Deep Density-aware Count Regressor

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Abstract

We seek to improve crowd counting as we perceive limits of currently prevalent density map estimation approach on both prediction accuracy and time efficiency. We show that a CNN regressing a global count trained with density map supervision can make more accurate prediction. We introduce multilayer gradient fusion for training a density-aware global count regressor. More specifically, on training stage, a backbone network receives gradients from multiple branches to learn the density information, whereas those branches are to be detached to accelerate inference. By taking advantages of such method, our model improves benchmark results on public datasets and exhibits itself to be a new solution to crowd counting problem in practice. Our code is publicly available at: https://github.com/GeorgeChenZJ/deepcount

1. Introduction

Crowd counting is a task to count people in image. It is mainly used in real-life for automated public monitoring such as surveillance and traffic control. Different from object detection, crowd counting aims at recognizing arbitrary sized targets in various situations including sparse and cluttering scenes at the same time. Figure 1 illustrates some of those challenging scenarios. In recent years, crowd counting has drawn more attention from computer vision researchers and has been in significant progress.

Early methods [1,10,12,22,34] attempt to solve the problem by detecting each individual pedestrian in the crowd. These methods often perform poorly in the face of complex conditions such as those illustrated. The recent development of crowd counting comes from DNN-based methods which have achieved commendable performance. These methods [4,5,6,7,11,15,35,36,37] concentrate on generating the demanding density maps before integrating them to the count. They are therefore categorised into density map-based methods. However, density maps have yet in effect to show too much importance in practice except for opportunely providing for demonstration, but are expensive to compute, and their quality is difficult to guarantee. Meanwhile, methods that regress the global count directly have remained untouched for a while in research frontiers.

Raising state-of-the-art performances in many works, density maps have shown undeniable contribution to the improvement of prediction precision. One advantage of being density map-based may be that information with respect to location, scale alike is fed to the network through density supervision. Consequently, multi-scale or multi-column architectures [4,5,6,11,15] are usually adopted to fuse features from different scales to capture these kinds of information. Still, there exists two main drawbacks: first, computational cost drastically increases along with the growth of number of columns; second, useful information learned by low-level detectors might be lost through forward propagation. Likewise, supervision information contained in gradients would be attenuated through backward propagation, making low-level detectors difficult to learn.

Besides, noise locally occurs due to uncertainty of annotation position on large-scale targets while Gaussian dispersion can only alleviate the issue to short extend. On the contrary, a global count is immune to local noise, but
does not carry location information which can be crucial for the network to develop attention on elusive targets.

To address these problems, we propose a novel Gradient Fusion based model called DeepCount for crowd counting (network architecture shown in Figure 2), making efforts to both averting expenditure of multi-column architecture and enhance resistance to local annotation noise. As in Figure 2, our proposed model contains a backbone network with convolution layers deeply regressing a global count. Some auxiliary modules branch out to produce density maps with corresponding spatial dimensions and to feed gradients back to the backbone. There are five branches having different depths and independent parameters so as to learn features in different aspects. Each branch will directly access different levels of the backbone to inculcate knowledge to it deeply and make it more perceptive on the density distribution of the image, namely to be density-aware.

In inference phase, the backbone network can be used unaccompanied by any branches as a regressor to solely predict the global count at fastest speed, or, if needed, with an auxiliary branch to also visualise a density map. Expensive computation is taken out, but with functionality promised.

Compared to other multi-column methods, our model fuses gradients other than features and avoids relying on the noisily supervised and computationally expensive density maps to make prediction. By so doing, our model incorporates advantages of accuracy, flexibility, and efficiency.

Extensive experimental results on four benchmark datasets demonstrate significant improvements of our method against the state-of-the-art methods on Shanghai Tech Part A, Part B and UCF-QNRF datasets and excellent performance on Mall dataset.

The rest of the paper is structured as follow: we review literatures for crowd counting in section 2; section 3 provides the detailed interpretation of our method; section 4 reports experiment results; in section 5, we further discuss our findings and insights; the paper is to be concluded in section 6.

