Learn to Scale: Generating Multipolar Normalized Density Map for Crowd Counting

Chenfeng Xu\textsuperscript{1}\textsuperscript{*}, Kai Qiu\textsuperscript{2}, Jianlong Fu\textsuperscript{2}, Song Bai\textsuperscript{3}, Yongchao Xu\textsuperscript{1}, Xiang Bai\textsuperscript{1}

\textsuperscript{1}Huazhong University of Science and Technology, \textsuperscript{2}Microsoft Research Asia, \textsuperscript{3}University of Oxford

{xuchenfeng, yongchaoxu, xbai}@hust.edu.cn, {kaqiu, jianf}@microsoft.com, songbai.site@gmail.com

Abstract

Dense crowd counting aims to predict thousands of human instances from an image, by calculating integrals of a density map over image pixels. Existing approaches mainly suffer from the extreme density variances. Such density pattern shift poses challenges even for multi-scale model ensembling. In this paper, we propose a simple yet effective approach to tackle this problem. First, a patch-level density map is extracted by a density estimation model, and is further grouped into several density levels which are determined over full datasets. Second, each patch density map is automatically normalized by an online center learning strategy with a multipolar center loss (MPCL). Such a design can significantly condense the density distribution into several clusters, and enable that the density variance can be learned by a single model. Extensive experiments show the best accuracy of the proposed framework in several crowd counting datasets, with relative accuracy gains of 4.2\%, 14.3\%, 27.1\%, 20.1\% over the state-of-the-art approaches, in ShanghaiTech-Part A, Part B, UCF-CC_50, UCF-QNRF dataset, respectively.

1. Introduction

A robust crowd counting system is of significant values in many real-world applications such as video surveillance, security alerting, event planning, etc. In recent years, the deep learning based approaches have been the mainstream of crowd counting, because of the powerful learning representation ability produced by convolutional neural works (CNN). To estimate the count, predominant approaches generate a density map by CNN, from which the count of instances can be integrated over image pixels.

Although crowd counting has been extensively studied by previous methods, handling the large density variances which cause huge density pattern shift in crowd images is still an open issue. As illustrated in Fig. 1 (a), the densities of crowd image patches can vary significantly, which change from a bit sparse (e.g., Shanghai-B) to extremely dense (e.g., UCF-QNRF). Such large density pattern shifts usually bring grand challenges to density prediction by a single CNN model, due to its fixed sizes of receptive fields. Remarkable progresses have been achieved by learning a density map through designing multi-scale architectures \cite{22} or aggregating multi-scale features \cite{23, 33}, which indicate that the ability to cope with density variation is crucial for crowd counting methods. Although density maps with multiple scales can be generated and aggregated, robustness is still hard to ensure when the density variances

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{(a) Three examples from ShanghaiTech-Part A dataset, which show extreme density variances. (b) The Mean Relative Error (MRE) over four crowd counting datasets (the scale variances get larger from left to right) of different approaches. Results show the robustness of the proposed approach to extreme scale variances, compared with recent works. [best viewed in color].}
\end{figure}
get increasing a lot. As shown in Fig. (b), most recent works obtain a higher MRE on datasets with larger density variances, which indicates that the extreme density variance and pattern shift in crowd counting remains huge challenge.

In this paper, we propose a simple yet effective method to relieve the problem from extreme density variances. The core idea is learning to scale (denoted as L2S) image patches and to facilitate the density distribution condensing to several clusters, and thus the density variance can be reduced. The scale factor of each image patch can be automatically learned during training, with the supervision of a novel multipolar center loss (MPCL). More specifically, all the patches from each density level are optimized to approach a density center, which can be updated by online calculating a mean value for each density level.

In particular, the proposed L2S framework consists of two closely-related steps. First, given an image, an initial density map is generated by a CNN model. After that, each density map is divided into $K \times K$ patches, and all the patch-level density maps are further evenly divided into $G$ groups, according to their density levels. Second, each patch is scaled by a learned scale factor, and thus the density of this patch can converge to a center of its density level. The final density map for the input image can be obtained by concatenating the $K \times K$ patch-level density maps.

