Dual Path Multi-Scale Fusion Networks with Attention for Crowd Counting

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Abstract

The task of crowd counting in varying density scenes is an extremely difficult challenge due to large scale variations. In this paper, we propose a novel dual path multi-scale fusion network architecture with attention mechanism named SFANet that can perform accurate count estimation as well as present high-resolution density maps for highly congested crowd scenes. The proposed SFANet contains two main components: a VGG backbone convolutional neural network (CNN) as the front-end feature map extractor and a dual path multi-scale fusion networks as the back-end to generate density map. These dual path multi-scale fusion networks have the same structure, one path is responsible for generating attention map by highlighting crowd regions in images, the other path is responsible for fusing multi-scale features as well as attention map to generate the final high-quality high-resolution density maps. SFANet can be easily trained in an end-to-end way by dual path joint training. We have evaluated our method on four crowd counting datasets (ShanghaiTech, UCF_CC_50, UCSD and UCF-QRNF). The results demonstrate that with attention mechanism and multi-scale feature fusion, the proposed SFANet achieves the best performance on all these datasets and generates better quality density maps compared with other state-of-the-art approaches.

1. Introduction

Crowd counting has gained much more attention in recent years because of its various applications such as video surveillance, public safety, traffic control. However, due to problems including occlusions, perspective distortions, scale variations and diverse crowd distributions, performing precise crowd counting has been a challenging problem in computer vision. Some of early methods solve crowd counting problem by detecting each individual pedestrian in a crowd [6, 9, 13], while some methods rely on hand-crafted features from multi-source [8]. These methods may have low performance for the heavily occlusions and diverse crowd distribution scenes.

To tackle it, some new methods recently have been developed by utilizing Convolutional Neural Networks (CNNs) for accurate crowd density map generation and precise crowd counting. These methods mainly aim to solve two major difficult problems: large head scale variations caused by camera perspective and diverse crowd distributions with high background noisy scenes. As shown in Figure 1, head scale near the camera is much larger than that far from the camera in top row images, while bottom row images show diverse crowd distribution with trees and building background noise. Certain CNN-based methods deal the issue of scale variations via multi-column or multi-resolution network [30, 16] to achieve better accuracy. Though these methods show improvement in scale variations, they are still restricted by the hand-crafted filters size and multi-column structure. In MCNN [30], each column is dedicated to a certain level of congested scene, however Li et al. 2018 [14] shows that each column in such branch structure learns nearly identical features. For the issue of diverse crowd distributions with high background noise scenes, MA Hossain et al. 2019 [7] tried to apply attention mechanism to guide the network to automatically focus on certain global and local scales appropriate for the image. But this method
only uses the attention model to represent three different scale levels and still base on multi-columns structure, thus it doesn’t perform well for congested crowd scenes.

In this paper, we propose a novel method to address the above-mentioned two major difficult problems of precise crowd counting. The network is designed as dual path multi-scale fusion network architecture with attention mechanism called SFANet. Figure 2 shows the network architecture used in the proposed method. Our network adopts the first 13 layers from VGG16-bn as the front-end feature map extractor (FME) to extract multi-scale feature maps which contain not only the different level semantics information but also the different scale feature information. The low level and small scale features can well represent the detail edge patterns which are essential for regressing the value of congested region in density map, but don’t have sufficient information to distinguish head regions from those of tree leaves, buildings, cluttered backgrounds etc. On the other hand, the high level and large scale features have useful semantics information to eliminate the background noise but in lower resolution caused by max-pooling operation etc.

Based on the above two points, we design a path of multi-scale feature fusion as density map path (DMP) to combine these two advantages of different level features. Another advantage of multi-scale feature fusion structure is that we can gain the high-resolution density map by upsampling operation.

Another issue is that DMP network does regression for every density map pixel, while do not explicitly give more attention to head regions during training and testing. In the other word, the training loss, e.g euclidean distance between ground-truth and estimated density maps, may be serious effected by the background noise. To further tackle the high background noise issue, we adopt another path of multi-scale feature fusion as attention map path (AMP) with the same structure to learn a probability map that indicates high probability head regions. Then this attention map is used to suppress non-head regions in the last feature maps of DMP, which makes DMP focus on learning the regression task only in high probability head regions. We also introduce a multi-task loss by adding a attention map loss for AMP, which improves the network performance with more explicit supervised signal.