2. Related works

2.1. Detection-based methods

Early crowd counting methods tend to rely on detection approach. Low-level hand-crafted features such as Histograms of Oriented Gradients, silhouette-oriented features are exploited for traditional classifiers such as Support Vector Machine and Random Forest [1, 10, 12, 22, 34]. Following are CNN-based methods (e.g. Faster R-CNN [28]) which have shown credible precision [23]. Nonetheless, in such times when the subject of crowd counting was more on the stage of pedestrian detection,

Figure 2. The architecture of the proposed DeepCount Model. Module in the grey box is the backbone regressor, below which are 5 branches predicting density maps. Large-size numbers on the blocks are referred to in detailed configuration in Table 1, while numbers in smaller font indicate the feature map dimensions.

2.2. Count regression-based methods

Count regression-based methods are proposed to overcome limits encountered by detection-based methods. The idea of these methods is to regress a global count from the input image. There are methods using ridge regression [13, 14], log-linear regression [17] or MLP [20] on low-level hand-crafted features to estimate the count. While they work satisfactorily on invariant scenes of sparse density, hand-crafted features can hardly represent enough variance and intricacy in complex counting scenarios. Alternatively, with the development of deep learning, features can be black-boxed and deeply learned to target the goal. Early success of applying deep learning methods on crowd counting would be the end-to-end deep CNN regression model by Wang et al. [18]. Though, deep learning methods quickly narrowed onto density map-based methods which have prevailed over the years since, and it was not until recently in [29] that Idrees et al. reported excellent experiment results on global count regression by advanced CNNs: Resnet101 [25] and Densenet201 [26].
notwithstanding their focus on density map estimation.

2.3. Density map-based methods

Rodriguez et al. [21] first suggest the use of density map can improve crowd counting results significantly. It is supported by Zhang et al. [7] whose model produces small density map patches as well as the patch count at its last layer. Following this density map approach, Zhang et al. [4] propose a multi-column architecture (MCNN) to also address scale variance of the targets. Inspired by such, Cao et al. [11] introduce Scale Aggregation Network (SANet) which aggregates multi-scale features and fuses them in every layer. Likewise, Switching-CNN [5] has independent columns of CNN similar to multi-column network with different receptive fields, and ic-CNN [15] aims at predicting high-resolution density maps with two branches. Another set of methods devote themselves to trace context information as well as other abstractions all in a bit to improve the predicted density maps [6, 35, 36, 37]. On the other hand, CSRNet [16] builds dilated convolution layers upon a VGG-16 [19] backbone straightforward without too many manoeuvres, yet it reports excellent results and therefore becomes more practiced at present.

Differently, our method embodies heterogeneity of multi-column methods and straightforwardness of CSRNet whilst appearing as an existence that is both regression-based and density map-based.

3. DeepCount

3.1. Gradient Fusion

We regard our methodology of designing the network as Gradient Fusion. Multi-column methods such as MCNN [4] and CP-CNN [6] are feature fusion methods assembling different columns features from which are fused and gradients to which are separated. Fusing feature maps of multiple columns entails lots of computation overhead since each column cannot be without in order to make prediction. In contrast, the method of gradient fusion fuses only gradient matrices in backpropagation during training. We acknowledge that similar mechanisms are implemented in many works where they may be called otherwise. We use the name Gradient Fusion here to serve descriptive purpose to distinguish our methodology from other multi-column methods on crowd counting.

In our network configuration (see section 3.1), the backbone module is mostly shared with branches which produce different density maps of different scales. Multi-source gradients are fused together to train this critical backbone. Complexities of solving location estimation still exists for optimization of the parameters of the backbone. This restricts the backbone to be learning location information to help branches to predict density maps. This is a process which instils density-awareness to the backbone.