We conduct the experiments on several popular benchmark datasets, including Shanghaitech [33], UCF_CC_50 [9], UCF-QNRF [11]. Extensive evaluations show significantly superior performance over the prior arts. Moreover, the cross validation on these datasets further demonstrates that the proposed L2S framework has a powerful transferability. In summary, the main contributions in this paper are two-fold:

- We proposed a Learning to Scale Module (L2SM) to solve the density variation issue in crowd counting. With L2SM, different regions can be automatically scaled so that they have similar densities, while the quality of their density maps is significantly improved. L2SM is end-to-end trainable when adding it into a CNN model for density estimation.

- The proposed L2SM significantly outperforms state-of-the-art methods for crowd counting on three widely-adopted challenging datasets, demonstrating its effectiveness in handling density variation. Furthermore, L2SM also has a good transferability under cross validation on different datasets, showing the generality of the proposed method.

2. Related Work

Crowd counting has attracted much attention in computer vision. Early methods frame the counting problem as detection task [7, 29] that explicitly detects individual heads, which has major difficulty in occlusion and dense areas. The regression-based methods [4, 6, 8, 10] greatly improve the counting performance on dense areas via different regression functions such as Gaussian process, ridge regression, and random forest regression. Recently, with the development of deep learning, the mainstream crowd counting methods switch to CNN-based methods [21, 32, 2, 33, 11, 5, 18]. These CNN-based methods address the crowd counting via regressing density map representation introduced by lempitsky et al. [14], and achieve better accuracy and transferability as compared to the classical methods. Recent methods mainly focus on two challenging aspects faced by current CNN-based methods: huge scale and density variance and severe over-fitting.

Methods addressing huge scale and density variance. Multi-scale change is a challenging problem for many vision tasks including crowd counting. It is difficult to accurately count the small heads in dense areas. There are many methods attempting to handle huge scale variance. The existing methods can be roughly divided into two categories: methods that explicitly rely on scale information and methods that implicitly cope with multi-scale changes.

1) Some methods explicitly make use of scale information for crowd counting. For instance, the methods in [32, 19] adopt deep CNN using provided geometric or perspective information. Yet, these scale related information is not always readily available. In [28, 23], the authors first use a network to estimate the scale level and density degree for the corresponding whole or partial region based on manually set scale degree. Then, the obtained scale related information is fused with another network or used to design different networks for dividing and counting. To overcome the difficulty in manually setting the scale degree, the authors design an incrementally growing CNN in [11] to deal with areas of different density degrees without involving any handcraft steps.

2) Some other works aim to implicitly cope with multi-scale problem. Zhang et al. [33] propose to build a multi-column CNN to extract multi-scale feature and fuse them together for density map estimation. Each column is limited to cover a subset of scale variance. To ameliorate the multi-column structure, the authors in [3] propose a multi-stage structure such that each stage exploits the multi-column convolution and combines the multi-scale feature to regress the density map. The author in [17] encodes the scale of the contextual information required to accurately predict crowd density. In [15], the authors propose to increment the receptive field size in CNN to better leverage multi-scale information. In addition to these specific network designs for

*MRE is calculated by MAE/P, where MAE denotes the standard Mean Average Error and P is the average count of a dataset
3. Method

3.1. Overview

The mainstream crowd counting methods model the problem as density map regression using CNN. For a given image, the ground-truth density map $D$ is given by spreading binary head locations to nearby regions with Gaussian kernels. For sparse regions, the ground-truth density only depends on a specific person, resulting in regular Gaussian blobs. For dense regions, multiple crowded heads may spread to the same nearby pixel, yielding high ground-truth density with very different density pattern compared with sparse regions. This density pattern shift makes it difficult to accurately predict the density map for both dense and sparse regions in the same way.

To improve the counting accuracy, we aim to tackle the problem of pattern shift due to large density variations, improving the prediction for highly dense regions. Specifically, the proposed method mimics a rational behaviour when humans count crowds. For a given crowd image, we are prone to begin with dividing the image into partitions of different crowding level before attempting to count the people. For sparse regions of large heads, it is easy to directly count the people on the original region. Whereas, for dense regions composed of crowded small heads, we need to zoom in the region for more accurate counting. An example of this counting behaviour is depicted in Fig. 2.