These two multi-scale feature fusion paths, AMP and DMP co-works in the way like that human being does to solve this problem, firstly locate the head regions then count the head numbers.

In summary, our main contributions of this paper are as follows:

- We design a multi-scale fusion network architecture to fuse the feature maps from multi-layers to make the network more robust for the head scale variation and background noise, and also generating high-resolution density maps.
- We incorporating the attention model into the network by adding a path of multi-scale feature fusion as attention map path, which makes the proposed method focus on head regions for the density map regression task, therefore improving its robustness to complex noise.
backgrounds and diverse crowd distributions.

- We propose a novel multi-task training loss, combining Euclidean loss and attention map loss to make network convergence faster and better performance. The former loss minimizes the pixel-wise error and the latter one focus on locating the head regions.

2. Related work

**Traditional counting methods:** Traditional counting methods for crowd counting relied on hand-crafted representations to extract low level features. These methods can be categorized into two: detection-based methods and regression-based methods.

Detection-based methods estimate the number of people using sliding window based detection algorithms and hand crafted features extracted from heads or bodys with low-level descriptors such as Haar wavelets and HOG. However severe occlusions make these methods perform poorly in congested scenes.

To overcome the problem of occlusions, regression-based methods aim to learn the mapping between features extracted from cropped image patches to their count or density. The extracted features are used to generate low-level information, which is leaned by a regression model. Instead of directly regressing the total crowd count, Lempitsky et al. propose a method to solve counting problem by modeling a linear mapping between features in the image region and its density maps. Pham et al. observed the difficulty of learning a linear mapping and proposed method to learn a non-linear mapping using a random forest regression.

**CNN-based counting methods:** Recently CNN-based methods have shown a great success in crowd counting and density estimation. Walach et al. used CNNs with boosting and selective sampling. Zhang et al. propose a deep convolutional neural network for crowd counting with two related learning objectives, crowd density and crowd count. Different from the existing patch-based estimation methods, Shang et al. used a network that simultaneously predict local and global counts for whole input images by taking advantages of contextual information. Boominathan et al. use a dual-column network combining shallow and deep layers to generate density maps. Zhang et al. designed multi-column CNN (MCNN) to tackle the large scale variation in crowd scenes. With similar idea, Onoro et al. proposed a scale-aware network, called Hydra, to training the network with a pyramid of image patches at multiple scales. Based on multi-scale CNN architecture, Sam et al. proposed switch CNN by training a switch classifier to select the best CNN regressor for image patches. Sindagi et al. proposed contextual pyramid network for generating high-quality crowd density by explicitly incorporating global and local contextual information.

More recently, Li et al. proposed CSRNet by using the dilated convolutional layers to aggregate the multi-scale contextual information in the congested scenes. Zhang et al. proposed a scale-adaptive CNN (SaCNN) concatenating multiple feature maps of different scales with a VGG backbone. Cao et al. presented encoder-decoder network for scale aggregation. The encoder extracts multi-scale features with scale aggregation modules and the decoder generates high-resolution density maps by using a set of transposed convolutions.

**Counting methods with Attention:** Recently, with attention model widely used for various computer vision tasks, such as image classification, segmentation and object detection, some researchers attempted to use the method in crowd counting. Liu et al. proposed framework named DecideNet to estimate crowd counts via adaptively adopting detection and regression based count estimations under the guidance from the attention mechanism. However, training both detection and regression needs large amount of computation. MA Hossain et al. proposed a scale-aware attention network by combining different global and local scale levels. Because the attention model is only applied to three different scale level column branches, it can’t handle large scale variation in complex crowd scene.

3. Proposed Approach(SFANet)

Inspired by the success use of feature pyramid networks and attention mechanism, we proposed SFANet consist of VGG16-bn backbone feature map extractor(FME) and dual path multi-scale fusion networks with attention(DMP and AMP). Input images are first feed into FME to extract multi-scale features. The density map path(DMP) use concatenate and upsample to fuse multi-scale features, while the attention map path(AMP) incorporates attention model to emphasize head regions to tackle background noise and non-uniformity of crowd distributions. In addition, a attention map loss is introduced to compensate Euclidean loss with more explicit supervised information. The architecture of the proposed SFANet is illustrated in Fig. and discussed in detail as follows.