3.2. Network configuration

In order to signify our central point by comparing our model to others, we demonstrate a relatively simple network design in this paper. As shown in Figure 2, our proposed model consists of a straightforward down-sampling backbone and five branches interconnected to it. The backbone by itself has relatively low complexity. It functions as a deep CNN regressor which takes the crowd image as input and predicts the global count by regression. We design the network to have input size of 384×512 to cater most aspect ratios in practical uses, whereas arbitrary larger input image sizes are tackled by division and combination. Correspondingly, there are density maps of sizes \([48 \times 64, 24 \times 32, 12 \times 16, 6 \times 8, 3 \times 4]\) produced.

Specifically, the backbone has a frontend which extracts features from the input image. We transplant the first ten convolution layers from pretrained VGG-16 as our frontend model similar to CSRNet [16]. The frontend produces feature maps of 8 times smaller spatial width and height relative to the input. Following are some 3×3 convolution layers to further dwindle the size of feature maps until when its spatial dimension matches the input dimension of a 3×4 convolution layer entering to produce a 1×1024 vector. We use 3×3 convolution with strides of 2 to halve the spatial dimension of the feature maps in the backend. In addition, a standard 3×3 convolution layer is put between two down-sampling layers to further deepen the network and to smooth the reduction of features.

As for branches, they work in an up-sampling manner. Branches stemming from the last feature layer (1×1024) of the backbone use transposed convolutions to up-sample the feature maps. To the output of each transposed convolution layer the deeper feature maps from backbone with the same dimension are channel-wise appended. Together, they form the input to the next transposed convolution layer. 1×1 convolution is used to reconstruct channels to produce density map prediction. At the end of the backbone, a scalar value is produced as the global count prediction. We call our network DeepCount in short for deep CNN count regressor. Table 1 details the network configuration.

3.3. Generating ground truth density maps

To produce ground truth density maps for training, we first apply convolution by fixed Gaussian kernel with standard deviation \(\sigma = 5\) (on the contrary of geometry-adaptive kernel adopted in most works) to generate density map of the same resolution as the original image, before sum pooling is employed to produce different sizes of density maps. Five density maps are produced. Element sum of the density map is the ground truth count for the image.
Table 1. Configuration of DeepCount network. In the table, Conv and Conv-tr mean convolution and transposed convolution respectively. The pattern $H \times W \times C \times C'$ represents the dimension of convolution kernel. $S$ denotes strides.

| Module | Backbone | Branch 1 | Branch 2 | Branch 3 | Branch 4 | Branch 5 |
|--------|----------|----------|----------|----------|----------|----------|
| Input  | Image $384 \times 512 \times 3$ | 1×1024 | 1×1024 | 1×1024 | 1×1024 | 1×1024 |
| 1      | VGG 16 Layers 1-10 | Conv-tr S1 $3 \times 3 \times 512 \times 256$ | Conv-tr S1 $3 \times 3 \times 512 \times 256$ | Conv-tr S1 $3 \times 3 \times 512 \times 256$ | Conv-tr S1 $3 \times 3 \times 512 \times 256$ | Conv-tr S1 $3 \times 3 \times 512 \times 256$ |
| 2      | Conv-S1 $3 \times 3 \times 512 \times 256$ | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation |
| 3      | Conv-S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-S1 $1 \times 1 \times 512 \times 1$ |
| 4      | Conv-S1 $3 \times 3 \times 512 \times 256$ | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation |
| 5      | Conv-S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-S1 $1 \times 1 \times 512 \times 1$ |
| 6      | Conv-S1 $3 \times 3 \times 512 \times 256$ | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation |
| 7      | Conv-S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-S1 $1 \times 1 \times 512 \times 1$ | Depth Concatenation |
| 8      | Conv-S1 $3 \times 3 \times 512 \times 256$ | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation |
| 9      | Conv-S2 $3 \times 3 \times 512 \times 256$ | Conv-tr S2 $3 \times 3 \times 512 \times 256$ | Conv-S1 $1 \times 1 \times 512 \times 1$ | Depth Concatenation | Depth Concatenation |
| 10     | Conv-S1 $3 \times 3 \times 512 \times 256$ | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation |
| 11     | Conv-S1 $3 \times 4 \times 512 \times 256$ | Conv-S1 $1 \times 1 \times 512 \times 1$ | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation |
| 12     | Fc 1024×1 | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation | Depth Concatenation |
| Output | P. Count | P. Density Map $48 \times 64$ | P. Density Map $24 \times 32$ | P. Density Map $12 \times 16$ | P. Density Map $6 \times 8$ | P. Density Map $3 \times 4$ |

