Deformable Vision Transformer Based Single-Stage Pedestrian Detector

Anonymous Author(s)
Affiliation
Address
email

Abstract

Pedestrian detection is a challenging field in computer vision, which requires both fast inference and high accuracy. Single-stage detectors are faster than region of interest based two-stage detectors at the expense of accuracy mainly due to the lack of spatially adaptive features. To this end, we propose a single-stage anchor-free pedestrian detector with enhanced spatial and multi-scale features based on the deformable vision transformer aiming to achieve the balance between speed and accuracy. The design of the architecture is investigated in depth. Comprehensive comparisons with state-of-the-art single- and two- stage detectors on various pedestrian datasets are performed. The proposed detector achieves leading performance on both Caltech and Citypersons datasets among single- and two- stage methods using less parameters compared to the baseline. The log-average miss rates for Reasonable (3.8%) and Heavy (36.5%) are decreased to 2.6% and 28.0% on Caltech, and 10.6% and 36.7% on Citypersons validation datasets respectively. It even outperforms SOTA two-stage detectors in Heavy subset by 3% on Citypersons validation set.

1 Introduction

Pedestrian detection is a popular task subordinate to object detection in computer vision. This task aims at accurately locating and classifying pedestrians in images or videos obtained via visible-light cameras, infrared cameras etc. In this paper, we focus on the detection from RGB images. Pedestrian detection is very important as it serves as the prerequisite of various vision tasks [1], such as human centric tasks (person re-identification [2, 3], person search [4], human pose estimation [5] etc.) and more generic multi-object tracking [6]. It has been applied to autonomous driving [7, 8], video surveillance [9] and action tracking.

Pedestrian detection is very challenging mainly due to the varying appearances resulted from the significant occlusion and varying scales. On the one hand, significant intra- and inter- class occlusion occur when a pedestrian is occluded by other pedestrians or objects like cars, bicycles etc., in busy areas. Due to the heavy occlusion, only a small part of the human body is visible which significantly reduces the discriminative features. On the other hand, when the target is far away from the camera, its height and width reflected in the image decrease, and vice versa. Large pedestrians tend to have more informative features but are difficult to be fully extracted from a vast region while features of small targets are compact but relatively ambiguous with less preserved details. In summary, the fluctuating amount and varying shape of effective features are the root problems. These intrinsic problems challenges the capabilities of feature extraction modules, which act as a long-standing bottleneck in pedestrian detection and almost all other object detection tasks.

To deal with these problems, deep Convolutional Neural Networks (CNNs) based approaches, especially two-stage methods [10–15] based on Fast and Faster R-CNN [16, 17] have pervaded

Submitted to 36th Conference on Neural Information Processing Systems (NeurIPS 2022). Do not distribute.

pedestrian detection tasks owing to the high detection accuracy. These methods first make coarse predictions of targets in the Region Proposal Network (RPN), then refine the bounding boxes and predict the final scores based on the features inside the proposal regions. In addition to methods for general object detection, pedestrian detectors take the advantage of unique characteristics of targets, such as the mask of visible parts [49, 10] and key-points of human bodies [25]. However, the inference speed of these methods is limited by the repeated prediction. This requires longer training time per epoch and is hard to be applied to some real-world scenes. Secondly, the design of the anchors in RPN is seriously parameter depended. Lastly, the procedures of jointly training two networks are complicated.

To achieve faster inference and easier training procedures, single-stage approaches, which only make a single round prediction, are developed [18] and applied to pedestrian detection [19–23]. However, they suffer from decreased detection accuracy. The miss rates of two-stage methods in Reasonable subset on Caltech are smaller than 4% [14][10, 24, 25], while those for single-stage methods are larger than 4.5% [21]. For Citypersons validation set, the miss rates for the former is less than 40% in Heavy subset, which is much lower than the latter (42% [23]). Our research purpose is to improve the detection performance of single-stage pedestrian detectors, especially the detection accuracy of Reasonable and Heavy subsets, and to narrow the gap between single- and two- stage methods.

