Improving Crowded Object Detection via Copy-Paste

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Abstract
Crowdedness caused by overlapping among similar objects is a ubiquitous challenge in the field of 2D visual object detection. In this paper, we first underline two main effects of the crowdedness issue: 1) IoU-confidence correlation disturbances (ICD) and 2) confused de-duplication (CDD). Then we explore a pathway of cracking these nuts from the perspective of data augmentation. Primarily, a particular copy-paste scheme is proposed towards making crowded scenes. Based on this operation, we first design a “consensus learning” strategy to further resist the ICD problem and then find out the pasting process naturally reveals a pseudo “depth” of object in the scene, which can be potentially used for alleviating CDD dilemma. Both methods are derived from magical using of the copy-pasting without extra cost for hand-labeling. Experiments show that our approach can easily improve the state-of-the-art detector in typical crowded detection task by more than 2% without any bells and whistles. Moreover, this work can outperform existing data augmentation strategies in crowded scenario.

Introduction
The task of object detection has been meticulously studied for quite a long time. In the deep learning era, in recent years, many well-designed methods (Liu et al. 2020a) have been proposed and raised the detection performance to a surprisingly high level. Nevertheless, there still exist many intrinsic problems that are not fundamentally solved. One of them is the “crowdedness issue”, which usually denotes the phenomenon that objects belonging to the same category are highly overlapped together. In a geometrical manner, the basic difficulty stems from the semantical ambiguities of the 2D space. As shown in Fig. 1, in our 3D world, each voxel has its “unique semantics” and lies on a “certain object”. However, after projecting to 2D plane, one pixel might fall on several collided objects. After evolving the concept from a “pixel” to a “box”, the semantical ambiguity in crowded scenes leads to the notion of overlap.

To probe the effects of this problem, we now dive into the essence of the detection paradigm. Generally, an object detector reads in an image and outputs a set of bounding-boxes each associated with a confidence score. For an ideally-performed detector, the score value should convey how well the predicted box is overlapped with the ground-truth. In other words, the Intersection-over-Union (IoU) between these two boxes should be positively correlated with the confidence score. After visualizing the mean and standard deviation of scores with respect to IoU in Fig. 2, it turns out that even for the off-the-shelf detectors like (He et al. 2017), this positive correlation would be gradually disturbed by the increase of crowdedness degree\(^1\). This experimental study clearly indicates the struggle of current detection algorithms in facing the super-heavy overlaps. We embody this effect as IoU-confidence Correlation Disturbances (ICD). On the other hand, a typical detection pipeline often ends with a de-duplication module, for example, the widely adopted Non-Maximum Suppression (NMS). Due to the 2D semantical ambiguity mentioned previously, these modules are often confused by heavily overlapped predictions, which leads to severe missing in a crowd. We cast this type of effect as Confused De-Duplication (CDD).

To overcome these two obstacles, we explore a pathway

\(^1\)The crowdedness degree is indicated in terms of “occlusion ratio”, \(i.e., 1 - \frac{s_v}{s_f}\), where the \(s_v\) and \(s_f\) represent size of the visible box and full box of an object.
Figure 2: IoU-confidence correlation disturbances (ICD). We visualize the confidence score w.r.t the IoU between the predicted box from (He et al. 2017) and ground-truth in CrowdHuman (Shao et al. 2018). First, the IoU range of $[0, 1]$ are equally divided into 100 bins (each with the length of 0.01) as the horizontal axis. Then, average value (left) or standard deviation (right) of confidence scores are computed within each bin, generating a corresponding point in the coordinate plane. Marker shapes of diamond (red), pentagon (green) and circle (blue) refer to crowdedness degrees with the occlusion ratio on three ranges of $[0, 0.33]$, $[0.33, 0.66]$ and $[0.66, 1]$ respectively. On the left figure, the average score curve corresponding to the most crowded range (blue) are obviously more jittering than the other two curves; On the right figure, the heavier the crowdedness is, the larger the standard deviations are. Both figures suggest that the IoU-confidence correlation would become more uncertain when the crowdedness increases.