We propose a network to mimic such human behaviour for crowd counting. The overall pipeline is depicted in Fig. 3, consisting of two modules: 1) Scale preserving network (SPN) presented in Sec. 3.2. We leverage multi-scale feature fusion to generate an initial density map prediction, which provides accurate prediction on sparse regions and indicates the density distribution over image; 2) Learning to zoom module (L2SM) detailed in Sec. 3.3. We divide the image into $K \times K$ non-overlapping regions, and select some dense regions (based on the initial density estimation) to re-predict the density map. Specifically, we leverage SPN to compute a scaling factor for each selected dense region, and scale the ground-truth density map by changing the distance between blobs and keeping the same peaks. The density re-prediction for the selected regions is then performed on the scaled features. The key of this re-prediction process lies on computing appropriate scaling factors. For that, we adopt the center loss to centralize the density distributions into multipolar centers, alleviating the density pattern shift issue and thus improving the prediction accuracy. The whole network is end-to-end trainable whose training objective is depicted in Sec. 3.4.

3.2. Scale Preserving Network

We follow the mainstream crowd counting methods by regressing density map. Precisely, we use geometry-adaptive kernels to generate ground-truth density maps in highly congested scenes. For a given image containing $P$ person, the ground-truth annotation can be represented via a delta function on each pixel $p$: $H(p) = \sum_{i=1}^{P} \delta(p - p_i)$, where $p_i$ is the annotated location of $i$-th person. The density map $D$ on each pixel $p$ is then generated by convolving $H(p)$ with a Gaussian kernel $G$: $D(p) = \sum_{i=1}^{P} \delta(p - p_i) * G_{\sigma_i}$, where the Gaussian kernel $\sigma_i$ is a spread parameter.

We develop a CNN to regress the density map $D$. For a fair comparison with most methods, we adopt the
VGG16 [26] as the backbone network. We discard the pooling layer between stage4 and stage5 as well as the last pooling layer and the fully connected layers that follow to preserve accurate spatial information. It is well-known that deep layers in CNN encode more semantic and high level information, and shallow layers provide more precise localization information. We extract features from different stages by applying $3 \times 3$ convolutions on the last layer of each stage. Then we pool these features extracted from stage1 to stage5 into $16 \times 16$, $8 \times 8$, $4 \times 4$, $2 \times 2$, and $1 \times 1$, respectively. This results in a pyramid structure. Each spatial unit in the pooled feature indicates the density level, hence scale of the underlying region mapped to the original image. These pooled scale preserving features are then upsampled to the size of conv5 by bilinear interpolation and stacked together with features in conv5 $f_b$. We then feed the stacked feature $f_s$ to three successive convolutions and one deconvolution layer for regressing density map $\hat{D}$.

### 3.3. Learning to Scale Module

The initial density prediction is accurate on sparse regions thanks to the regular individual Gaussian blobs, but the prediction is less accurate on dense regions composed of crowded heads lying very close to each other. As indicated in Sec. 3.1, this triggers the pattern shift on the target density map. Following the rational human behaviour in crowd counting, we zoom in the dense regions for better counting accuracy. In fact, on the zoomed version, the distance between nearby heads is enlarged, which results in regular individual Gaussian blobs of target density map, alleviating the density pattern shift. Such density pattern modulating facilitates the prediction. Inspired by this, we first evenly divide the image domain into $K \times K$ (e.g. $K = 4$) non-overlapping regions. We then select the dense regions based on the average initial density $\hat{D}_{i}$ = $\sum_{p \in R_i} D(p)/|R_i|$ for each region $R_i$, where $|R_i|$ denotes the area of region $R_i$.

We propose to mimic human behaviour in crowd counting by learning to scale the selected dense regions. For that, we first leverage the scale preserving pyramid features described in Sec. 3.2 to compute the scaling ratio $r_i$ for each selected region $R_i$. Precisely, we downsample/upsample the pooled features described in Sec. 3.2 to $K \times K$, and concatenate them together. This is followed by a $1 \times 1$ convolution to produce the scale factor map $r$. Each value in this $K \times K$ map $r$ represents the scaling ratio for the underlying region.