Massive studies have been carried out to enhance the single-stage pedestrian detectors based on Center and Scale Prediction (CSP) [21], a typical single-stage and anchor-free pedestrian detector which significantly accelerates the inference [1]. In the past year, most research focuses on the fusion of representative features [26–31]. For example, [29] enhances the features via increasing semantic information at low-level and enriches the localization information at high-level. Similarly, [31] fuses the feature maps with different scales in adequate proportions. [28, 30] also explore new strategies to aggregate multi-level features. These feature enhancements are mainly performed along the feature map level dimension, which makes sense because of the intrinsically unbalanced feature information between shallower feature maps and deeper ones. However, this unbalance problem also exists in two-stage detectors. This means that it is not the root cause of the poorer accuracy of single-stage methods.

To address the root cause, the general architecture of single- and two- stage detectors are compared in Figure 1. Assume that the training strategies and the detection head are the same for both methods, the difference in the architechture lies in the information fed into the detection head. For two-stage methods, both positions and features of the proposal regions are fed into the detection head. These proposals contain potential pedestrians. Thereby, the detection head classifies via spatially target-focused features with less background interruptions and refines the bonding boxes by predicting small offsets from the proposal positions. For single-stage methods, each pixel in the feature map serves as the 'proposal region' with no pre-estimated positions. These pixels share the same receptive field size which may be too small to include sufficient information for large targets or so large that the background information overwhelms the useful features for detection. Obviously, this is more challenging for the classifier compared to two-stage methods. Additionally, single-stage methods have to regress from scratch, which is more difficult than simple refinement in two-stage methods. According to the analysis, the lack of spatially target-focused feature representation and the prediction of bounding boxes from scratch serve as two key bottlenecks hindering the improvement of single-stage detectors.

To make the features fed into the detection head concentrating on the targets or other useful information automatically without the assistance of proposal regions, we take the advantage of vision transformers. Vision transformers describe the pairwise dependency of each entity in the feature map with attention weights. The output weighted averaged feature is the adaptive aggregation of important entities (with higher attention weights) while the disturbing information is suppressed (with lower attention weights). Using such attention mechanism on top of the backbone enables the single-stage detector to supplement spatially filtered features easily for subsequent classification and regression tasks. Thus, the modified detector makes the best use of the fast inference originated from single-stage methods and more effective and cleaner features. Our main contributions are as follows:

- Proof the effectiveness of using the deformable vision transformer to improve the accuracy of single-stage pedestrian detectors while maintaining fast inference.

- Propose a novel feature extractor which enhance features along both scale and spatial dimensions. Comprehensive experiments show that the performance gap between the presented method and two-stage methods is narrowed on various pedestrian datasets.
- Extend the application of vision transformers on top of the backbone in pedestrian detection tasks.

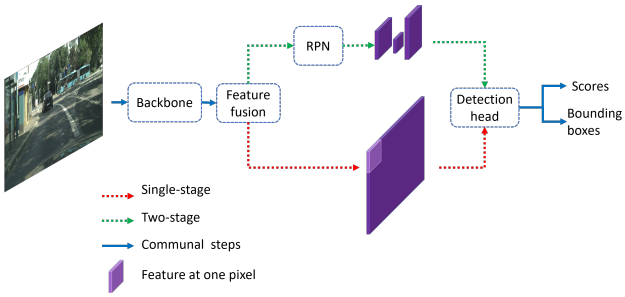

Figure 1: Generic detection pipeline of the single- and two- stage detectors. The detection head consists of two parallel branches for classification and regression.

2 Related works

Vision transformers in Computer Vision (CV) originates from the transformers widely utilized in Natural Language Processing (NLP). Thanks to the attention mechanism, vision transformers are applied to image feature extraction as (like ViT [32] and Swin Transformer [33]) or on top of the backbone like DETR [34]. Our detector belongs to the latter category. DETR consists of the convolutional backbone, six encoder-decoder pairs and the prediction head. It is an inspiring end-to-end detector which has aroused plenty studies based on it. One typical variant of DETR is the deformable DETR [35]. It is known that DETR requires massive memory to store the self-attention weights within each Multi-Head Self-Attention (MHSA) layer. The memory cost is linear to the number of attention heads and is square to the number of pixels in the down sampled feature map. Additionally, first and second order momentum in optimizers introduce in further memory cost in training. To achieve accurate detection, more attention heads and relatively large down sampled feature map are preferred, which results in memory explosion. To overcome this problem, the fast-converging and memory-saving deformable DETR is proposed. It only calculates the attention weights at several sampling locations rather than each pixel in the feature map, so that the memory is linear to the number of pixels, which makes training with high resolutions and limited memory resources possible. Experiments show that deformable DETR outperforms Faster R-CNN [17] and DETR on COCO 2017 validation set [36].