3.1. SFANet architecture

**Feature map extractor(FME):** Most previous works using the multi-column architecture with different filter sizes to deal with the large scale variation due to perspective effect. We instead use a single backbone network with a single filter size as the feature map extractor. We adopt all 3*3 filters in the network, which require far less computation than large filters and can build deeper network. We choose a pre-trained VGG16 with batch normalization as the frond-
end feature map extractor due to its strong feature represent
ability and easily to be concatenated by the back-end dual path networks. The first 13 layers from conv1-1 to conv5-3 are involved to output feature maps with sizes 1/2, 1/4, 1/8 and 1/16 of the original input size. Four source layers, conv2-2, conv3-3, conv4-3 and conv5-3, which represent multi-scale features and multi-level semantic information, will be concatenated by both DMP and AMP.

**Density map path(DMP):** The DMP of SFANet is constructed in feature pyramid structure as illustrated in Fig.2. Conv5-3 feature maps firstly is upsampled by factor 2, and then concatenate feature maps of conv4-3. The detail of transfer connection block T is shown as Fig.3, which contains concat, conv1×1×256, conv3×3×256 and upsample sub-layers. The second T block has the similar structure concatenating conv3-3 with only different channel size 128, that is concat, conv1×1×128, conv3×3×128 and upsample. Then concatenated outputs of second T block and conv2-2 are feed into header block H with concat, conv1×1×64, conv3×3×64 and conv3×3×32 shown as Fig.3. Every 1×1 convolution before the 3×3 is used to reduce the computational complexity. Due to previous three upsample layers, we can retrieve the final high resolution feature maps with 1/2 size of the original input. Then element-wise multiple is applied on attention map and the last density feature maps to generate refined density feature maps $F_{refine}$ as equation 1:

$$F_{refine} = f_{den} \otimes M_{Att}$$  (1)

where $f_{den}$ is the last density features, $M_{Att}$ is attention map, $\otimes$ denotes element-wise multiply. Before this operation, $M_{Att}$ is expanded as the same channel as $f_{den}$. At last, we use a simple convolution with kernel 1×1×1 to generate the high-quality density map $M_{den}$. Batch normalization is applied after every convolutional layer because we find that batch training and batch normalization can stabilize the training process and accelerate loss convergence. We also apply Relu after every convolutional layer except the last one.

**Attention map path(AMP):** The AMP of SFANet has the similar structure with DMP, and output probability map to indicate head probability in each pixel of the density feature map. In this work, we introduce the attention model as follows. Suppose convolutional features output by head block as $f_{att}$, the attention map $M_{Att}$ is generated as:

$$M_{Att} = Sigmoid(W \odot f_{att} + b)$$  (2)

where $W, b$ is the 1×1×1 convolution layer weights and bias, $\odot$ denotes the convolution operation and $Sigmoid$ denotes the sigmoid activation function. The sigmoid activation function gives out (0, 1) probability scores to make network discriminate head location and background.

**Figure 3:** The structure of the proposed Transfer Connection Block and Head Block. A convolutional layer is denoted as Conv (kernel size) × (kernel size) × (number of channels)-stride. BN, Relu represent for standard batch normalization and Relu layers.

The visualization of $M_{att}$ can be seen in Fig.4. The proposed attention map loss will be further discussed the next section.

**3.2. Loss Function**

Most of previous methods use Euclidean distance as the loss function for crowd counting. The Euclidean loss is used to measure estimation error at pixel level, which is defined as follows:

$$L_{den} = \frac{1}{N} \sum_{i=1}^{N} \left\| F(X_i; \Theta) - D_i^{GT} \right\|^2$$  (3)

where $F(X_i; \Theta)$ is the estimated density map. $\Theta$ is a set of learnable parameters in the proposed network. $X_i$ is the input image and $D_i^{GT}$ is the ground truth density map. $N$ is the number of train batch.

Besides the density map regression, we introduce another attention map loss function in attention map path training process. The attention map loss function is a binary class entropy, defined as equation 4:

$$L_{att} = -\frac{1}{N} \sum_{i=1}^{N} (A_i^{GT} \log(P_i) + (1 - A_i^{GT}) \log(1 - P_i))$$  (4)

where $A_i^{GT}$ is the attention map groundtruth. $P_i$ is the probability of each pixel in predict attention map activated by sigmoid function.

The entire network is trained using the following unified loss function:

$$L = L_{den} + \alpha L_{att}$$  (5)
where $\alpha$ is a weighting weight that is set as 0.1 in the experiments. We use this multi-task combine loss to do end-to-end dual path joint training.