Once we have the scale factor map $r$, we scale the feature $f_b$ on the selected regions accordingly through bilinear upsampling. Based on the scaled feature map corresponding to each selected region $R_i$, we apply five successive convolutions to re-predict the density map for scaled $R_i$. Then we resize the re-predicted density map to the original size of $R_i$ and multiply the density on each pixel by $r_i^2$ to preserve the same counting result. The initial prediction on selected regions is replaced with resized density map re-prediction.

To guide the density map re-prediction on the selected regions, we also adjust the ground-truth density map for each region accordingly. For each selected region $R_i$, instead of straightforwardly scaling the ground truth density map in the same way as feature map scaling, we first scale the binary head location map, and then recompute the ground-truth density map $\hat{D}'_i$ for $R_i$ by $\hat{D}'_i(p) = \sum_{m=1}^{P_i} \delta(p - r_i \ast p_m) * G_{\sigma_m}(p)$, where $P_i$ is the number of people in $R_i$. As shown in Fig. 4, such ground-truth trans-
formation for density map re-computation reduces the density pattern gap between sparse regions and dense regions, facilitating the density map re-prediciton.

The main issue of this density map re-prediction by learning to scale dense regions is to compute appropriate scale ratios for the selected dense regions. Yet, there is no explicit target scale suggesting how much region $R_i$ should be zoomed ideally. We would like to have the estimated average density $\hat{D}_i$ approaches the ground truth average density on the $i$-th region. The relative density degree of region $R_i$ could be well reflected by $d_i = D_i / r_i^2$. Assuming that we make the value of $d_i$ for each region close to one of multiple learnable centers, then we centralize all the selected regions to multiple similar density levels, alleviating the large density pattern shift and thus improving the prediction accuracy. This motivates us to resort to center loss on $d_i$ with multipolar centers. Put it simply, we attempt to centralize all the selected regions into $C$ centers following their average density $\bar{D}$ acting as the unsupervised clustering.

We first initialize the $C$ centers with increasing random values for more and more dense regions. Then for each center $\bar{d}_c$, we follow the standard process of using center loss and update the center for $(t+1)$-th iteration as below:

$$\Delta \bar{d}_c^t = \frac{\sum_{i=1}^{n_c} (\bar{d}_c^t - \frac{D_i}{r_i^2})}{1 + n_c}, \quad \bar{d}_c^{t+1} = \bar{d}_c^t - \alpha \cdot \Delta \bar{d}_c^t, \quad (1)$$

where $n_c$, $D_i$, and $r_i^2$ refer to the number of regions, average density map, and scaling ratio for $i$-th region, respectively, that will be centralized to the $c$-th center in an underlying image, and $\alpha$ denotes the learning rate for updating each center. During each iteration, we use the selected $N = \sum_{c=1}^{C} n_c$ dense regions to compute the center loss $L_c$ with multiple centers and update network parameters as well as the centers. The supervision on $r$ using center loss with multiple centers is the key to bring all the selected regions to multiple similar density levels, leading to robust density estimation.

### 3.4. Training objective

The whole network is end-to-end trainable, which involves three loss functions: 1) L2 loss for initial prediction of density map $L_D$ given by $L_D = \| D - \hat{D} \|_2^2$. 2) L2 loss for density map re-prediction on $N = \sum_{c=1}^{C} n_c$ selected regions $L_r$ given by $L_r = \sum_{i=1}^{N} \| \frac{D_i}{r_i^2} - \bar{d}_c \|_2^2$, where $\hat{D}$ denotes the re-predicted density map on the scaled selected region $R_i$. 3) Center loss on relative density level $d$ for the selected regions $L_c$ computed by:

$$L_c = \sum_{c=1}^{C} \sum_{i=1}^{n_c} \left\| \frac{D_i}{r_i^2} - \bar{d}_c \right\|_2^2, \quad (2)$$

The final loss function $L$ for the whole network is the combination of the above three losses given by:

$$L = L_D + \lambda_1 \times L_r + \lambda_2 \times L_c, \quad (3)$$

where $\lambda_1$ and $\lambda_2$ are two hyperparameters. Note that we optimize the loss function $L$ in Eq. (3) to update not only the overall network parameters but also the centers $\{\bar{d}_c\}$.

### 4. Experiments

#### 4.1. Datasets and Evaluation Metrics

We conduct experiments on three widely adopted benchmark datasets including ShanghaiTech, UCF_CC-50, and UCF-QNRF to demonstrate the effectiveness of the proposed method. These three datasets and the adopted evaluation metrics are shortly described in the following.

