PANet: Perspective-Aware Network with Dynamic Receptive Fields and Self-Distilling Supervision for Crowd Counting

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Abstract

Crowd counting aims to learn the crowd density distributions and estimate the number of objects (e.g., persons) in images. The perspective effect, which significantly influences the distribution of data points, plays an important role in crowd counting. In this paper, we propose a novel perspective-aware approach called PANet to address the perspective problem. Based on the observation that the size of the objects varies greatly in one image due to the perspective effect, we propose the dynamic receptive fields (DRF) framework. The framework is able to adjust the receptive field by the dilated convolution parameters according to the input image, which helps the model to extract more discriminative features for each local region. Different from most previous works which use Gaussian kernels to generate the density map as the supervised information, we propose the self-distilling supervision (SDS) training method. The ground-truth density maps are refined from the first training stage and the perspective information is distilled to the model in the second stage. The experimental results on ShanghaiTech Part A and Part B, UCF_QNRF, and UCF_CC_50 datasets demonstrate that our proposed PANet outperforms the state-of-the-art methods by a large margin.

1. Introduction

Crowd counting is an important topic in computer vision and has been widely applied in many tasks, such as video surveillance, urban traffic management, and passenger flow volume statistics. CNN-based density estimation methods have achieved remarkable performance. However, there are still some challenging problems in crowd counting, such as the perspective effect. Earlier works [55, 33, 2, 37, 43, 28, 26] adopt multi-column networks to implement the variety of the perspective response in an image. However, the receptive fields are still fixed for all images. Recently proposed methods [13, 29] implement self-adaptive receptive fields with deformable convolution [8]. [1] corrects the annotations by EM algorithm and proposes adaptive dilated convolution. The dynamic receptive fields in these works are trained by end-to-end schemas thus are not explainable. In this paper, we propose a perspective-aware network called PANet, which addresses the perspective problem from the following two aspects.

Firstly, we propose the dynamic receptive fields (DRF) learning framework, which creates an association between the scale of the receptive fields and the density distributions. The adjustment of receptive field scales in crowd counting models is important to cope with the scale variation of dif-
different perspective areas. As illustrated in Fig. 1, the near-end objects are sparser than the far-end ones in the image due to the perspective effect. In the commonly used fully-convolutional architecture, the network learns to regress the counting score for each point in the down-sampled heatmap based on the image information within the receptive field of this point. Considering two adjacent points in the output heatmap, the overlap of the receptive fields of these two points becomes larger as the receptive field increases. In other words, larger receptive fields provide more similar input visual signals to the network for adjacent predicted points. It can be observed that the supervised density map is smooth in the near-end area, but has obvious variations in the far-end area. In the far-end area, the ground-truth may change dramatically in a local region. It is difficult for the network to estimate the variation of the counting score based on the highly overlapped input patches. Thus, the model ought to apply small receptive fields in the far-end to learn more discriminative features for adjacent regions. Meanwhile, large receptive fields ought to be used in the near-end to involve the necessary context of big objects. Based on this assumption, we adjust the receptive fields according to the density variation. A rough network is trained for learning a rough density estimation, which is transformed to the dilation map embedded in the precise network, i.e., the network for the count prediction, by a linear transformer.

Secondly, we make improvements in perspective-aware supervision strategies. Commonly used crowd counting datasets provide point annotations as ground truth labels. Most previous state-of-the-art works [55, 37, 23, 5, 36, 54, 29] use Gaussian kernels to smooth annotated dots. However, applying Gaussian distributions is sub-optimal due to the constrained scale of response areas, especially when there is large scale variation due to the perspective effect. In this paper, we propose a two-stage training framework called self-distilling supervision (SDS). Motivated by knowledge distillation [4, 14], in the first learning stage, the precise network distills the perspective information and generates refined density maps that are more network-friendly and reflect the actual scale variation of the perspective response better. In the second stage, we train the same precise network with the refined density maps. The perspective information is distilled from the teacher network to the student network. SDS benefits the training process and achieves better evaluation performance than Gaussian-based supervision.