So far, vision transformers seem inspiring and potential, but it is rarely applied in pedestrian detection in the form of DETR or its variants. [37] found that deformable DETR not only behaves worse than Faster R-CNN on CrowdHuman dataset [38], but also costs tenfold training time. Although it narrowed the performance gap using dense object queries and the rectified attention field, the modified deformable DETR still show limited advantage over the traditional Faster R-CNN. This implies that rigidly putting the whole six encoder-decoder pairs into the pedestrian detector may not be cost-effective. As an example, BoTNet [39] only substitutes the convolutional layers in residual bottleneck blocks in the last stage of ResNet [40] for MHSA layers, but it produces strong performance on ImageNet validation set [41]. Inspired by this and the aforementioned limitation, our work only utilizes a single encoder of the deformable DETR as an adaptive feature extractor and applies it to the single-stage anchor-free CSP.

3 Method

Deformable Transformer Encoder: Figure 2 shows the deformable encoder in the multi-scale deformable vision transformer. This encoder takes the multi-scale feature maps $\left\{z^l\right\}_{l=1}^{L}$ ($L = 3$ is the number of feature maps) with height H_l and width W_l at scale l and reference points, which are

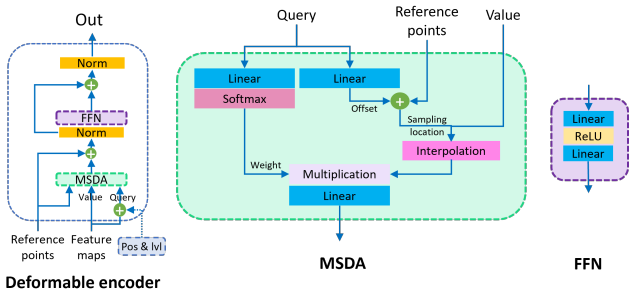

Figure 2: Structure of the deformable encoder in the multi-scale deformable vision transformer and embedded multi-scale deformable attention (MSDA) layer. **Left**: The deformable encoder is the same as the encoder in DETR except for that MSDA does not need the key tensor while reference points are required instead. **Mid**: The MSDA averages the features at sparse sampling locations on different scales with weights computed from the query tensor. **Right**: Feed-Forward Network (FFN).

the positions of grid centers of the feature maps, as inputs. It outputs the enhanced feature maps with the same resolution as the input. The input feature maps are first added by fixed encoded positional [34] and learnable level information [35] to disambiguate spatial and scale positions, then projected to the query feature map $\boldsymbol{z}_q$ via linear projection. The feature maps also generate the value feature maps $\boldsymbol{z}_v$ with a linear layer but no encodings. The query feature map $\boldsymbol{z}_q$, value feature map $\boldsymbol{z}_v$ together with the pre-generated reference points are sent to the Multi-Scale Deformable Attention (MSDA) layer to enhance spatially adaptive features, followed by a Fee-Forward Network (FFN). In summary, the encoder supplements the semantic information of input feature maps via the embedded attention layer and FFN.

Multi-Scale Deformable Attention: The MSDA layer sums the selected entities in the value feature map $\boldsymbol{z_v}$ at sampling locations with predicted attention weights for each corresponding query entity. These attention weights $\boldsymbol{W}$ are the linear projection of query features $\boldsymbol{z_q}$ followed by a softmax operator along scale and sampling point dimensions. For a single query entity, it only needs $N_h N_l N_p$ attention weights, representing the significance of selected value features at different attention heads, scales, and points. Selections are decided by the sampling locations which are the summation of reference points $\boldsymbol{p}$ and sampling offsets $\Delta\boldsymbol{p}$ which is the embedding of the query features. At each float sampling location, selected value feature is bilinear interpolated for accuracy and training offset predictor. With weight, sampling locations and selected value features prepared, the q-th element of the separate output feature $\boldsymbol{z}^{\boldsymbol{so},h} \in \mathbb{R}^{N_q \times c_v} (N_q = \sum_{l=1}^{L} H_l W_l)$ at attention head h (total N_h heads) is