**ShanghaiTech Dataset.** The ShanghaiTech crowd counting dataset consists of 1198 annotated images with a total of 330,165 people, divided into two parts. Part A contains 482 images which are randomly crawled from the Internet, among which 300 images are used for training and the remaining 182 images are used for testing. Part B includes 716 images which are taken from the busy streets of metropolitan area in Shanghai, among which 400 images are used for training and 316 images for testing. The dataset also provides annotation in terms of coordinates of people heads in each image.

**UCF_CC-50 Dataset.** This dataset is a collection of 50 images of very crowd scenes, containing significantly varied number of people ranging from 94 to 4543 people in image. The large variance of total number of people and the small amount of images make this dataset very challenging. Following classical benchmarks on this dataset, we use 5-fold cross-validation to evaluate the performance of our method.

**UCF-QNRF:** UCF-QNRF dataset is the largest dataset to-date containing 1535 images which are divided into
Table 1. Quantitative comparison of the proposed method with state-of-the-art methods on three widely adopted datasets.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE/MAE</td>
<td>110.2/173.2</td>
<td>101.3/152.4</td>
<td>90.4/135.0</td>
<td>73.6/112.0</td>
<td>75.7/102.7</td>
<td>73.6/112.0</td>
<td>73.5/112.3</td>
<td>68.2/115.0</td>
<td>69.8/117.3</td>
<td>67.0/104.5</td>
<td>-</td>
<td>72.9/114.5</td>
<td>70.0/106.3</td>
<td><strong>64.2/98.4</strong></td>
</tr>
<tr>
<td>MSE/MSE</td>
<td>26.4/41.3</td>
<td>20.0/31.1</td>
<td>21.6/33.4</td>
<td>20.1/30.1</td>
<td>17.2/27.4</td>
<td>13.7/21.4</td>
<td>18.7/26.0</td>
<td>10.6/16.0</td>
<td>10.7/16.0</td>
<td>8.4/13.6</td>
<td>-</td>
<td>12.1/20.5</td>
<td>9.1/14.6</td>
<td><strong>7.2/11.1</strong></td>
</tr>
<tr>
<td>MAE</td>
<td>377.6/509.1</td>
<td>322.8/397.9</td>
<td>318.1/439.2</td>
<td>298.8/320.9</td>
<td>291.0/404.6</td>
<td>279.6/388.9</td>
<td>288.4/404.7</td>
<td>266.1/397.5</td>
<td>260.9/365.5</td>
<td>258.4/334.9</td>
<td>-</td>
<td>225.4/372.5</td>
<td>204.7/340.4</td>
<td><strong>188.4/315.3</strong></td>
</tr>
<tr>
<td>MAE</td>
<td>277/ -</td>
<td>252/ 514</td>
<td>228/ 445</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>120.6/190.2</td>
<td>110.3/184.6</td>
<td><strong>104.7/173.6</strong></td>
</tr>
<tr>
<td>MAE</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>205.2/245.7</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2. Ablation study on different settings of dense region selection, number of centers \( C \), and different ways of learning to scale: the proposed learning to scale module (L2SM) and straightforwardly scale to average density (S2AD).

<table>
<thead>
<tr>
<th>Method</th>
<th>SPN</th>
<th>L2SM (G=3)</th>
<th>L2SM (G=4)</th>
<th>L2SM/S2AD (G=5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>70.0</td>
<td>65.1</td>
<td>66.1</td>
<td>67.2/68.9</td>
</tr>
<tr>
<td>MAE</td>
<td>106.3</td>
<td>100.4</td>
<td>103.2/110.3</td>
<td>102.3/110.3</td>
</tr>
<tr>
<td>Cost time (s)</td>
<td>0.524</td>
<td>0.576</td>
<td>0.569</td>
<td>0.539/0.540</td>
</tr>
<tr>
<td>Cost time (s)</td>
<td></td>
<td></td>
<td></td>
<td>0.550/0.551</td>
</tr>
<tr>
<td>Cost time (s)</td>
<td></td>
<td></td>
<td></td>
<td>0.565/0.563</td>
</tr>
<tr>
<td>Cost time (s)</td>
<td></td>
<td></td>
<td></td>
<td>0.583/0.580</td>
</tr>
<tr>
<td>Cost time (s)</td>
<td></td>
<td></td>
<td></td>
<td>0.592/0.587</td>
</tr>
</tbody>
</table>

Table 3. Ablation study on \( K \times K \) image domain division for selecting dense region to re-predict under one center setting.