3.4. Objective function

Labelling congested crowd data is indeed a painstaking task for human annotators. In some highly congested cases where the factual number of people is inevitably untraceable. This results in many annotations in congestions themselves being estimations and the ground truths becomes noisy. Also, for large scale heads, the annotation position is difficult to be exact. Hence, L1-norm loss is adopted to enhance robustness against noise as well as to convey steady updates to the network. We first define our objective function as:

$$L(\theta) = \frac{1}{2N} \sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{i,j} (y_{nk} - f(X_n, \theta_k))_{ij}$$  \hspace{1cm} (1)

where $N$ is the size of the training batch, $K (K = 6 \& k \in \{1,2,\ldots,6\})$ enumerates outputs of all branches and the global count regressor, $y_{nk}$ is the ground truth density map (or the global count when $k = 6$), $X_n$ is the input image and $\theta_k$ denotes all parameters in model $f$ that contribute to making the corresponding $k$th prediction.

Given this objective function as basis, we add a multiplier $\beta$ to accentuate the importance of the global count prediction on backbone (where $k = 6$). We note it as a function of $k$:

$$B(k) = \begin{cases} \beta, & k = 6 \\ 1, & k \neq 6 \end{cases}$$  \hspace{1cm} (2)

Moreover, we add another hyperparameter $\omega$ to approximately adjust the loss to a reasonably small value (<10). An L2 regularisation term is also added to the function in an attempt to reduce overfitting. Hence, the objective function finally becomes:

$$L(\theta) = \frac{1}{2N} \sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{i,j} (y_{nk} - f(X_n, \theta_k))_{ij} \cdot B(k) \cdot \omega + \frac{\lambda}{2} \|\theta\|^2_2$$  \hspace{1cm} (3)

3.5. Implementation

VGG-16 model pretrained on ImageNet is used to initialise the frontend of the backbone. Therefore, input images are normalised in the same manner as how the VGG-16 model is trained. As for initialising the remaining part of the model, we use Xavier [33] initialisation for weights and a constant value 0 for biases. With the exception of the VGG-16 frontend where ReLU is the activation function, we set parametric ReLUs (leaky ReLU):

$$a(x) = \begin{cases} x, & x > 0 \\ \alpha x, & x \leq 0 \end{cases}$$  \hspace{1cm} (4)

following every convolution layer. We sweep hyperparameters and choose $\lambda = 1 \times 10^{-5}$, $\omega = 1 \times 10^{-2}$ and $\beta = 16$ for the objective function in equation (3), and
\( \alpha = 0.2 \) for the activation parameter [31] in equation (4). We use Gradient Descent optimisation with momentum 0.9 and initial learning rate \( 1 \times 10^{-4} \) to train our model, except for pretrained parameters in frontend where learning rate is divided by a factor of 2 to initially \( 5 \times 10^{-5} \). Batch size \( N \) is set to 32. On benchmark datasets, we train the network for around a hundred epochs.

As alluded to above, to cope with images of varied sizes, we divide the original image to \( 384 \times 512 \) crops to feed into our network. In inference, results from cropped images are to be merged to assemble the original ones again.

4. Evaluation

In this section, we report evaluation results yielded by our method introduced above. We evaluate our DeepCount network on four different public datasets: Shanghai Tech Part A and Part B [4], UCF-QNRF [29] and Mall [13]. Training details for all datasets are the same as mentioned in implementation section (section 3.5). In order to make fair comparison with benchmark results, we do no more data augmentation than random cropping and mirroring during training.