$$\boldsymbol{z}_q^{\boldsymbol{so},h} = \sum_{p=1}^{N_p} \sum_{l=1}^{L} W_{plhq} \boldsymbol{v}_{\boldsymbol{p}_{ql} + \Delta \boldsymbol{p}_{plhq}} \tag{1}$$

where p, q, l and h index the sampling offsets, elements of the deformable attention feature $\boldsymbol{z}^{\boldsymbol{o}}$, the scale of value $\boldsymbol{v}$ and attention head. W_{plhq} is a value from the weight $\boldsymbol{W} \in \mathbb{R}^{N_q \times N_h \times L \times N_p}$. $\boldsymbol{p} \in \mathbb{R}^{N_q \times L \times 2}$ and $\Delta\boldsymbol{p} \in \mathbb{R}^{N_q \times N_h \times L \times N_p \times 2}$ are the reference points and sampling offsets. $\boldsymbol{p}_{ql}$ and $\Delta\boldsymbol{p}_{plhq}$ denote the position of a single reference point and one of its corresponding sampling offsets respectively. The separate output features from N_h attention heads are projected to the q-th element of the final output deformable attention feature $\boldsymbol{z}^o$ by a linear layer expressed as

$$\boldsymbol{z}_q^{\boldsymbol{o}} = \sum_{h=1}^{N_h} \boldsymbol{W}'_h \boldsymbol{z}_q^{\boldsymbol{so},h} \tag{2}$$

where $\boldsymbol{W}'_h \in \mathbb{R}^{c \times c_v}$ denotes the learnable weight for the h-th attention head.

Center and Scale Prediction: The architecture of CSP is simple. It concatenates multi-scale feature maps and fed them to the detection head. Two main innovations of CSP are the anchor-free structure and predicting the center heatmap, height ("scale" is used in the original work, however, we use "height" in case of confusion with feature map scale) map and the optional offsets w.r.t. the centers instead of the traditional bounding boxes. With no anchors applied, less hyper-parameters are required

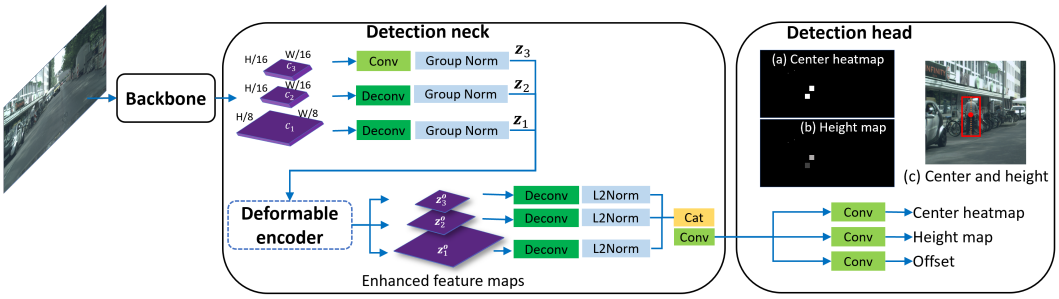

Figure 3: The overall architecture of the proposed advanced single-stage pedestrian detector. The input images are fed into the backbone, followed by the detection neck with a deformable encoder to enhance both the spatial and multi-scale information. The detection head is the same as CSP. **(a)**: The ground truth center heatmap highlights pedestrian centers with white squares. **(b)**: The ground truth height map contains the logarithm of heights. **(c)**: Sketch of the center (red node) and height (orange dotted line) ground truths and their relation to the bounding box (red box) depicted on part of the input image.

which simplifies training and design. The sample center and scale ground truths are shown in Figure 3. Centers of all pedestrians are assigned as positives in the center heatmap, while negatives for other positions. For the height map, these points are assigned with the logarithm of the object height.