1201 training and 334 testing images. The number of people in an image varies from 49 to 12,865, making this dataset feature huge density variation. Furthermore, the images in this dataset also have very high resolution variance (e.g., ranging from \( 400 \times 300 \) to \( 9000 \times 6000 \)).

Evaluation metrics. We employ two standard metrics, i.e., Mean Absolute Error (MAE) and Mean Squared Error (MSE). MAE and MSE are defined as

\[
\text{MAE} = \frac{1}{M} \sum_{i=1}^{M} |c_i - \hat{c}_i|, \\
\text{MSE} = \frac{1}{M} \sum_{i=1}^{M} (c_i - \hat{c}_i)^2,
\]

where \( c_i \) (resp. \( \hat{c}_i \)) represents the ground-truth (resp. estimated) number of pedestrians in the \( i \)-th image, and \( M \) is the total number of test images.

4.2. Implementation Details

We follow the setting in [15] to generate the ground-truth density map. For a given dataset, we first evenly divide all the images in a dataset into \( G \) groups of regions with increasing density, and then attempt to centralize the most dense \( C \) groups of regions to \( C \) similar density levels (i.e., \( C \) centers involved in the center loss), respectively. In the following, without explicitly specifying, \( G \) is set to 5, and \( C \) is set to 3 for all involved datasets except for UCF_CC_50 dataset. Since images in UCF_CC_50 dataset consist of crowded people over the whole image domain, we centralize all regions to \( C = 5 \) similar density levels. Without explicitly specifying, the hyperparameter \( K \) involved in dividing each image into \( K \times K \) regions is set to 4.

The loss function described in Eq. (3) is used for the model training. We set \( \lambda_1 \) to 1 and discuss the impact of \( \lambda_2 \) in Eq. (3) in the following. We use Adam [12] optimizer to optimize the whole architecture with the learning rate initialized to 1e-4. When training on the UCF-QNRF dataset containing images of very high resolution (e.g., \( 9000 \times 6000 \)), we first down-sample the image of resolution larger than \( 1080p \) to \( 1920 \times 1080 \). Then we divide each image into \( 2 \times 2 \) and combine them into a tensor with batch size equal to 4. When training on the other dataset, we directly input the whole image to our network.

During inference, we first generate an initial density map \( \hat{D} \) for the whole input image, and then select dense regions from \( K \times K \) division based on the average initial density
Table 4. Cross dataset experiments on ShanghaiTech, UCF_CC_50, and UCF-QNRF dataset for assessing the transferability of different methods.

D_i on each region R_i. If D_i is larger than a pre-defined value for selecting the top C groups of regions in training, we replace the initial density map prediction with scaled re-prediction for each selected dense region R_i.

The proposed method is implemented in Pytorch [20]. All experiments are carried out on a workstation with an Intel Xeon 16-core CPU (3.5GHz), 64GB RAM, and a single Titan Xp GPU.

4.3. Experimental Comparisons

We evaluate the proposed method on ShanghaiTech dataset, UCF_CC_50, and UCF-QNRF datasets. The proposed method outperforms all the other competing methods on all the benchmarks. The quantitative comparison with the state-of-the-art methods on these three datasets is depicted in Table 1.

ShanghaiTech. The proposed method outperforms the state-of-the-art method SANet [3] by 2.8 MAE and 6.1 MSE on ShanghaiTech Part A and 1.2 MAE and 2.5 MSE on ShanghaiTech Part B. It also can be seen in Table 1 that L2SM improves the performance of our SPN baseline by 5.8 MAE and 7.9 MSE on ShanghaiTech Part A, and 1.9 MAE and 3.5 MSE on ShanghaiTech Part B. In fact, Shanghai Part A contains images more crowded than ShanghaiTech Part B, and the density distribution of Shanghai Part A varies more significantly than that of Shanghai Part B. This may explain that the improvement of the proposed L2SM on ShanghaiTech Part A is more significant than that on ShanghaiTech Part B.