4. Training method

In this section, we illustrate details of SFANet end-to-end training method.

4.1. Density map groundtruth

To obtain the ground-truth density maps $D_{GT}$, we follow the method of generating density maps in [25] by using the same size of Gaussian kernels for all objects. Supposing there is a point at pixel $x_i$ that denote the position of pedestrian head in the scene, the corresponding ground-truth density map $D_{GT}$ can be computed by blurring each head annotation using a Gaussian kernel. The generation of density map $D_{GT}$ can be formulated as:

$$D_{GT} = \sum_{i=1}^{C} \delta(x - x_i) \times G_{\mu,\rho^2}(x)$$  \hspace{1cm} (6)

For each annotation target head $x_i$ in the ground truth $\delta$, we convolve $\delta(x - x_i)$ by a Gaussian kernel $G_{\mu,\rho^2}$ with parameter $\mu$ (kernel size) and $\rho$ (standard deviation), where $x$ is the position of pixel in the image, $C$ is number of head annotations. In experiment, we set $\mu = 15$ and $\rho = 4$ for all datasets except UCF-QRNF. Due to the large image size in UCF-QRNF dataset, we resize the image to $1024 \times 768$ for both training and testing. So we firstly use a adaptive Gaussian kernel with $\mu = 1 + 15 \times w/1024/2 \times 2$ and $\rho = (\mu + 4)/4$, where $w$ is the image width, then resize density map groundtruth to the same size as image resized.

4.2. Attention map groundtruth

Based on density map groundtruth, we continue use Gaussian kernel to compute attention map groundtruth as follows:

$$Z = D_{GT} \times G_{\mu,\rho^2}(x)$$  \hspace{1cm} (7)

$$\forall x \in Z, A_{GT}^i(x) = \begin{cases} 0, & x < th \\ 1, & x \geq th \end{cases}$$  \hspace{1cm} (8)

where $th$ is the threshold set as 0.001 in our experiments. With equation (7, 8) we obtain a binary attention map groundtruth in order to guide the AMP to focus on the head regions and also the surround places. In experiment, we set $\mu = 3$ and $\rho = 2$ for generating attention map groundtruth.

4.3. Training details

In training procedure, we firstly resize the short side of image to 512 if the short side is less than 512, followed by a random scale change with ratio $[0.8, 1.2]$. Images patches with fixed size $(400 \times 400)$ are cropped at random locations, then they are randomly horizontal flipped with probability 0.5 and processed by gamma contrast transform using parameter $[0.5, 1.5]$ with probability 0.3 for data augmentation. For those datasets with gray images eg. ShanghaiTech
A, we also randomly change the color images to gray with probability 0.1. As discussion in above section, we resize the image to fixed $1024 \times 768$ before any data augment for UCF-Q.RNF dataset. In order to match the output size of SFANet, density map and attention map groundtruth are both resized to half resolution of input image patches.

First 13 layers of pre-trained VGG16 with batch normalization is applied as the front-end feature extractor. The rest network parameters are randomly initialized by a Gaussian distribution with mean 0 and standard deviation of 0.01. Adam[11] optimizer with learning rate of $1e^{-4}$ and weight decay of $5e^{-3}$ is used to train the model, because it shows faster convergence than standard stochastic gradient descent with momentum in our experiments. We use batch size 30 in training procedure, which stabilizes the training loss change.

5. Experiments

In this section, we present the experimental details and evaluation results on 4 public challenging datasets: ShanghaiTech[30], UCF_CC_50[8], UCF-QRNF[10] and UCSD[3]. We evaluate the performance via the mean absolute error (MAE) and mean square error (MSE) commonly. These metrics are defined as follows:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |C_i - C_i^{GT}|$$

$$MSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (C_i - C_i^{GT})^2}$$

where $N$ is the number of test image set, $C_i$ and $C_i^{GT}$ are the estimated count of people and the ground truth of counting respectively.