The main contributions of this paper are summarized as follows:

1. We propose a perspective-aware dynamic receptive fields (DRF) learning framework guided by rough density distributions, which is able to dynamically adjust the receptive field according to the input image.

2. We propose a two-stage supervision framework called self-distilling supervision (SDS). The refined density map serves as a better supervision for the model training.

3. Comprehensive experiments on four datasets demonstrate that our approach outperforms state-of-the-art methods, e.g., 45.2 MAE on ShanghaiTech Part_A, 5.9 MAE on ShanghaiTech Part_B, 49.1 MAE on UCF_QNRF and 160.3 MAE on UCF_CC_50.

2. Related Work

Early works such as [45, 22, 21, 10, 3, 56, 12, 9, 24] consider crowd counting as a detection based problem. However, these approaches have poor estimation results on images with extremely dense crowds. In recent years, CNN-based density estimation methods [11, 49, 46] outperform the traditional detection based methods and have achieved considerable progress in dense crowd counting. In this section, we mainly review two mainstream improvement aspects for crowd counting.

2.1. Network Architectures

Some works improve the performance by designing better network architectures to adjust the receptive fields of the models.

MCNN [55] utilizes three branches with multi-size convolution kernels, aiming at solving the scale variation. Hydra-CNN [33] learns a multi-scale model which uses a pyramid of image patches with different scales. CrowdNet [2] combines shallow and deep network branches, capturing the high-level and the low-level features. In Switch-CNN [37], a switch layer is designed to select the best regression network. In CP-CNN [43], the model incorporates global and local context. Adversarial loss and pixel-level loss are combined for fusing all the features. DRSAN [28] proposes a Spatial Transformer Network to cope with variations in scales and rotations. DecideNet [26] generates the detection-based and regression-based density maps respectively. TDF-CNN [35] proposes a bottom-up network along with a separate top-down network to generate feedback. McML [7] estimates mutual information between columns. DADNet [13] takes advantage of dilated-CNN and adaptive deformable convolution. D-ConvNet [41] proposes a new learning strategy called deep negative correlation learning. CSRNet [23] employs dilated convolution to expand the receptive fields. In SANet [5], the encoder extracts features with different receptive fields using scale aggregation modules, and transposed convolution is used in the decoder. ADCrowdNet [29] combines an attention map generator and multi-scale deformable convolutional scheme. TEDNet [18] is a trellis encoder-decoder network that contains multiple decoding paths to aggregate features. CAN [30] encodes multi-level contextual information into an end-to-end pipeline adaptively. S-DCNet [51] divides dense re-
regions sub-region counts are within a closed set. RPNet [53] proposes a reverse perspective network to correct the perspective distortions. However, the prior knowledge that the scale of receptive fields is corresponding to the perspective information is not well utilized yet. Based on this assumption, our dynamic receptive fields framework learns to adjust the receptive fields according to the density variation.

### 2.2. Supervision Strategies

Recently, methods based on effective supervision strategy have achieved significant progress in dense crowd counting. IG-CNN [36] introduces a growing CNN tree to adapt to the wide variability seen. ACSCP [38] employs an adversarial loss and a scale-consistency regularizer. CFF [40] obtains a focus from segmentation and a focus from global density besides density maps from point annotations. In RAZ-Net [25], a recurrent attentive zooming network is proposed for precise localization. There are some works which apply different loss functions to optimize models better, such as [38, 6, 19, 48, 32]. ACSCP [38] employs an adversarial loss and a scale-consistency regularizer. In SPANet [6], Maximum Excess over Pixels loss is proposed to incorporate spatial context. Other methods are exploring potential supervision information or generating new density maps as labels from point annotations, such as [40, 1, 47, 31]. CFF [40] obtains a focus from segmentation and a focus from global density besides density maps from point annotations.

