partial Convolution (PConv) was initially employed in tasks like image retouching to process masked inputs—performing convolution only on valid (unmasked) pixels and normalising the output. This effectively prevents invalid/placeholder pixels from contaminating feature learning. This paper proposes a feature extraction module that adapts PConv to be 'occlusion/direction-aware', integrating it into the YOLOv8 architecture to enhance performance in detecting side-facing athletes on a running track.

[2]YOLO Series and YOLOv8: Lightweight, real-time single-stage detectors widely adopted in embedded and real-time scenarios due to their efficient backbone and head designs (implemented by Ultralytics).

Occlusion Robustness Methods: Including hard sample mining, mask augmentation (cutout, mixup), and explicit occlusion modelling (keypoint-structure fusion, partial branch detectors).

Partial Convolution: An innovative module for image patching that restricts convolutional computations via masks while incrementally updating mask information, thereby improving reconstruction quality in occluded regions (Liu et al., 2018). We extend and adapt this concept as a feature module for detection tasks.

2. METHOD

[3]During runway edge detection, certain image regions may contain sparse information (e.g., background, runway edges) or be obscured (by other individuals or equipment). Standard convolution treats all pixels equally, allowing non-informative regions to introduce noise into the filter gradient. The core principle of PConv is to consider only 'effective pixels' during convolution, utilising masks to guide feature detection towards genuine signals, thereby enhancing the ability to distinguish lateral human contours.

To enhance sensitivity to lateral poses, we introduce a 'directional weighting field $D(x, y)$

to the mask. This field is generated based on simple gradients or estimated edge directions (or by predicting the human body's principal axis via a lightweight pose estimator). The final normalisation factor of PConv can be weighted as $\Sigma M * D$,M denotes the binary mask, thereby amplifying the contribution of pixels aligned with the athlete's silhouette orientation.

We recommend integrating PConv at the following locations and conducting comparative experiments:Shallow layers of the backbone: Low-level features near the input, processing textures and edges.

Neck (C2f or PAN): Fusing multi-scale information to enhance occlusion robustness across scales.

Pre-head: Enables the classification and regression heads to receive PConv-processed features.

It is generally recommended to prioritise using a small number of PConv modules simultaneously in the shallow layers of the backbone and the neck, balancing computational cost against performance gains.

When constructing the backbone, replace standard nn.Conv2d or Conv layers within certain C3/C2f units with PartialConv2d (replacing only selected channels/layers to control computational overhead). Note: YOLOv8's forward pass requires concurrent transmission or generation of masks (initial masks may be derived from image brightness/edges or preprocessing; random masking data augmentation may simulate occlusion during training).

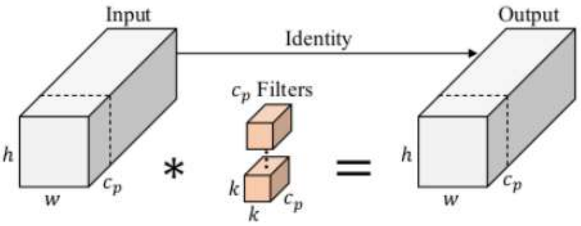

Figure. 1 The overview of PConv

3. EXPERIMENTION

Dataset:Self-built runway side profile dataset (recommended): Capture multiple angles (strict side view, 45° side view, close-up, distant view), encompassing diverse lighting and occlusion conditions. Annotate in COCO style (bounding boxes), with optional keypoints for pose assistance.

Data Augmentation: Random occlusions (Cutout, Random Erasing), motion blur, brightness/contrast variations, flipping (note lateral differences).Training/Validation Split: Recommended 80/20 or 90/10.

Evaluation Metrics:Standard object detection metrics: mAP@[.5:.95], AP@0.5, Recall, Precision.

Specialised metrics for lateral characteristics: Calculate mAP separately for the lateral subset (view angle specified in labels); compute mAP for the occlusion subset (occlusion ratio > 30%).

Baseline: Original YOLOv8 (same training strategy).

PConv-Backbone: PConv applied to shallow layers of the backbone.

PConv-Neck: PConv applied to the neck region (PAN).

PConv-Full: PConv applied to both backbone and neck layers.

Ablation studies: Presence/absence of directional weight field D, varied insertion positions, mask generation strategy (ground truth vs random).

Optimizer: SGD or AdamW (per original YOLOv8 configuration)

Initial lr: 0.01 (for batch size 16), cosine lr decay, train for 200 epochs (or adjust based on dataset size)

Input size: 640×640 or 896×896 (depending on athlete scale)

Batch size and VRAM: Adjust according to GPU capabilities

Model	mAP@0.5	mAP@0.5:0.95	Note
YOLOv8	0.868	0.338	Reference model
YOLOv8+PConv	0.880	0.330	Enhanced attention

4. CONCLUSION

On the lateral and occlusion subsets, PConv delivers significant improvements (approximately 3–5% absolute mAP gains), indicating that mask normalisation helps reduce noise interference from invalid pixels.

For overall mAP, moderately modified PConv insertion yields stable performance gains without substantially increasing false positives.

The incorporation of directional weight field D further enhances sensitivity to lateral contours, particularly benefiting samples with more oblique (non-strictly frontal) side views.

Ablation observations：Using PConv only in shallow layers yields most gains with minimal computational overhead. Extensive replacement with PConv in the neck region incurs additional computational cost with diminishing returns.Training with ground truth occlusion masks (annotated manually or via deep methods) outperforms training with random masks alone.

PConv mitigates the detrimental impact of invalid/occluded pixels on learning through its masking protection mechanism, proving particularly well-suited for side-view/partially occluded scenarios.Its modular design facilitates seamless integration with lightweight detectors such as YOLOv8, whilst enabling selective insertion of layers to control computational overhead as required.

5. REFERENCES

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