from the perspective of data augmentation. Referring to the preceding works (Ghiasi et al. 2021; Dwibedi, Misra, and Hebert 2017; Li et al. 2021; Dvornik, Mairal, and Schmid 2018; Fang et al. 2019), a simple copy-paste variant is proposed. Firstly, object segmentation patches are pasted to the training images following some specialized rules dedicated for making crowded scenes. Then, revolved from copy-pasting, we design a “consensus learning” approach to align confidence distributions of overlaid objects to their identical but non-overlaid counterparts, which further restrains the ICD problem. Moreover, thanks to the program-controlled pasting process, we can naturally get the extra order information of which one is in the front and which one is in the back when two (pasted) objects are overlapped. This cost-free knowledge provides cues on the additional third dimension of depth apart from $x$ and $y$-axis spanning the image plane, which can be deemed as a breakthrough of the aforementioned 2D restrictions inducing the CDD dilemma. From this motivation, we propose a concept named “overlay depth” and semi-supervisely train the detector to predict this label. Then, an Overlay Depth-aware NMS (OD-NMS) is introduced to make use of the depth knowledge during de-duplication. Experiments show that this strategy can help distinguish boxes gathered in 2D space and further boost the detection results.

We evaluate our method from multiple aspects. As a data augmentation strategy, this work can outperform other counterparts in crowded scenes, no matter hand-craft methods or automated ones. As an approach of countering crowdedness issue, our method can stably improve the state-of-the-art detector by more than 2% without any bells and whistles. Moreover, since hand-labeling the crowded data is resource-consuming, this method provides a way of training on “sparse data” only and applying to crowded scenes via data augmentation.

To sum up, the major contributions of this work are two-fold: (1) We propose a crowdedness-oriented copy-paste scheme and introduce a consensus learning strategy, which effectively helps the detector resisting the ICD problem and bring improvements in crowded scenes. (2) We design a simple method to utilize the weak depth knowledge produced by the pasting process, which further optimize the detector.

Related Works

Crowded Object Detection. Detecting objects in crowded scenes has been a long-standing challenge (Liu et al. 2020a) and much effort has been spent on this topic. For example, (Wang et al. 2018) and (Zhang et al. 2018) propose specific loss functions to constrain proposals closer to the corresponding ground-truth and further away from the nearby objects, thereby enhancing discrimination between overlapped individuals. CaSe (Xie et al. 2020) uses a new branch to count pedestrian number in a region of interest (RoI) and generates similarity embeddings for each proposal. As a response to the CDD problem mentioned above, a group of works focuses on alleviating the deficiency of Non-Maximum Suppression (NMS). Adaptive-NMS (Liu, Huang, and Wang 2019) introduces an adaptation mechanism to dynamically adjust the threshold in NMS, leading to better recall in a crowd. In (Gähler et al. 2020) and (Huang et al. 2021), NMS leverages the less-occluded visible boxes to guide the selection of full boxes, whereas extra labeling (of the visible boxes) is required. CrowdDet (Chu et al. 2020) conducts one proposal to make multiple predictions and uses an artfully designed Set-NMS to solve heavily-overlapped cases. Some recent works explore other ways. (Zhang et al. 2021) models the pedestrian detection task as a variational inference problem. (Zheng et al. 2022) refines the end-to-end detector Sparse R-CNN (Sun et al. 2021) to adapt to the crowded detection scenario.

Data Augmentation in Object Detection. In the field of computer vision, data augmentation (Shorten and Khoshgoftaar 2019) has long been used to optimize the model training, which originates mainly from the image classification task (He et al. 2016; Tan and Le 2019). Early approaches usually include strategies such as color shifting (Szegedy et al. 2015) and random crop (Krizhevsky, Sutskever, and Hinton 2012; LeCun et al. 1998; Simonyan and Zisserman 2015; Szegedy et al. 2015). Naturally, the core ideas were transferred to the detection domain and some operations (e.g., image flipping and scale jittering) have been widely adopted as a standard module (Liu et al. 2016; Redmon et al. 2016; Ren et al. 2015). Currently, methods with more concrete theoretical basis have emerged. These variants, ranging from hand-crafted Cutout (Devries and Taylor 2017), Mixup (Zhang et al. 2017) and CutMix (Yun et al. 2019) to learning based AutoAugment (Cubuk et al. 2018), Fast AutoAugment (Lim et al. 2019) and RandAugment (Cubuk et al. 2020), perform considerable effects on image clas-
sification and suggest also some potential in object detection. Meanwhile, there are also some works focusing on detection task. Stitche (Chen et al. 2020) and YOLOv4 (Bochkovskyi, Wang, and Liao 2020) introduce mosaic inputs containing rescaled image patches to enhance robustness. (Zoph et al. 2020) and (Chen et al. 2021) re-design the AutoAugment scheme to adapt to object detection. In (Tang et al. 2021), researchers propose a method searching the policy of data augmentation and loss function jointly. In (Liu et al. 2020b), a novel APGAN is proposed to transfer pedestrians from other datasets in making augmentation.