Proposed Single-stage Detector with Enhanced Features: The proposed detector consists of the ResNet 50 backbone, the detection neck, and head as shown in Figure 3. The detection head predicts the center and scale (height) maps and offsets to slightly adjust the positions of pedestrians. The features are enhanced in the detection neck where we take the advantage of the deformable transformer encoder, particularly the embedded MSDA mechanism to supplement the spatially adaptive features across multiple scales. In the neck, input feature maps are first upsampled with deconvolutional layers or encoded with the convolutional layer to generated multi-scale feature maps $\{\boldsymbol{z}^l\}_{l=1}^3$. They are followed by group normalization to prevent the Internal Covariate Shift (ICS) that might be inducted by subsequent linear operations in the deformable encoder. The encoder yields enhanced multi-scale feature maps. Enhanced features are upsampled to keep the resolution as $(H/4, W/4)$ for accurate detection. They are normalized via L2Norm [21] before concatenation along the channel dimension. This makes the features at different scales contribute equally to the final feature representation fed into the detection head. Concatenated features are compressed along the channel dimension to reduce the network parameters. Compared to the architecture of CSP, the proposed detector adopts the novel multi-scale deformable attention mechanism in the detection neck. Other parts maintain the same except for an additional convolutional layer is applied in CSP detection head before the branches.

Training: Same ground truth and loss functions as [21] are utilized. The overall loss consists of three parts as:

$$L = \lambda_c L_{center} + \lambda_s L_{height} + \lambda_o L_{offset} \tag{3}$$

where the center heatmap loss L_{center}, height map loss L_{height} and offset loss L_{offset} are given in the supplementary. Weights for each loss λ_c, λ_s and λ_o are set as 0.01, 1 and 0.1 [21].

Inference: Predicted scores above 0.01 are kept. The predicted pedestrian centers are the summation of the offsets and positions of those qualified scores. The predicted width is the height multiplied by the uniform aspect ratio 0.41 [21]. The predicted sizes are remapped to the original image size and fed to NMS.

4 Experiments

4.1 Settings

Datasets: The proposed detector is evaluated on two commonly used public pedestrian datasets: **Caltech** [42] and **Citypersons** [43]. The Caltech dataset is an approximately 10 hours of 480x640 video taken in a single urban city. The standard training set contains about 250k frames with 350k bounding boxes. In our experiments, the training data augmented by 10 folds containing 42782

images with 13674 persons and the standard test set containing 4024 images with corresponding new annotations [44] and fixed aspect-ratio for bounding boxes [45] are used. Citypersons training set recorded across 18 different cities, 3 seasons and various weather conditions with 19654 persons in 2975 high resolution (1024x2048) images. The validation set contains 500 images across 3 cities.

Training Details: Our network is based on the CSP reproduction provided by Pedestron [45]. ResNet 50 pretrained on ImageNet, Adam with moving average weights [46] and step learning rate schedule are applied. Data augmentation techniques including random horizontal flip and scaling are applied. For Caltech, additional random color distortion and cropping are implemented. The input images are rescaled to 336x448 for Caltech and 640x1280 for Citypersons dataset. The proposed network is trained with a single NVIDIA GeForce RTX 3090 GPU for 10 and 75 epochs with batch size 16 and 4 on Caltech and Citypersons respectively. The learning rate and related hyperparameters will be presented afterwards according to different designs of architectures. All the training is performed with a randomly chosen and fixed seed.

Metrics: Log-average Miss Rate (denoted as MR^{-2} or miss rate in this paper) over False Positive Per Image (FPPI) in the range $[10^{-2}, 10^{0}]$ is calculated over Reasonable, Small, Heavy, and All subsets defined in Table 1. The lower the MR^{-2} the better.

Table 1: The experimental settings of four subsets.

Subset	Reasonable	Small	Heavy	All
Height	[50, inf]	[50, 70]	[50, inf]	[20, inf]
Visibility	[0.65, inf]	[0.65, inf]	[0.2, 0.65]	[0.2, inf]

4.2 Ablation studies

Feature Maps Scales: Different combinations of multi-scale feature maps $\{\boldsymbol{z}^l\}_{l=1}^{3}$ with three downsampling ratios ($1/4$, $1/8$ and $1/16$) are compared in Table 2. In this comparison, only $\boldsymbol{z}_3^o$ which has the same resolution as $\boldsymbol{z}^3$ upsampled to $(H/4, W/4)$,and is fed into the detection head without intermediate concatenation and L2Norm. Results show that feature maps with ratios $1/4$, $1/8$, and $1/6$ for each scale produce the best performance, which is yield by upsampling $\boldsymbol{c}_1$ and $\boldsymbol{c}_2$ by two times while maintaining the scale of $\boldsymbol{c}_3$.