4.1. Evaluation metrics

For evaluation, we compute mean-absolute-error (MAE) and root-mean-squared error (RMSE):

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} | C_i - C_i^{GT} | \\
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} ||C_i - C_i^{GT}||^2}
\]

where \( N \) is the number of testing images, \( C_i \) and \( C_i^{GT} \) meaning predicted count and ground truth count respectively.

4.2. Shanghai Tech

Shanghai Tech [4] dataset includes Part A and Part B. Part A is the dataset for congested crowd counting. It has 241,677 annotations in 300 training images and 182 testing images with an average number 501. On the other hand, images in Part B are relatively sparse and all taken from streets in Shanghai. Our DeepCount model achieves state-of-the-art performance on both datasets. Test results are shown in Table 2.

4.3. UCF-QNRF

The UCF-QNRF [29] dataset has a greater number of annotations (1,251,642) in higher quality images of a wider variety of scenes, including sparse and dense ones. There are extremely dense scenes in this dataset, so much so that a single image may have maximumly 12,865 of annotations in UCF-QNRF. It is considered a harder one. Our method outperforms current methods (see Table 3).

4.4. Mall

Unlike the above datasets, images from Mall dataset [13] are surveillance video frames from a static viewpoint at a same venue. There are 800 frames for training and the other 1200 for testing. Since crowds in the dataset are sparse, Mall is not as challenging as others. Although previous methods have shown very promising results on this dataset, we still evaluate our model on it to demonstrate its excellent performance on invariant scene and as well to make comparison with some detection-based methods. (see Table 4).

5. Discussion

5.1. Capacity and velocity

Arguably, the more parameters a neural network has, the greater its potential is to have high capacity to model the

| Method                  | MAE  | RMSE | MAE  | RMSE  |
|-------------------------|------|------|------|-------|
| MCNN [4]                | 110.2| 173.2| 26.4 | 41.3  |
| Switching CNN [5]       | 90.4 | 135.0| 21.6 | 33.4  |
| DecideNet [23]          | -    | -    | 20.75| 29.42 |
| CP-CNN [6]              | 73.6 | 106.4| 20.1 | 30.1  |
| ic-CNN [15]             | 68.5 | 116.2| 10.7 | 16.0  |
| CSRNet [16]             | 68.2 | 115.0| 10.6 | 16.0  |
| SANet [11]              | 67.0 | 104.5| 8.4  | 13.6  |
| DeepCount (ours)        | 65.2 | 112.5| 7.2  | 11.3  |

Table 2. Test results on Shanghai Tech Part A and Part B

| Method                  | MAE  | RMSE |
|-------------------------|------|------|
| R-FCN [27]              | 6.02 | 5.46 |
| Faster R-CNN [28]       | 5.91 | 6.60 |
| COUNT Forest [30]       | 4.40 | 2.40 |
| Weighted VLAD [32]      | 2.41 | 9.12 |
| DecideNet [23]          | 1.52 | 1.90 |
| DeepCount (ours)        | 1.55 | 2.00 |

Table 3. Test results on UCF-QNRF.

| Method                  | MAE  | RMSE |
|-------------------------|------|------|
| Mall [13]               | 29.42| 33.4 |
| Switching CNN [5]       | 228  | 445  |
| MCNN [4]                | 277  | 426  |
| CMTL [24]               | 190  | 277  |
| Densenet201[26]         | 163  | 226  |
| Idrees et al. (2018) [29]| 132  | 191  |
| DeepCount (ours)        | 95.7 | 167.1|

Table 4. Test results on Mall
underlying relationship of the random variables. Although many cases suggest otherwise, we do often see positive correlation between extra parameters and increments of performance [16, 19, 25, 38]. Be that as it may, we still tend to avoid expensive computation a larger network would bear in practice. Trading off between capacity and velocity has been a dilemma for long. Hereby, we explicate how the idea of our DeepCount network is able to pursue both capacity and velocity at the same time. Trading off between capacity and velocity our proposed DeepCount model has the ability of accommodating more variations while making faster and better prediction. This implies its nature of outstanding capacity and efficiency.