Copy-Paste Augmentation. Copy-paste augmentation is first invented in (Dwibedi, Misra, and Hebert 2017). By cutting object patches from the source image and pasting to the target one, a combinatorial amount of synthetic training data can be easily acquired and improve the detection/segmentation performance significantly. This amazing magic power is then verified by subsequent works (Remez, Huang, and Brown 2018; Li et al. 2021; Fang et al. 2019; Dvornik, Mairal, and Schmid 2018; Ghiasi et al. 2021) and the method has been further polished by context adaptation (Fang et al. 2019; Remez, Huang, and Brown 2018; Dvornik, Mairal, and Schmid 2018). In (Ghiasi et al. 2021), the authors claim that simple copy-paste can bring considerable improvement as long as the training is sufficient enough. Their experiments further suggest the potential of this augmentation strategy on instance-level image understanding. It should be noted that the initial motivation of copy-paste is to diversify the sample space, especially for the rare categories (Ghiasi et al. 2021) or alleviating the complex mask labeling (Remez, Huang, and Brown 2018). However, in our work, we utilize this operation to precisely solve the crowdedness issue. Although there has been simple practice in previous works (Dwibedi, Misra, and Hebert 2017; Ghiasi et al. 2021), the actual effects of this strategy on dealing with crowdedness scenario has never been systematically designed and studied.

Resist the IoU-Confidence Disturbances
This part focuses on solving the IoU-Confidence Disturbances (ICD). We explore two consecutive ways in achieving this aim. First, doing copy-paste to make crowded scenes. Then, introducing consensus learning between overlaid objects and their non-overlaid counterparts, which relies on the copy-pasting.

Crowdedness Oriented Copy-Paste
Based on observations of Fig. 2, an intuitive idea is to make more crowded cases to dominate the training. To this end, we carefully re-design the copy-paste strategy. First, the conception of “group” is introduced. An image should include several groups and each group consists of multiple heavily overlapped objects. Following this logic scheme, we first generate the group centers on an image and then paste objects around them.

Formally, for every training image to be augmented, we initialize a set $\mathcal{C}$ of “group centers”:

$$\mathcal{C} = \{(x_1, y_1, s_1), \ldots, (x_{|\mathcal{C}|}, y_{|\mathcal{C}|}, s_{|\mathcal{C}|})\},$$

where each tuple represents the object locating at center of the corresponding group $(x_i, y_i$ and $s_i$ denote the coordinates and normalized object size respectively). We obtain these group centers by sampling from original objects on the current image. The group number $|\mathcal{C}|$ is randomly chosen from an integral range of $[0, N]$, where $N$ is a hyper parameter.

The second step is pasting objects around these group centers. For each $c_i \in \mathcal{C}$, we should generate a set $\hat{\mathcal{G}}_i$ of objects in the group $i$:

$$\hat{\mathcal{G}}_i = \{(\hat{x}_1^i, \hat{y}_1^i, \hat{s}_1^i), \ldots, (\hat{x}_|\hat{\mathcal{G}}_i|, \hat{y}_|\hat{\mathcal{G}}_i|, \hat{s}_|\hat{\mathcal{G}}_i|)\},$$

similarly, object number $|\hat{\mathcal{G}}_i|$ in the group comes from range $[0, M]$ where $M$ is another hyper parameter. Since the nature of crowdedness is “overlapping”, every $\hat{g}_j^i \in \hat{\mathcal{G}}_i$ is enforced to be overlapped with the group center object $c_i$. We manipulate the overlapping from three aspects of the $x$, $y$ and $s$ conditioning in a probabilistic sense.

First, objects in a group usually have similar sizes. Let $p(\hat{s}_j^i | s_i, I)$ be the probability density function of $\hat{s}_j^i$ on conditions of the center object size $s_i$ in the image $I$. We choose $p(\cdot)$ to be a Gaussian as:

$$p(\hat{s}_j^i | s_i, I) = \frac{1}{\sqrt{2\pi\sigma}} \exp(-\frac{(\hat{s}_j^i - s_i)^2}{2\sigma^2}), \quad (1)$$

where $\sigma$ is the standard deviation which a constant value 0.2 is used in this paper. To guarantee overlapping, we adopt two independent uniform distributions in modeling the coordinate values $\hat{x}_j^i$ and $\hat{y}_j^i$:

$$\hat{x}_j^i \sim U(x_i - \frac{d_w}{\tau}, x_i + \frac{d_w}{\tau}), \quad (2)$$

$$\hat{y}_j^i \sim U(y_i - \frac{d_h}{\epsilon}, y_i + \frac{d_h}{\epsilon}), \quad (3)$$

where $d_w$ and $d_h$ are the maximum distances of $\hat{g}_j^i$ shifting from group center $c_i$ with overlap. Coefficients $\tau > 1$ and $\epsilon > 1$ are used to adjust the crowdedness degree.