Table 2: The experimental settings of four subsets.

$\boldsymbol{z}^1$	$\boldsymbol{z}^2$	$\boldsymbol{z}^3$	Reasonable	Heavy
1/4	1/8	1/16	**4.1**	**44.7**
1/4	1/16	1/16	4.2	45.9
1/8	1/8	1/16	4.6	48.5
1/4	1/8	1/8	5.9	47.8

Enhanced Feature Map Scales: Fix the downsampling ratios of $\{\boldsymbol{z}^l\}_{l=1}^{3}$ as $1/4$, $1/8$, and $1/16$, feed different collections of multi-scale enhanced feature maps $\{\boldsymbol{z}_l^o\}_{l=1}^{3}$ to the detection head. Note that the deformable encoder keeps the resolutions of the input feature maps, the downsampling ratios for $\{\boldsymbol{z}_l^o\}_{l=1}^{3}$ are $1/4$, $1/8$ and $1/6$ respectively. All the enhanced feature maps are first upsampled to $(H/4, W/4)$, if needed, followed by normalization when multiple feature maps are utilized. They are then processed in three ways: 1. Cat: Concatenate them along the channel dimension followed by a compression layer to reduce the number of channels to 256. 2. Add: Implement elementwise sum of the enhanced feature maps. 3. Sep: No fusion operations across multi-scales; send them separately to the detection head which doubles the number of predictions. Table 3 compares various strategies to fuse the multi-scale enhanced feature maps. It shows that concatenation followed by L2Norm produces the overall best results in both Reasonable and Heavy subsets on Caltech test set.

Choice of the Normalization Method Applied to $\{\boldsymbol{c}^l\}_{l=1}^{3}$: As Table 3 shows, GN performs best in Reasonable subset while L2N in Heavy subset. Considering that the miss rate of GN is 11.6% lower in Reasonable subset and only 1.2% higher in Heavy subset compared to L2N, GN is utilized in our experiments as the blue blocks above enhanced feature maps in Figure 3 indicate.

Table 3: Combinations of enhanced feature maps with different scales in different ways followed by three Normalization Methods (NM). L2N, LN and GN stand for L2Norm, Layer Normalization and Group Normalization respectively. [1] train boldly without any learning rate schedules. [2] Normalization methods applied to the enhacned feature maps after upsampling. [3] Normalization methods applied to the feature maps produced by the backbone before sent to the encoder.

z_1^o	✓			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
z_2^o		✓												✓
z_3^o			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cat							✓	✓	✓	✓	✓	✓	✓	✓
Add				✓	✓									
Sep						✓								
NM[2]					L2N	L2N		GN[1]	LN[1]	L2N[1]	L2N	L2N	L2N	L2N
NM[3]	GN	GN	GN	GN	GN	GN	GN	GN	GN	GN	GN	L2N	BN	GN
Reasonable	4.3	5.7	4.1	7.0	**3.7**	4.2	5.9	6.4	4.0	3.9	**3.7**	4.3	4.5	5.3
Heavy	44.5	48.8	44.7	51.3	45.5	48.1	50.7	49	47.4	44.5	42.8	**42.6**	44.6	44.1

Number of Encoders: Based on the settings in the last part, different numbers of encoders are tested. These encoders are connected in series. Table 4 presents that although more encoders can provide higher level semantic information, the best result is observed when only a single encoder is applied. This phenomenon supports the design of BotNet [39] to some extent, which indicates that following the whole set of six encoder-decoder pairs in (deformable) DETR may not be suitable for specific object detection tasks. A single encoder can also work effectively with least number of learnable parameters, which prevents overfitting.

Table 4: Using 1 to 4 encoders in the detection neck.