However, the manual-designed density maps are suboptimal for training the model. In this paper, we propose self-distillation supervision and achieve remarkable progress by the perspective information distilled from the teacher model to the student model.

### 3. Methodology

We propose a perspective-aware framework for crowd counting named PANet, which is illustrated in Fig. 2. In this Section, we introduce the two components of our PANet respectively. First, we provide the principle of our dynamic receptive fields (DRF) framework and then we present our self-distilling supervision (SDS) framework.

#### 3.1. Dynamic Receptive Fields

To address the scale variation of the receptive fields in scenes with large density variations in crowd counting, we propose a perspective-aware learning framework called dynamic receptive fields (DRF). Due to the perspective effect, the objects in the near-end regions are sparse than those in the far-end regions. The overlap of the receptive fields of adjacent positions becomes larger with the scale of the receptive fields, as illustrated in Fig. 1. We denote the overlap of the receptive fields by the Intersection over Union (IoU) to quantify this observation. Assume that the distance between two positions in one row of the output density map is $n$ pixels and the down-sample ratio of the precise network is $k$. The variation of the IoU about the scale of receptive fields in the precise network is formulated as:

$$
\text{IoU} = \frac{X - kn}{X + kn}, \quad X \geq kn
$$

(1)

where $X$ is the scale of the receptive fields. Thus, the IoU of the receptive fields at a pair of fixed positions increases with the scale of the receptive fields. In more congested regions in an image, the variation of the density map is more dramatic, while the large overlap of the adjacent receptive fields restricts the model to discriminatively estimate the counting score. Thus, the IoU of the receptive fields needs to be smaller in the dense area. So we propose the dynamic receptive fields, which are smaller in the denser regions and are larger in sparser regions to involve necessary context. To validate the rules above, we implement some comparison experiments with different dilated convolution methods and different ground truth annotations in Sec. 4.3.

The proposed DRF adjusts the scale of receptive fields by the dilated convolution parameters corresponding to density. As illustrated in Fig. 2, the rough density map is generated using Gaussian kernels with large spreads. The rough network is trained to predict the rough density map, using $L_1$ distance as the loss function with the same definition in Eq. 5. We use a linear transformer module to transform the rough prediction to the dilation map. Instead of a fixed dilation rate, the dilation map is embedded in the last three layers of the precise network, named refined dilated convolutional layers. Thus, the dilation rates are different in regions with different rough density estimations when training the precise network.

The dilation rates in the output dilation map are transformed to $[0, R]$ by a negative linear transformer, which means the receptive fields are smaller in the denser regions. The operation of the linear transformer is formulated as:

$$
L(x) = \begin{cases} 
R, & x \leq 0 \\
R - \gamma x, & 0 < x < \frac{R}{\gamma} \\
0, & x \geq \frac{R}{\gamma}
\end{cases}
$$

(2)

where $R$ is the pre-set upper bound, $\gamma$ is a positive coefficient, and $x$ is the rough prediction of the rough network.

The value at the $k$th position in the output feature map of the refined dilated convolutional layer $F_{out}(x_k)$ is calculated as:

$$
F_{out}(x_k) = \sum_{i,j \in D} F_{in}(x_k + \hat{r} \times (i,j)) \times w_{i,j},
$$

(3)

where $\hat{r}$ is the dilation rate at the $k$th position computed by $L(x)$, $w$ denotes the weights in convolution kernels, and $D$
Figure 2. Overview of PANet. The training process can be divided into three steps. (1) The input image is fed into the rough network to generate a rough prediction first, supervised by the rough density map. After a linear transformer, the rough prediction is used as a dilation map in the refined dilated convolution layers of the precise network. (2) The learning of the precise network can be divided into two stages. Firstly the input image is fed into the precise network to distill the perspective information by upgrading the precise density map. (3) After count correctness, the refined density map with the perspective information distilled from the first stage serves as the new ground truth for training the precise network. The two training stages of the precise network share the same network structure.

is the collection of unitized offsets defined as:

\[ D = \{-1, 0, 1\}. \]  

Bilinear interpolation is used to calculate the values at continuous sampling points.