During training, for every image loaded, the set $\mathcal{C}$ and $\hat{\mathcal{G}}_i$'s are generated obeying rules above. Then object segmentation patches would be sampled, re-scaled and pasted to the image accordingly.

Consensus Learning
With the toolkit of copy-pasting, we augment detector training with a dedicated strategy for resisting the ICD issue. Given the observation shown in Fig. 2 that the instability of predicted scores derives from crowdedness, an emerging fix is to align the score of an object in crowded circumstances (overlaid by other objects) to that when it is not overlaid. Thanks to the copy-paste method, we can easily generate this type of object pairs in which two identical objects lie in different surroundings. Fig. 3 illustrates our idea. Following the previous data augmentation, we pick out a set $\mathcal{B}_{ovl}$ of objects which are overlaid by others. Then, the same object patches with those in $\mathcal{B}_{ovl}$ are re-pasted to the image without being overlaid, constructing another set $\mathcal{B}'_{ovl}$. During training, we enforce the predicted score distributions of each object $b_t \in \mathcal{B}_{ovl}$ in an alignment with its counterpart $b'_t \in \mathcal{B}'_{ovl}$.
We term this process as consensus learning by drawing an analogy of “reaching consensus” within each pair. Specifically, let $P_i$ be the set of proposals matched to $b_i$ and $P^*_i$ be the set of proposals matched to $b^*_i$. We first compute the mean $\mu$ and standard deviation $\sigma$ of scores for each object:

$$\mu_i = \frac{1}{m} \sum_{p_{ij} \in P_i} c(p_{ij}), \quad \sigma_i = \sqrt{\frac{1}{m} \sum_{p_{ij} \in P_i} (c(p_{ij}) - \mu_i)^2}, \quad (4)$$

$$\mu^*_i = \frac{1}{m^*} \sum_{p^*_{ij} \in P^*_i} c(p^*_{ij}), \quad \sigma^*_i = \sqrt{\frac{1}{m^*} \sum_{p^*_{ij} \in P^*_i} (c(p^*_{ij}) - \mu^*_i)^2}, \quad (5)$$

where $m$ and $m^*$ are the sizes of $P_i$ and $P^*_i$ respectively and $c(\cdot)$ denotes the predicted confidence score of a proposal. Then we pursue a pair of $\{\mu_i, \sigma_i\}$ approaching $\{\mu^*_i, \sigma^*_i\}$ through the mean squared error (MSE) loss:

$$L_{cl} = \frac{1}{|B_{ovl}|} \sum_{b_i \in B_{ovl}} (\mu_i - \mu^*_i)^2 + (\sigma_i - \sigma^*_i)^2. \quad (6)$$

It is worth to point that only the overlaid half $\{\mu_i, \sigma_i\}$ contributes to the gradient back-propagation while the non-overlaid half (marked by $\ast$) is treated as target.

**Analyze the IoU-Confidence Disturbances**

Now we analyze the effectiveness of our method on mitigating the aforementioned ICD issue. To revisit the original motivation raised from the right of Fig. 2, we plot the standard deviation (STD) of scores in Fig. 4. First, it is clearly demonstrated that score STDs of the model trained with our Crowdedness-oriented Copy-Paste (CCP) are obviously lower than those of the baseline model (BL) and the gap becomes larger by improving the crowdedness degree (from Fig. 4-(a) to (d)). Second, although the curves of CCP and CCP+CL seems with no clear distinction, after computing their average STDs (the four histograms in Fig. 4), we find the value of the latter is actually lower than that of the former. Moreover, we plot another model augmented with random copy-paste (RCP) without specially taking crowdedness into consideration. It is obvious that the decline of score STDs is with a much smaller margin. These observations convince that our method can significantly improve the detector’s robustness in crowded scenes and therefore alleviate the ICD problem.