5.2. Comparison on branches

As we have obtained the global count regressed by backbone, we can as well integrate the output density map to make count prediction like common density map-based methods. In the following, we compare predictions made between branches on MAE. Besides, we compute FLOPs for each branch to analyse their computational costs. Results are shown in Table 7.

As shown, the larger the density map, the harder it is to
be precise. Immediate reasons for this may be that larger density maps are sparser and usually awash with noise caused mostly by annotations of large-scale heads. Our method avoids predicting the count relying merely on density maps but exploits useful information from them to rather train the global count regressor. This allows more accurate predictions to be achieved.

Despite extra computation, there are situations in which density map, which gives extra information about the distribution, becomes a requirement. Our model can make directly count inference with backbone at its full speed while optionally producing density maps of multiple resolutions. User can choose smaller density maps to reduce computational expensiveness or larger ones to get more illuminating impression about the crowd distribution. Using bilinear interpolation and separable Gaussian filter, the largest density map produced can be efficiently up-sampled to original resolution for high-definition display, thus we argue it is unworthy to train a network to produce a high-resolution density map. Figure 4 shows our predicted density maps compared to their ground truths.

| Output Size | Branch 1 | Branch 2 | Branch 3 | Branch 4 | Branch 5 | Backbone |
|------------|----------|----------|----------|----------|----------|----------|
| Million FLOPs | 6034     | 2432     | 1216     | 648      | 34       | 1×1      |
| Shanghai Tech Part A | 79.2  | 73.4     | 69.7     | 66.7     | 65.8     | 65.2     |
| Shanghai Tech Part B | 9.7   | 8.9      | 8.0      | 7.4      | 7.2      | 7.2      |
| UCF-QNRF | 193.3  | 185.0     | 155.3   | 112.3    | 96.9     | 95.7     |
| Mall                 | 4.74  | 2.89      | 2.46     | 1.77     | 1.56     | 1.55     |

Table 7. Comparing between outputs on different branches.
5.3. Significance of gradients

Gradients are considered crucial to the achievement of our model. Hence, we detail more experiments to further cast light on the importance of them. Since derivatives of ReLU are a staircase function suppressing the negative direction, gradients in half of its activation space are set to naught. The back-propagation gradient matrices are sparse and may hinder propagation of gradient flow and counterproductively cause a large part of the network underused. Instead, Parametric ReLU has non-zero gradients in all quadrants allowing the network to fully learn. Table 8 shows results of training a network with all ReLU activations in comparison with our baseline network. As shown in Table 8, when gradients are sparse, the capability of the network drops.

| Activation | SHT Part B MAE |
|------------|----------------|
| ReLU       | 8.3            |
| PReLU      | 7.2            |

Table 8. Comparing results between using ReLU (sparse gradients) and PReLU (full gradients).

Also, the idea of being density-aware by gradient fusion is to leverage gradients sourced from supervision of multi-scale density maps. In ablation experiments (see Table 9), as we detach branches one by one from the largest to the smallest in training, the backbone receives less gradients in each case, and then the trend of performance degradation becomes more and more apparent. We also find that the model results satisfactorily when even trained with only global count on a dense dataset, while on a difficult one (sparse, non-uniform) it does not converge always, but we see it resolve if pretrained on dense dataset.

| Ablation     | SHT Part B MAE |
|--------------|----------------|
| No ablation  | 7.2            |
| Branch 1 ablated | 7.4        |
| Branches 1-2 ablated | 7.7       |
| Branches 1-3 ablated | 8.2       |
| Branches 1-4 ablated | 8.3       |
| Branches 1-5 ablated | 9.1       |

Table 9. Ablation on branches.

By means of this, we are now safer to conclude that the abundance of gradients has advantageous influence on our network and parameters in branches are indeed instrumental in the training of backbone. Giant as it may be, the network of branches is not a concern in an inference deployment. Unless training efficiency is also in a serious consideration, having a rationally greater number of parameters in this auxiliary module should be deemed innocuous as long as performance does not remain stagnant.