With the refined dilated convolutional layers, the precise network is able to adjust the receptive fields for different local regions based on the input image, and learns to predict more discriminative estimations.

### 3.2. Self-Distilling Supervision

The traditional learning strategies of Crowd Counting often use Gaussian density maps as the ground truth. However, the Gaussian annotations have constrained scales of response areas. This drawback is particularly obvious when there is a large density variation in images. These density maps need to be refined for better learning of the perspective effect. Motivated by knowledge distillation, we propose a two-stage learning framework called self-distilling supervision (SDS), considering that the predicted density map is more aligned with the actual scales of the response areas and is more sensitive to the variation of the perspective information.

Our SDS is a two-stage learning framework, where the purpose of the first stage is to distill the perspective information extracted from the teacher network to the student network. The teacher and student networks share the same architecture of the precise network, as shown in Fig. 2, so our method is called self-distilling. In the first stage, the teacher network is trained to estimate the crowd counting, supervised by the precise density maps, which are smoothed by Gaussian kernels with small spreads. This stage is the same as other CNN-based density estimation methods. A pixel-wise loss function is needed for training the network. The \( L_1 \) distance is adopted in our method, which is defined as:

\[ L_1(\hat{Y}, Y) = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i|. \]  

An interesting observation is that the refined density map predicted by the teacher network is self-adaptive and reflects the actual perspective information after training of deep CNN. Fig. 3 shows visualization examples of both the
Gaussian annotations and the refined density maps for comparison. The refined density maps have more reasonable density variations according to perspective information and the target objects. Thus the refined density maps serve as better supervision targets than the Gaussian annotations and are utilized to optimize the student network in the second learning stage.

Although the refined density map contains sufficient perspective information, it cannot be used as the ground-truth heatmap directly due to the inevitable counting error caused by the teacher network. Thus we need to correct the total count of the refined density map while keeping the relative data distribution by the count correctness process, which is formulated as:

$$h_i = \frac{\sum_{j=1}^{\eta} \hat{y}_j y_i}{\sum_{j=1}^{\eta} \hat{y}_j}$$  

(6)

where $\hat{y}_i$ is the $i$-th value of the refined density map predicted by the teacher network, and $y_i$ is the $i$-th value of the Gaussian annotation heatmap. Then the total count in the refined density map becomes identical to the original annotations. After this adjustment, the student network is trained with $L_1$ loss again with new supervision targets for the final count estimation.

The refined density map facilitates the supervision process and leads to higher prediction accuracy because it utilizes self-distillation to upgrade the supervision targets. The perspective information is distilled in the first stage and has better guidance for the training of the model.

4. Experiments

4.1. Datasets

We validate the effectiveness of our PANet on four challenging crowd counting datasets, including ShanghaiTech [55] Part_A and Part_B, UCF_QNRF [16] and UCF_CC_50 [15].

ShanghaiTech Part_A [55] contains 482 images randomly crawled from the Internet, in which 300 images and 182 images are used as the training and test sets respectively. There are congested scenes in most of the images. There is a wide range of density variations in images.

ShanghaiTech Part_B [55] contains 716 images of sparse scenes, taken from busy streets in Shanghai. There are 400 images in the training set and 316 images in the test set. There is a small number of head annotations in most of the images.

UCF_QNRF [16] contains 1535 images and is divided into training the training set with 1201 images and the test set with 334 images. This dataset has a large number of head annotations.

UCF_CC_50 [15] collects only 50 images and has a large span in object count among images, so it is an especially challenging dataset. 5-fold-cross-validation is used following [15].