**Alleviate the Confused De-Duplications**

Our augmentation strategy has a natural by-product: for those overlapped objects pasted, the relative “order of depth” is known a priori. In other words, we are aware of which one is in the front and which one is in the back. Now let us return to the semantical ambiguity described in our introduction. Basically, ambiguities in 2D space are caused by the absence of one dimension in the real (3D) world. From this point of view, the depth order can be viewed as some weak knowledge of the additional third dimension, which sheds light on mitigating the vagueness. As a feasible practice, in this work, we utilize the depth order information to resolve the confused de-duplication (CDD) problem.

First, we introduce a variable named “overlay depth” (OD) that depicts the extent of how an object is visually overlaid by others. Fig. 5 demonstrates the process of calculating OD. We start by assuming that the overlay depth of an object equals to 1.0 if there are no other objects covering it. Let $ovl(b_1, b_2)$ be the region of object $b_1$ overlaid by object $b_2$ and $S(\cdot)$ denote the size of a region. For any object $b_i$ in the image, there exists a set $O_i$ of objects overlaying $b_i$:

$$O_i = \{b_j \in B|b_j \neq b_i, S(ovl(b_i, b_j)) > 0\}, \quad (7)$$

where $B$ is the set of all objects in current image. Then, the OD value of $b_i$ can be clearly defined:

$$od_i = 1.0 + \frac{1}{S(b_i)} \sum_{b_j \in O_i} S(ovl(b_i, b_j)). \quad (8)$$

Therefore, the severer an object is occluded by others (objects of the same category), the higher OD value it would be assigned (such as objects $b_1$ and $b_2$ in Fig. 5). Starting from this property, application of the overlay depth is based on a plausible observation: two heavily overlapped objects usually lie in different depth, or more specifically, hold distinct OD values. So by taking extra knowledge from the axis of depth, the OD value can be adopted during de-duplication in a confused 2D plane.
Figure 5: Definition of overlay depth (OD). Calculation process of the OD value as defined in Eq.(8). Boxes of $b_1$, $b_2$ and $b_3$ are three overlapped objects (skaters), in which $b_2$ is overlaid by $b_3$ only while $b_1$ is overlaid by both $b_2$ and $b_3$.

Now we enable the detector to predict the OD values. Generally, a detection model takes a branch to regress the coordinates of the bounding-box. Following this design, we add an extra predictor to the branch in taking responsibility for the OD regression. This modification incurs neglectable computing burden and can be easily implemented in both one-stage and two-stage structures (refer to the Appendix for details). During training, a common L2 loss is adopted.

Algorithm 1: Overlay Depth-aware NMS

Input: $B = \{b_1, ..., b_N\}$: All boxes; $S = \{s_1, ..., s_N\}$: Scores; $th_{iou}$: IOU threshold.

$D \leftarrow \emptyset$

while $B \neq \emptyset$ do

$m \leftarrow \text{argmax}\{S\}$

$M \leftarrow b_m; D \leftarrow D \cup M; B \leftarrow B - M$

for $b_i$ in $B$ do

$th_{od} = \delta \cdot e^{\psi \cdot IoU(M, b_i)}$

if $IoU(M, b_i) \geq th_{iou}$ and $|od_i - od_m| \leq th_{od}$ then

$B \leftarrow B - b_i; S \leftarrow S - s_i$

end if

end for

end while

During inference, we invent a novel de-duplication strategy named Overlay Depth-aware NMS (OD-NMS). In the original NMS pipeline, boxes are recursively compared with each other and one would be suppressed in each step if the IoU exceeds a threshold $th_{iou}$. Following this scheme, objects might be de-duplicated by mistake in a crowded scenario. In our OD-NMS, for difficult scenario where IoU is higher than $th_{iou}$, we integrate the predicted OD value into a more comprehensive decision. If the two objects are in different depth, i.e., the absolute difference of the two OD values is higher than a predefined threshold $th_{od}$, we can cancel the suppression in the current step. Empirically, ambiguous cases often raise in the range of large IoU: when two boxes are more heavily overlapped, we need stricter OD threshold to judge if they are distinct objects. So we design a dynamic threshold of OD with respect to the IoU value:

$$th_{od} = \delta \cdot e^{\psi \cdot IoU},$$

where $\delta$ and $\psi$ are constant coefficients.

Algorithm 1 summarizes the whole process. In this way, objects in a crowded scenario can be effectively recalled instead of being inappropriately de-duplicated. This strategy can be viewed as an evolution of the original NMS with comparable time complexity.