6. Conclusion

In this paper, we discuss advantages and limitations of current crowd counting methods, in light of which we propose a novel DeepCount network to be both fast and precise on count prediction and flexible on density map generation. State-of-the-art performance on public datasets evidences the effectiveness of our method. Our code is publicly available at: https://github.com/GeorgeChenZJ/deepcount

References

[1] W. Ge and R. T. Collins, "Marked point processes for crowd counting," 2009 IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, 2009, pp. 2913-2920.
[2] H. Idrees, K. Soomro and M. Shah, "Detecting Humans in Dense Crowds Using Locally-Consistent Scale Prior and Global Occlusion Reasoning," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 37, no. 10, pp. 1986-1998, 1 Oct. 2015.
[3] H. Idrees, I. Saleemi, C. Seibert and M. Shah, "Multi-source Multi-scale Counting in Extremely Dense Crowd Images," 2013 IEEE Conference on Computer Vision and Pattern Recognition, Portland, OR, 2013, pp. 2547-2554.
[4] Y. Zhang, D. Zhou, S. Chen, S. Gao and Y. Ma, "Single-Image Crowd Counting via Multi-Column Convolutional Neural Network," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 589-597.
[5] D. B. Sam, S. Surya and R. V. Babu, "Switching Convolutional Neural Network for Crowd Counting," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 4031-4039.
[6] V. A. Sindagi and V. M. Patel, "Generating High-Quality Crowd Density Maps Using Contextual Pyramid CNNs," 2017 IEEE International Conference on Computer Vision (ICCV), Venice, 2017, pp. 1879-1888.
[7] C. Zhang, H. Li, X. Wang and Xiaokang Yang, "Cross-scene crowd counting via deep convolutional neural networks," 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, 2015, pp. 833-841.
[8] V. A. Sindagi and V. M. Patel, "A survey of recent advances in cnn-based single image crowd counting and density estimation," Pattern Recognition Letters, no. 107, pp. 3-16, 2018.
[9] M. S. Zitouni, H. Bhaskar, J. Dias, and M. E. Al-Mualla, "Advances and trends in visual crowd analysis: A systematic survey and evaluation of crowd modelling techniques," Neurocomputing, no. 186, pp. 139-159, 2016.
[10] Viola, Jones and Snow, "Detecting pedestrians using patterns of motion and appearance," Proceedings Ninth IEEE International Conference on Computer Vision, Nice, France, 2003, pp. 734-741 vol.2.
[11] X. Cao, Z. Wang, Y. Zhao, and F. Su, "Scale aggregation network for accurate and efficient crowd counting," in Proceedings of the European Conference on Computer Vision (ECCV), pp. 734-750, 2018.
[12] J. Gall, A. Yao, N. Razavi, L. Van Gool and V. Lempitsky, "Hough Forests for Object Detection, Tracking, and Action Recognition," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 11, pp. 2188-2202, Nov. 2011.
[13] K. Chen, C. C. Loy, S. Gong, and T. Xiang, "Feature mining for localised crowd counting," in British Machine Vision Conference (BMVC), vol. 1, no. 2, pp. 3, 2012.

[14] A. B. Chan, Zhang-Sheng John Liang and N. Vasconcelos, "Privacy preserving crowd monitoring: Counting people without people models or tracking," 2008 IEEE Conference on Computer Vision and Pattern Recognition, Anchorage, AK, 2008, pp. 1-7.

[15] V. Ranjan, H. Le, M. Hoai, "Iterative crowd counting," in Proceedings of the European Conference on Computer Vision (ECCV), pp. 270-285, 2018.

[16] Y. Li, X. Zhang and D. Chen, "CSRNet: Dilated Convolutional Neural Networks for Understanding the Highly Congested Scenes," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, 2018, pp. 1091-1100.