Number of encoders	1	2	3	4
Reasonable	**3.7**	4.9	4.8	5.5
Heavy	**42.8**	46.6	43.1	45.1

Importance of Enhanced Feature Maps: We evaluated the baseline CSP detector and the proposed detector which improves CSP by adopting the deformable encoder-based feature enhancement module in the detection neck. Both the single and concatenated enhanced feature map(s) are assessed. Evaluation is conducted on Caltech (Table 5) and Citypersons (Table 6) respectively. Results from both datasets indicate that with the enhanced feature map(s), the miss rates are decreased significantly in Reasonable, Heavy and All subsets, in particular, the Heavy subset witnesses a decrease up to 7.9%, and Reasonable subset up to 3.1%. This means that the idea of extracting spatially adaptive features works effectively for the single-stage detector. With the concatenation of multi-scale enhanced feature maps (third row), the performance is further improved comprehensively on Caltech dataset compared to the single feature map (second row). This owes to the deformable sampling locations and attention weight maps allowing to adaptively extract useful features, such as visible features, for the task. Furthermore, the feature map at scale 1 focuses on the visible part of the pedestrian when the reference point locates on the visible part of the target, complementing the lack of occluded target's information with the sole use of the feature map at scale 3 as shown in the supplementary. Due to the additional interpolation operation in the deformable self-attention layer, the proposed detectors require longer inference time compared to the baseline, however, they contain less learnable parameters as shown in Table 7.

Table 5: Comparison of the baseline CSP detector and the proposed detectors with enhanced features and additional concatenated feature maps on Caltech test set. FPS stands for frames per second evaluated during test process with input size 480x640.

	Reasonable	Heavy	All	FPS
Baseline	6.8	50.7	62.3	39.2
+Enhanced feature	4.1 (2.7↓)	44.7 (6.0↓)	57.9 (4.4↓)	32.1
++Cat z_1^o,z_3^o	3.7 (3.1↓)	42.8 (7.9↓)	56.97 (5.3↓)	29.5

Table 6: Comparison of the baseline CSP detector and the proposed detectors with enhanced features and additional concatenated feature maps on Citypersons validation set. FPS stands for frames per second. FPS stands for frames per second evaluated during test process with input size 1024x2048.

	Reasonable	Small	Heavy	All	FPS
Baseline	11.7	14.4	41.8	38.2	8.2
+Enhanced feature	10.6 (1.1↓)	14.9 (0.5↑)	36.7 (5.1↓)	36.4 (1.8↓)	7.3
++Cat z_1^o,z_3^o	10.9 (0.8↓)	13.7 (0.7↓)	38.6 (3.2↓)	37.2 (1.0↓)	6.8

Table 7: The number of learnable parameters in the baseline and proposed detectors.

	Backbone	Neck	Head	Total Param
Baseline	23.51M	14.68M	1.77M	39.96M
+Enhanced feature		8.60M	1.03K	32.11M
++Cat z_1^o,z_3^o		8.73M		32.24M

4.3 Comparison with the state-of-the-arts

We compared two proposed architectures, namely the single enhanced feature map z_3^o and the concatenation of z_3^o and z_1^o, with the state-of-the-art single- and two- stage detectors on Caltech and Citypersons datasets. Proposed detectors are trained with the hyperparameters presented in Table 8. Table 9 and Table 10 show that the proposed detectors achieve lowest miss rates in Reasonable and Heavy subsets and leading performance in All subset on both datasets among presented single-stage detectors.

Table 8: Hyperparameters for training the proposed detectors on Caltech and Citypersons datasets respectively. The training starts from the base learning rate l_r which drops to $r\times$ after s epochs.

Dataset	Type	l_r	s	r
Caltech	Single	1e-4	5	0.2
	Cat	0.5e-4	6	0.5
Citypersons	Single	2e-4	40	0.4
	Cat	0.5e-4	60	0.5

For Caltech dataset, the lowest miss rate (3.7%) of the proposed detector in Reasonable subset is 0.2% smaller than that of the two-stage KGSNet presented in the upper part of Table 9. With pretraining on Citypersons dataset, the miss rates on all three subsets of Caltech dataset are reduced significantly and reach the lowest compared to other pretrained detectors as shown in the bottom part of Table 9. For Citypersons dataset, the proposed two detectors even outperform the competitive two-stage detectors in Reasonable and especially Heavy subset with miss rate 36.7% which is 3% lower than that of the best of two-stage detectors.