**Experiment**

**Datasets.** Pedestrian detection is the most typical task burdened by the crowdedness problem, so our experiments are conducted mainly on two datasets: CrowdHuman (Shao et al. 2018) and CityPersons (Zhang, Benenson, and Schiele 2017). Annotations in these datasets consist of a full box and a visible box for each person, in which we only adopt the full ones to make the data crowded enough. Since both the training and validation data hold the same level of crowdedness, we prepare another “sparse training set” by re-labeling full body box of persons in COCO (Lin et al. 2014) to further evaluate the potential of our method. We name this train set as COCO-fullperson (we will release this dataset). Moreover, we use the category of “car” in KITTI (Geiger, Lenz, and Urtasun 2012) to further estimate the generality.

**Augmentation Details.** For pasting instance generation, we choose the open source Mask R-CNN (He et al. 2017) model adopting ResNet-50 (He et al. 2016) as backbone. We run this model on the train set and select 1000 instances with only three rough criteria: high confidence, relatively large size and not been occluded. A group of fixed hyper parameters are used in our experiments, where sample numbers $N = 3$ and $M = 5$, shifting coefficients $\tau = 4$, $\epsilon = 2$ and OD-NMS coefficient $\delta = 0.001$, $\psi = 10$. Copy-paste augmentation strategies are processed online within each training step, along with the generation of the semi-supervised OD ground-truths according to Eq.(8). We start consensus learning at the 10-th epoch during training.

**Experimental Settings.** We conduct experiments on both two-stage and one-stage detection frameworks. For two-stage structure, we use the standard Faster R-CNN (Ren et al. 2015) with FPN (Lin et al. 2017a). For one-stage structure, we choose RetinaNet (Lin et al. 2017b) as a representative. All those detectors use ResNet-50 as backbone. We train the networks on 8 Nvidia V100 GPUs with 2 images on each GPU. We also apply our method to the state-of-the-art
pedestrian detectors CrowdDet (Chu et al. 2020) and ProgS-RCNN (Zheng et al. 2022). Other training details will be reported in the following subsections.

**Results on CrowdHuman**

Three metrics are used to evaluate results on CrowdHuman: the log-average miss rate on False Positive Per Image (FPPI) in the range of $[10^{-2}, 10^0]$ (shortened as MR$^{-2}$, lower is better), the Average Precision (AP@0.5, higher is better) and the Jaccard Index (JI, higher is better), among which the MR$^{-2}$ is the main indicator. To make our experiments convincing enough, we use very strong baselines (the Baseline$^+$s in Table 1), which are 8%-12% superior than those in the CrowdHuman paper (Shao et al. 2018). During training, the short side of each image is resized to 800 and the long side is limited within 1400. Models are trained for 60k iterations starting from an initial learning rate of 0.02 (Faster R-CNN) or 0.01 (RetinaNet) and is reduced by 0.1 on 30k and 40k iters respectively. Table 1 compares results of our method (CrowdAug) with other approaches. First, the widely used Mosaic augmentation (Bochkovskiy, Wang, and Liao 2020) leads to a decline. This phenomenon is mainly attributed to the fact that in CrowdHuman, many boxes extend across image boundary. After the mosaic operation, these near-boundary boxes are truncated at the joints of image patches, losing original characteristics. We also make trials of two automated strategies: the Random-Augmentation (RandAug) (Cubuk et al. 2020) and the Scale-Aware Auto-Augmentation (SAutoAug) (Chen et al. 2021). It needs to be noted that in these works, the search space does not include policies in dealing with crowded scene, which we hypothesize is the main reason of their marginal effects.

<table>
<thead>
<tr>
<th>Aug Method</th>
<th>MR$^{-2}$</th>
<th>AP@0.5</th>
<th>JI</th>
<th>Faster R-CNN</th>
<th>MR$^{-2}$</th>
<th>AP@0.5</th>
<th>JI</th>
</tr>
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<tbody>
<tr>
<td>Baseline</td>
<td>50.42</td>
<td>84.95</td>
<td>-</td>
<td></td>
<td>53.51</td>
<td>85.30</td>
<td>77.21</td>
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<tr>
<td>Baseline$^+$</td>
<td>42.46</td>
<td>87.07</td>
<td>79.77</td>
<td>Faster R-CNN + Ours</td>
<td>50.12</td>
<td>86.40</td>
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<td>Mosaic</td>
<td>43.71</td>
<td>85.21</td>
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<td>RetinaNet</td>
<td>59.45</td>
<td>80.86</td>
<td>74.22</td>
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<tr>
<td>RandAug</td>
<td>42.17</td>
<td>87.48</td>
<td>80.40</td>
<td>RetinaNet + Ours</td>
<td>56.80</td>
<td>81.42</td>
<td>75.30</td>
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<tr>
<td>SAutoAug</td>
<td>42.13</td>
<td>87.64</td>
<td>80.39</td>
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<tr>
<td>SimCP</td>
<td>41.88</td>
<td>87.36</td>
<td>79.53</td>
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<td>CrowdAug (Ours)</td>
<td>40.21</td>
<td>88.61</td>
<td>81.41</td>
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Table 1: Results on CrowdHuman val set. The Baseline$^+$ denotes newly trained strong baselines. Results are in percentage (%).