4.2. Training Details

For datasets with high-density crowds such as ShanghaiTech Part_A, UCF_QNRF, UCF_CC_50 datasets, we augment the training data using horizontal flipping and cropping with crop size $256 \times 256$. The batch size is set to 32. For ShanghaiTech Part_B, the crop size is set to $512 \times 512$ and the batch size is set to 8 considering the low-density crowds in this dataset. For UCF_QNRF, considering the large size of images, we resize the longer side to 1024 pixels with the constant aspect ratio. There is no data augmentation except resizing during the testing process.

Adam Optimizer [20] is applied with a fixed learning rate at $10^{-5}$ and weight decay at $10^{-4}$ in the training process. In the second training stage of SDS, we copy the precise network parameters from the first stage and finetune it with the new supervision targets.

Our baseline is CSRNet [23] with first ten convolutional layers of VGG16 bn [42, 17] pretrained on ImageNet [34], labeled as CSRNet*, which is also our backbone of both the precise and the rough network. To guarantee the efficiency and the lightweight of PANet, only the last three layers of the precise network are replaced by our refined dilated convolutional layers. Even though our DRF is only applied to a small portion of the precise network, the estimation performance is improved remarkably.

The original precise ground truth density maps are generated by a fixed spread Gaussian kernel for ShanghaiTech Part_B, UCF_QNRF, and UCF_CC_50, and we set $\sigma = 15$. We use the K-Nearest Neighbors (KNN) algorithm to compute the adaptive spread of Gaussian kernels for ShanghaiTech Part_A following [55]. To construct the rough density maps, we set $\sigma = 50$ in the Gaussian kernel for all four datasets. The output density map is 1/8 size of the original

Figure 3. Visualization examples of different ground truth density maps. (a) The Gaussian annotated density maps. (b) Our refined density maps. The density maps are normalized in each local patch for better visualization.
Table 1. Ablation study of DRF and SDS on four datasets.

| Methods  | ShanghaiTechA MAE | ShanghaiTechA RMSE | ShanghaiTechB MAE | ShanghaiTechB RMSE | UCF_QNRF MAE | UCF_QNRF RMSE | UCF_CC.50 MAE | UCF_CC.50 RMSE |
|----------|-------------------|-------------------|-------------------|-------------------|--------------|--------------|--------------|--------------|
| Baseline | 57.4              | 88.9              | 7.6               | 12.1              | 115.9        | 185.4        | 250.1        | 335.4        |
| SDS      | 53.4              | 85.5              | 7.0               | 11.0              | 101.9        | 170.5        | 192.6        | 269.1        |
| DRF      | 47.1              | 74.3              | 6.2               | 10.1              | 79.6         | 135.6        | 211.1        | 273.6        |
| PANet    | 45.2              | 73.1              | 5.9               | 9.3               | 49.1         | 106.0        | 160.3        | 223.7        |

Table 2. Performance of DRF with different $\gamma$ in the linear transformer on ShanghaiTech Part A.

| $\gamma$ | MAE   | RMSE  |
|----------|-------|-------|
| 1        | 56.2  | 48.9  |
| 5        | 47.1  | 49.4  |
| 10       | 49.4  | 52.0  |
| 15       | 52.0  |       |
| 20       | 52.0  |       |

Table 3. Performance of different methods with dilated convolution on ShanghaiTech Part A.

| Methods                  | MAE   | RMSE  |
|--------------------------|-------|-------|
| Dila. 1                  | 59.2  | 96.5  |
| Dila. 2                  | 57.4  | 88.9  |
| Deformable Conv. [8]     | 59.4  | 92.9  |
| Adaptive Dila. [1]       | 56.8  | 94.5  |
| DRF                      | 47.1  | 74.3  |

input image, so we downsample the ground truth density map while keeping the total count constant.

The Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) are used as our evaluation metrics, following previous works, which are computed as follows:

\[
\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |C'_i - C_i|, \quad (7)
\]

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (C'_i - C_i)^2}, \quad (8)
\]

where $C_i$ is the ground truth count and $C'_i$ is the predicted count for the $i$th image, and $N$ is the number of image samples.