Overall, it can be observed that with the enhanced spatially adaptive and multi-scale features, the gap between single- and two- stage detectors in Reasonable and Heavy subsets on different detectors has been narrowed. Surprisingly, the proposed single-stage method can produce better results than accurate two-stage methods on certain pedestrian dataset, such as Citypersons dataset. Therefore, our enhanced single-stage pedestrian detector not only predicts quickly, but also achieves accuracy comparable to complicated two-stage methods.

5 Conclusion

The paper proposes a single-stage anchor-free pedestrian detector with enhanced spatial and multi-scale features. This is fulfilled by the combination of deformable self-attention mechanism and Center and Scale Prediction (CSP). Comprehensive experiments over the architecture design in the detection neck and comparison with the state-of-the-arts are performed. More than 40% parameters are reduced in the detection neck compared to CSP; however, this detector still achieves the best

Table 9: Comparison with the state-of-the-art single- and two- stage pedestrian detectors on Caltech test set. † Results are cited from [21] for completeness. * Concatenated enhancned feature maps. Bottom part: Pretrained on Citypersons and tested on Caltech. Best and second-best results are in bold and underlined with red for two-stage methods (upper part) and black for single-stage methods.

Method	Backbone	Stage	Reasonable	Heavy	All
Faster R-CNN† [17]	ResNet50	2	8.7	53.1	62.6
ALFNet† [20]	ResNet50	1	8.1	51.0	59.1
RPN+BF† [47]	VGG16	2	7.3	54.6	59.9
RepLoss† [14]	ResNet50	2	5.0	47.9	59.0
CSP [21]	ResNet50	1	4.5	45.8	**56.9**
KGSNet [25]	ResNet50	2	3.9	**34.2**	**42.2**
JointDet [48]	ResNet50	2	3.0	-	-
PedHunter [10]	ResNet50	2	**2.3**	-	-
Proposed	ResNet50	1	4.1	44.7	57.9
Proposed*	ResNet50	1	**3.7**	**42.8**	56.97
ALFNet† [20]	ResNet50	1	4.5	43.4	56.8
RepLoss† [14]	ResNet50	2	4.0	41.8	58.6
CSP [21]	ResNet50	1	3.8	36.5	54.4
Proposed	ResNet50	1	3.2	32.2	56.5
Proposed*	ResNet50	1	**2.6**	**28.0**	**53.9**

Table 10: Comparison with the state-of-the-art pedestrian detectors on Citypersons validation set. * Concatenated enhancned feature maps. † Results are cited from [21] for completeness.[1] Less than 65% visibility instead of 20-65% visibility. Best and second-best results are in bold and underlined with red for two-stage methods and black for single-stage methods.

Method	Backbone	Stage	Reasonable	Heavy	All
FRCNN† [43]	VGG16	2	15.4	-	-
FRCNN+Seg†[43]	VGG16	2	14.8	-	-
TLL+MRF [22]	ResNet50	1	14.4	52.0	-
OR-CNN [15]	VGG16	2	12.8	55.7[1]	-
RepLoss [14]	ResNet50	2	13.2	56.9[1]	-
ALFNet [20]	ResNet50	1	12.0	51.9	-
CSP [21]	ResNet50	1	11.0	49.3	-
PRNet [23]	ResNet50	1	10.8	42.0	-
MGAN+ [49]	VGG16	2	**11.0**	**39.7**	-
KGSNet [25]	ResNet50	2	**11.0**	**39.7**	**36.2**
Proposed	ResNet50	1	**10.6**	**36.7**	36.4
Proposed*	ResNet50	1	10.9	38.6	37.2

results in Reasonable and Heavy subsets among presented single-stage detectors on both Caltech and Citypersons datasets. With pretraining, the miss rates for these subsets can be decreased to 2.6% and 28.0% which are far better than other single-stage methods and comparable to two-stage methods. It even outperforms SOTA two-stage detectors in Heavy subset by 3% on Citypersons. The proposed detector significantly improves the accuracy of the single-stage method with slightly decreased inference speed. These demonstrate that single-stage detectors can do better if spatially adaptive and multi-scale features are jointly adopted, thus making them cost-effective and promising. It should be mentioned that, false positives are introduced if the attention points of a negative reference point extend to the target areas. Although the performance has been improved with current deformable transformer, the generation of attention weights and sampling locations can be carefully designed to suppress the false positives for further improvements.

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   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
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