[17] Z. Ma and A. B. Chan, "Crossing the Line: Crowd Counting by Integer Programming with Local Features," 2013 IEEE Conference on Computer Vision and Pattern Recognition, Portland, OR, 2013, pp. 2539-2546.

[18] C. Wang, H. Zhang, L. Yang, L. Si, and X. Cao, "Deep people counting in extremely dense crowds," in Proceedings of the 23rd ACM international conference on Multimedia, 2015, pp. 1299-1302.

[19] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv:1409.1556 [cs.CV], Sep. 2014.

[20] D. Kong, D. Gray and Hai Tao, "A Viewpoint Invariant Approach for Crowd Counting," 18th International Conference on Pattern Recognition (ICPR'06), Hong Kong, 2006, pp. 1187-1190.

[21] M. Rodriguez, I. Laptev, J. Sivic and J. Audibert, "Density-aware person detection and tracking in crowds," 2011 International Conference on Computer Vision, Barcelona, 2011, pp. 2423-2430.

[22] M. Li, Z. Zhang, K. Huang and T. Tan, "Estimating the number of people in crowded scenes by MID based foreground segmentation and head-shoulder detection," 2008 19th International Conference on Pattern Recognition, Tampa, FL, 2008, pp. 1-4.

[23] J. Liu, C. Gao, D. Meng and A. G. Hauptmann, "DecideNet: Counting Varying Density Crowds Through Attention Guided Detection and Density Estimation," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, 2018, pp. 5197-5206.

[24] V. A. Sindagi and V. M. Patel, "CNN-Based cascaded multi-task learning of high-level prior and density estimation for crowd counting," 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSSS), Lecce, 2017, pp. 1-6.

[25] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 770-778.

[26] G. Huang, Z. Liu, L. v. d. Maaten and K. Q. Weinberger, "Densely Connected Convolutional Networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 2261-2269.

[27] J. Dai, Y. Li, K. He, and J. Sun, "R-fcn: Object detection via region-based fully convolutional networks," in Advances in neural information processing systems, 2016, pp. 379-387.

[28] S. Ren, K. He, R. Girshick and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 1 June 2017.

[29] H. Idrees, M. Tayyab, K. Athrey, D. Zhang, S. Al-Maadeed, N. Rajpoot and M. Shah, "Composition loss for counting, density map estimation and localization in dense crowds," in Proceedings of the European Conference on Computer Vision (ECCV), pp. 532-546, 2018.

[30] V. Pham, T. Kozakaya, O. Yamaguchi and R. Okada, "COUNT Forest: CO-Voting Uncertain Number of Targets Using Random Forest for Crowd Density Estimation," 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, 2015, pp. 3253-3261.

[31] B. Xu, N. Wang, T. Chen, and M. Li, "Empirical evaluation of rectified activations in convolutional network," arXiv:1505.00853 [cs.LG], 2015.

[32] B. Sheng, C. Shen, G. Lin, J. Li, W. Yang and C. Sun, "Crowd Counting via Weighted VLAD on a Dense Attribute Feature Map," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 28, no. 8, pp. 1788-1797, Aug. 2018.

[33] X. Glorot, and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in Proceedings of the thirteenth international conference on artificial intelligence and statistics, pp. 249-256, 2010.

[34] T. Zhao, R. Nevatia and B. Wu, "Segmentation and Tracking of Multiple Humans in Crowded Environments," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 30, no. 7, pp. 1198-1211, July 2008.

[35] L. Liu, H. Wang, G. Li, W. Ouyang, and L. Lin, "Crowd counting using deep recurrent spatial-aware network," arXiv:1807.00601 [cs.CV], 2018.

[36] D. B. Sam and R. V. Babu, "Top-down feedback for crowd counting convolutional neural network," in Thirty-Second AAAI Conference on Artificial Intelligence, 2018.

[37] Z. Shi et al., "Crowd Counting with Deep Negative Correlation Learning," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, 2018, pp. 5382-5390.

[38] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, "Mobilenets: Efficient convolutional neural networks for mobile vision applications," arXiv:1704.04861 [cs.CV], 2017.