In the test stage, the input image is fed into the rough network first to generate the dilation map that is embedded in the refined dilated convolutional layers. Then the precise network outputs the final estimation result.

### 4.3. Ablation Experiments

To validate the motivation of the DRF, i.e., the variation of the receptive scale according to the densities, we set different dilation rates in the baseline and visualize some predicted density maps in Fig. 4. It is obvious that although the precise network with the dilation rate of 1 has a larger count estimation bias on sparse scenes due to the restricted receptive fields, it predicts densities in congested regions more precisely, compared with the one with the dilation rate of 2. There is a wide range of density variations in plenty of scenes, so a fixed dilation rate leads to sub-optimal performance. Therefore, reducing the receptive fields in far-end regions and enlarging them in near-end regions are reasonable assumptions.

We also test different $\gamma$ in the linear transformer. The comparison experiments on ShanghaiTech Part A are illustrated in Tab. 2. The MAE and RMSE decrease with the increase of $\gamma$ at first and increase at last. We choose the coefficient $\gamma = 10$ for better performance of DRF.

To evaluate the effectiveness of DRF compared with other methods involving dilated convolution, we carry out ablation experiments on ShanghaiTech Part A, as shown in Tab. 3. The methods include dilated convolution with fixed dilation rate 1 and 2, the adaptive dilated convolution [1] and our DRF. The deformable convolution [8] and the adaptive dilated convolution [1] learn the dilation maps implicitly from end-to-end training and are inexplicable. In our DRF learning framework, the dilation map is trained separately with the rough density map as the supervision targets considering the perspective effect. In consequence, DRF outperforms the other methods by large margins.

Our DRF improves the estimation accuracy by reducing the scale of the receptive fields in regions where the ground truth varies dramatically and vice versa, so the methods of annotations may have an influence on the performance of our DRF. There are two main Gaussian annotation methods, one is fixed $\sigma$ and the other is adaptive $\sigma$. The adaptive $\sigma$
Figure 5. Visualization of estimated density maps on the ShanghaiTech dataset. From left to right, we display (a) input images, (b) Gaussian ground truth density maps, (c) estimations by our baseline CSRNet*, (d) estimations by PANet.

Table 4. The performance improvements of our DRF compared with the baseline using different ground truth annotations on ShanghaiTech Part A.

|          | Fixed $\sigma = 15$ | Adaptive $\sigma$ |
|----------|---------------------|-------------------|
|          | MAE     | RMSE    | MAE      | RMSE    |
| Baseline | 58.1    | 90.8    | 57.4     | 88.9    |
| DRF      | 49.5    | 78.3    | 47.1     | 74.3    |
| Improvement | 14.8% | 13.8% | 17.9% | 16.4% |

Table 5. The performance of different ground truth annotations.

|          | ShanghaiTech A | ShanghaiTech B |
|----------|----------------|----------------|
|          | MAE     | RMSE    | MAE      | RMSE    |
| Fixed $\sigma = 15$ | 58.1    | 90.8    | 7.6      | 12.1    |
| Adaptive $\sigma$ | 57.4    | 88.9    | 7.9      | 12.5    |
| SDS      | 53.4    | 85.5    | 7.0      | 11.0    |

annotation method, e.g., constructing kernels by KNN algorithm, has the more obvious perspective response, i.e., there is a significant difference in the amplitude of ground truth variations between regions with different densities. The experiment results are shown in Tab. 4. It can be observed that our proposed DRF brings larger improvements on baseline when using the adaptive $\sigma$ annotation than using fixed $\sigma$. These results demonstrate that taking the association between the overlap of the receptive fields and the perspective information into account has a better effect when the ground truth variation is larger.

We use different methods of generating the ground truth annotations including our SDS and compare their performance. We present the results in Tab. 5. SDS achieves the best estimation results on datasets with different scales of the perspective variations due to the utilization of self-distillation and the rich perspective information integrated in the density maps.