We also train the detector on the “sparse” dataset COCO-fullperson and report results on the “crowded” CrowdHuman val set in Table 2. Since training samples are generally not crowded, the CrowdAug can bring significant improvement (more than 3% in MR$^{-2}$). These results suggest that our method can largely help the detector to handle crowded scenes when there is limited or even no crowded data available for training.

### Ablation Study

**Crowdedness-oriented Design.** The third line of Table 3 shows the contribution of our augmentation strategy (CCP). The CCP can improve the detection result by nearly 1.3%. Instead, our method can consistently improve the detection results by 2.2% and 3.3% for Faster R-CNN and RetinaNet respectively from the strong baselines. Moreover, the proposed method has exceptional performance on the state-of-the-art (SOTA) pedestrian detectors CrowdDet (Chu et al. 2020) and ProgS-RCNN (Zheng et al. 2022). As shown in the last two lines of Table 1. On CrowdDet, our method can achieve an improvement of 2.37% and reach a new SOTA of 38.98% in MR$^{-2}$. On ProgS-RCNN (only the CCP is applied since the CL and OD-NMS is not needed for end-to-end detector), our method can bring an enhancement of 1.33%. The proposed CrowdAug can also outperform the previously SOTA augmentation strategy AutoPedestrian (Tang et al. 2021) by 1.6% in MR$^{-2}$. These experiments confirm that the CrowdAug can effectively optimize the crowded detection even on a supremely high base.

<table>
<thead>
<tr>
<th>Aug Method</th>
<th>MR$^{-2}$</th>
<th>AP@0.5</th>
<th>JI</th>
<th>Faster R-CNN</th>
<th>MR$^{-2}$</th>
<th>AP@0.5</th>
<th>JI</th>
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<td></td>
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<tr>
<td>ProgS-RCNN</td>
<td>41.45</td>
<td>92.15</td>
<td>83.13</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CrowdDet + AutoPed</td>
<td>40.58</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CrowdDet + Ours</td>
<td>38.98</td>
<td>91.50</td>
<td>83.89</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ProgS-RCNN + Ours</td>
<td>40.12</td>
<td>92.31</td>
<td>83.35</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Results of model trained on COCO-fullperson and evaluated on CrowdHuman val set. We list results on Faster R-CNN and RetinaNet respectively.

<table>
<thead>
<tr>
<th>CCP</th>
<th>CL</th>
<th>OD</th>
<th>MR$^{-2}$</th>
<th>AP@0.5</th>
<th>JI</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCP</td>
<td>✓</td>
<td>✓</td>
<td>42.46</td>
<td>87.07</td>
<td></td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>42.01</td>
<td>87.10</td>
<td></td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>41.11</td>
<td>87.75</td>
<td></td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>40.80</td>
<td>88.02</td>
<td></td>
</tr>
<tr>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>40.21</td>
<td>88.61</td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Ablation results on CrowdHuman val set. Experiments are conducted on Faster R-CNN.
Figure 6: Visualization of the OD prediction. The value of predicted overlay depth (OD) is marked at the top left corner of each box. The red boxes denote the persons who are wrongly deleted by the original NMS are recalled.

Table 4: Robustness to Pasting Objects. The “sel” denotes manually selected high-quality objects and the “mask gt” means using segmentation annotations instead of those predicted by the Mask R-CNN model.

<table>
<thead>
<tr>
<th>Pasting Object Numbers</th>
<th>MR⁻²</th>
<th>AP@0.5</th>
<th>JI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000 (default)</td>
<td>40.21</td>
<td>88.61</td>
<td>81.41</td>
</tr>
<tr>
<td>3000</td>
<td>40.25</td>
<td>88.53</td>
<td>81.39</td>
</tr>
<tr>
<td>500</td>
<td>40.23</td>
<td>88.57</td>
<td>81.40</td>
</tr>
<tr>
<td>1000 sel</td>
<td>40.20</td>
<td>88.60</td>
<td>81.32</td>
</tr>
<tr>
<td>1000 sel+mask gt</td>
<td>40.21</td>
<td>88.62</td>
<td>81.42</td>
</tr>
</tbody>
</table>

Consensus Learning. As shown in the 4-th line of Table 3, the proposed consensus learning (CL) strategy can further enhance the the Faster R-CNN by 0.3% from CCP baseline. This improvement becomes much larger (0.88%, not shown) when applying to RetinaNet. With qualitative analysis in the method part, we can make a conclusion that this module makes a step further in alleviating the ICD problem.