UCF_CC_50. We then compare the proposed method with other related methods on UCF_CC_50 dataset. To the best of our knowledge, UCF_CC_50 dataset is currently the most dense dataset publicly available for crowd counting. The proposed method achieves significant improvement over the state-of-the-art methods. Precisely, the proposed method improves SANet [3] from 258.4 MAE to 188.4 MAE, and from 334.9 MSE to 315.3 MSE.

UCF-QNRF. We have also conducted experiments on recent UCF-QNRF dataset containing images of significantly varied density distribution and resolution. By limiting the maximal image size to $1920 \times 1080$, our VGG16 baseline already achieves state-of-the-art performance. The proposed SPN brings an improvement of 10.3 MAE and 20.6 MSE compared with VGG16 baseline. The proposed L2SM further boost the performance by 5.6 MAE and 11.0 MSE.

4.4. Ablation Study

The ablation studies are mainly conducted on the ShanghaiTech part A dataset, as it is a moderate dataset, neither too dense nor too sparse, and covers a diverse number of people heads.

Effectiveness of different learning to scale settings. For the learning to scale process, we first evenly divide the images in a whole dataset into $G$ groups of regions with increasing density, and then attempt to centralize the most dense $C$ groups of regions to $C$ similar density levels. As shown in Table 2, the number of groups $G$ and number of centers $C$ are important for accurate counting. For a fixed number of groups (e.g., $G = 5$), centralizing more and more regions leads to slightly improved counting result. Yet, when we attempt to centralize every image region, we also re-predict the density map for very sparse or background regions, bringing more background noise and thus yielding slightly decreased performance. A relative finer group division with a proper number of centers performs slightly better. As depicted in Table 2 the proposed learning to scale using multipolar center loss performs much better than straightforwardly scaling to the average density (S2AD) in...
Figure 6. Qualitative visualization of predicted density map on two examples. From left to right: original image, prediction given by SPN, re-predicted density map with L2SM on selected regions (englobed by black boxes), and ground-truth density map.

Effectiveness of the division. We also conduct experiments by varying the $K \times K$ image domain division. As depicted in Table 3. The performance is rather stable across different image domain divisions.

4.5. Evaluation of Transferability

To demonstrate the transferability of the proposed method across datasets, we conduct experiments under cross dataset settings, where the model is trained on the source domain and tested on the target domain.

The cross dataset experimental results are presented in Table 4. We can observe that the proposed method generalizes well to unseen datasets. In particular, the proposed method consistently outperforms the state-of-the-art methods in [25] and MCNN [33] by a large margin. The proposed method also performs slightly well than the method in [18] in transferring models trained on ShanghaiTech Part A to UCF_CC_50. Yet, the improvement is not as significant as the comparison with [33, 25] on transferring between Shanghai Part A and Part B. This is probably because that the method in [18] also relies on extra data which may somehow help to reduce the gap between the two datasets. As depicted in Table 4, the proposed L2SM plays an important role in ensuring the transferability of the proposed method. Furthermore, as depicted in Table 1 and Table 4 the proposed method under cross-dataset settings performs competitively or even outperforms some methods [23, 28, 27, 33] using the proper training set. This also confirms the generalizability of the proposed method.

5. Conclusion

In this paper, we propose a Learn to Scale Module (L2SM) to tackle the problem of large density variation for crowd counting. We achieve density centralization by a novel use of multipolar center loss. The L2SM can ef-
fectively learn to scale significantly varied dense regions to multiple similar density levels, making the density estimation on dense regions more robust. Extensive experiments on three challenging datasets demonstrate that the proposed method achieves consistent and significant improvements over the state-of-the-art methods. L2SM also shows the noteworthy generalization ability to unseen datasets with significantly varied density distributions, demonstrating the effectiveness of L2SM in real applications.

Acknowledgement

This work was supported in part by the National Key Research and Development Program of China under Grant 2018YFB1004600, in part by NSFC 61703171, and in part by NSF of Hubei Province of China under Grant 2018CFB199, to Dr. Yongchao Xu by the Young Elite Scientists Sponsorship Program by CAST.

References