Furthermore, we implement ablation experiments on all four datasets. We carry experiments on self-distilling supervision (SDS) and dynamic receptive fields (DRF) separately. The results are illustrated in Tab. 1. Following ADSCNet [1], our baseline is CSRNet*, which is CSRNet [23] with Batch Normalization layers and outperforms the original CSRNet. The network is trained with Adam optimizer instead of SGD optimizer, which further increases the accuracy, following some papers like BL [32]. We use L1 loss instead of L2 loss, which is the same as ADSCNet [1]. This loss function also improves the performance of the baseline. In the experiments on SDS exclusively, the refined dilated convolutional layers in the precise network are replaced with vanilla dilated convolutional layers, where the dilation rate is a constant set as 2. When we validate the effectiveness of DRF alone, we use Gaussian annotated den-
Table 6. Performance comparisons with state-of-the-art methods on four datasets.

| Methods             | ShanghaiTechA MAE | ShanghaiTechB MAE | UCF_QNRF MAE | UCF_CC_50 MAE |
|---------------------|--------------------|-------------------|--------------|---------------|
| MCNN [55]           | 110.2              | 26.4              | 277          | 377.6         |
| Switching-CNN [37]  | 90.4               | 21.6              | 228          | 318.1         |
| A-SCP [38]          | 75.7               | 17.2              | -            | 291.0         |
| CP-CNN [43]         | 73.6               | 20.1              | 30.1         | 298.8         |
| IG-CNN [36]         | 72.5               | 13.6              | -            | 291.4         |
| CSRNet [23]         | 68.2               | 10.6              | -            | 266.1         |
| SAANet [5]          | 67.0               | 8.4               | -            | 258.4         |
| CFF [40]            | 65.2               | 7.2               | 93.8         | 214.2         |
| SFCN [50]           | 64.8               | 7.6               | 102.0        | 249.4         |
| TEDNet [18]         | 64.2               | 8.2               | 113          | 229.3         |
| ADA-CrowdNet [29]   | 63.2               | 7.6               | -            | 257.1         |
| BL [32]             | 62.8               | 7.7               | 88.7         | 229.3         |
| PACNN [39]          | 62.4               | 7.6               | -            | 241.7         |
| CAN [30]            | 62.3               | 7.8               | 107          | 212.2         |
| RPNet [53]          | 61.2               | 7.6               | -            | 200.3         |
| DSSInet [27]        | 60.6               | 6.9               | 99.1         | 216.9         |
| DM-Count [48]       | 59.7               | 7.4               | 85.6         | 211.0         |
| RANet [54]          | 59.4               | 7.9               | 111          | 239.8         |
| SPANet [6]+SANet [5]| 59.4               | 6.5               | 9.9          | 232.6         |
| M-SFANet+M-SegNet [44]| 57.6             | 6.3               | 85.6         | 162.3         |
| PGCNet [52]         | 57.0               | 8.8               | 13.7         | 244.6         |
| ADSNet [1]          | 55.4               | 6.4               | 11.3         | 198.4         |
| PANet               | **45.2**           | **5.9**           | **49.1**     | **160.3**     |

MAE, RMSE

5. Conclusion

In this paper, we present a novel perspective-aware learning framework named PANet for crowd counting, which consists of two major components. Based on the observation that smaller receptive fields ought to be used in far-end regions and vice versa, the dynamic receptive fields (DRF) framework learns the scales of receptive fields by supervision from rough density maps. DRF is more explainable and outperforms the existing methods of adjusting receptive fields. Motivated by knowledge distillation, the proposed two-stage framework, self-distilling supervision (SDS), refines the ground truth density map guided by the prediction in the first stage. The refined density map integrates rich perspective information and improves the precise network in the second stage.

Comprehensive experimental results support our assumptions and validate the effectiveness of each component of our method. Combining SDS and DRF, our PANet achieves state-of-the-art performance in terms of both MAE and RMSE on four challenging crowd counting datasets.
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