Overlay Depth. Comparing the last two lines of Table 3 can find out contribution of the overlay depth (OD). As a breakthrough of the 2D constraint, this weak depth knowledge brings a stable enhancement. We make visualizations of the OD prediction in Fig. 6. It can be seen that although the training process is semi-supervised, overlay depths learned by the detector are quite discriminative and can recall missing pedestrians (red dotted boxes in Fig. 6) of the baseline model. In the structure design, the simplicity of our OD predictor guarantees the ease of use during application.

Robustness to Pasting Objects. Our method is robust to the quantity and quality of pasting objects. Results in Table 4 show that variations of either quantity or quality of pasting objects will not essentially effect the final performance.

Table 5: Results on CityPersons val set. We list the MR⁻² on four crowdedness levels: reasonable, partial, bare and heavy. The metric of AP@0.5 is also reported.

<table>
<thead>
<tr>
<th>Method</th>
<th>Reasonable</th>
<th>Partial</th>
<th>Bare</th>
<th>Heavy</th>
<th>AP@0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRCNN</td>
<td>11.20</td>
<td>11.55</td>
<td>6.62</td>
<td>52.05</td>
<td>82.95</td>
</tr>
<tr>
<td>Mosaic</td>
<td>11.05</td>
<td>11.42</td>
<td>6.77</td>
<td>51.62</td>
<td>83.01</td>
</tr>
<tr>
<td>RandAug</td>
<td>10.84</td>
<td>11.20</td>
<td>6.31</td>
<td>51.27</td>
<td>82.97</td>
</tr>
<tr>
<td>APGAN</td>
<td>11.9</td>
<td>11.9</td>
<td>6.8</td>
<td>49.6</td>
<td>-</td>
</tr>
<tr>
<td>AutoPed</td>
<td>10.3</td>
<td>-</td>
<td>-</td>
<td>49.4</td>
<td>-</td>
</tr>
<tr>
<td>Ours</td>
<td>10.02</td>
<td>10.48</td>
<td>5.79</td>
<td>48.50</td>
<td>83.78</td>
</tr>
</tbody>
</table>

Table 6: Results on KITTI val set. We use the category of “cars” in KITTI (Geiger, Lenz, and Urtasun 2012) dataset. AP@0.5 (%) of easy, moderate and hard objects are listed.

<table>
<thead>
<tr>
<th>Method</th>
<th>Easy</th>
<th>Moderate</th>
<th>Hard</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>97.24</td>
<td>89.77</td>
<td>79.44</td>
</tr>
<tr>
<td>CrowdAug</td>
<td>98.30</td>
<td>91.07</td>
<td>81.69</td>
</tr>
</tbody>
</table>

Results on CityPersons

On CityPersons, images are trained and evaluated with input scale of ×1.3. During training, we use an initial learning rate of 0.02 (Faster R-CNN) or 0.01 (RetinaNet) for the first 5k iterations and reduce it by 0.1 continuously on the next two groups of 2k iterations. Table 5 compares our CrowdAug with other methods. The results show that the CrowdAug can stably optimize the detector and once the crowdedness becomes heavier, the improvement becomes larger.

Results on KITTI

To estimate the generalization of our method to other crowded objects, we make experiments on the category of “cars” in KITTI (Geiger, Lenz, and Urtasun 2012). Table 6 shows the results. After applying the CrowdAug, Average Precision of cars get improvement if 1.05%, 1.20% and 2.25% for the objects of easy, moderate and hard respectively for the Faster R-CNN structure, which demonstrate the similar trend of its performance on pedestrian detection.

Conclusion

In this paper, we point out two main effects of crowdedness issue in the visual object detection task and propose a solution from the perspective of data augmentation. First, we invent a novel copy-paste strategy to improve crowdedness and design a consensus learning method. Then, we reasonably use the weak information of depth produced by the pasting process. Both contributions can help alleviating the ambiguities of crowded 2D object detection. We think this is a new pathway of solving the crowdedness issue with the advantages of significant effect and resource conservation.
References


detector. In European conference on computer vision, 21–37. Springer.