5.1. ShanghaiTech dataset

ShanghaiTech crowd counting dataset contains 1198 annotated images with a total amount of 330,165 persons. This dataset consists of two parts, A and B. Part A contains 482 images with highly congested scenes randomly downloaded from the internet. Part B contains 716 images with relatively sparse crowd scenes taken from busy streets in Shanghai. Considering lack of training samples in these datasets, our models are pre-trained on UCF-QNRF, because it improves performance and speeds up convergence. We evaluate our method and compare it to other ten recent works and results are shown in Table 1. It shows that with the novel network integrating with attention model, our method achieves the best performance on both Part_A and Part_B datasets among all those approaches. Compared to the state-of-the-art method called SaNet, we get 17.9% MAE, 19.9% MSE improvement for Part_B. As and far as we know, our method is the first solution that can break through 8.0 MAE in Part_B. More samples of test results can be found in Fig 5.

| Method            | MAE  | MSE  |
|-------------------|------|------|
| Cross-Scene[28]   | 181.8| 277.7|
| MCNN[30] (2016)   | 110.2| 173.2|
| Switch-CNN[21]    | 90.4 | 135.0|
| CP-CNN[22] (2017)| 73.6 | 106.4|
| TDF-CNN[20] (2018)| 97.5 | 145.1|
| SaCNN[29] (2018)  | 86.8 | 139.2|
| ACSCP[23] (2018)  | 75.7 | 102.7|
| ic-CNN[18] (2018) | 68.5 | 116.2|
| CSRNet[14] (2018) | 68.2 | 115.0|
| SaNet[2] (2018)   | 67.0 | 104.5|
| SFANet w/o pretrain | 63.8 | 105.2|
| SFANet            | 59.8 | 99.3 | 6.9  | 10.9 |

Table 1: Estimation errors on ShanghaiTech dataset

5.2. UCF_CC_50 dataset

UCF_CC_50 is an extremely dense crowd dataset introduced by Idrees et al.[8]. It includes 50 images of different resolutions. The number of annotated persons per image ranges from 94 to 4543 with an average number of 1280. For better verification of model accuracy, 5-fold cross-validation is performed following the standard setting in [8]. Table 2 shows the experiment result of MAE and MSE compared with other approaches.

| Method       | MAE  | MSE  |
|--------------|------|------|
| Cross-Scene  | 467.0| 498.5|
| MCNN         | 377.6| 509.1|
| Switch-CNN   | 318.1| 439.2|
| CP-CNN       | 295.8| 320.9|
| TDF-CNN      | 354.7| 491.4|
| SaCNN        | 314.9| 424.8|
| ACSCP        | 291.0| 404.6|
| ic-CNN       | 260.9| 365.5|
| CSRNet       | 266.1| 397.5|
| SaNet        | 258.4| 334.9|
| SFANet       | 219.6| 316.2|

Table 2: Estimation errors on UCF_CC_50 dataset

5.3. UCF-QRNF dataset

UCF-QRNF dataset[10] is a new and the largest crowd dataset for evaluating crowd counting and localization
methods. It contains 1535 dense crowd images which are divided into train and test sets of 1201 and 334 images respectively. The UCF-QNRF dataset has the most number of high-count crowd images and annotations, and a wider variety of scenes containing the most diverse set of viewpoints, densities and lighting variations. Besides high-density regions, the dataset also contains buildings, vegetation, sky and roads as they are present in realistic scenarios captured in the wild, which makes this dataset more realistic as well as difficult. We train model on UCF-QNRF dataset only with VGG16-bn pre-train weights. Results are shown in Table 4. The SFANet obtains the best performance with 23.6% MAE and 8.6% MSE improvement compared with the second best approach in [10].

5.4. UCSD dataset

The UCSD dataset [3] has 2000 frames taken from a stationary camera. All videos are 8-bit grayscale, with dimensions \(238 \times 158\) at 10 fps, and the crowd count in each image varies from 11 to 46. The dataset also provides ROI region and perspective information. Since the image size is too small to generate high-quality density maps, we enlarge each image to \(960 \times 640\) size by bilinear interpolation. Among the 2000 frames, we use frames 601 through 1400 as training set and the rest of them as testing set according to [3]. All the frames and density maps are masked with ROI. The results in Table 4 indicate that our method can perform well not only for extremely dense crowds but also for sparse crowds.

| Method      | MAE  | MSE  |
|-------------|------|------|
| Idrees et al. [8] | 315.0 | 508.0 |
| MCNN [30]   | 277.0 | 426.0 |
| CMTL [24]   | 252.0 | 514.0 |
| Switch-CNN [21] | 228.0 | 445.0 |
| CL-CNN [10] | 132.0 | 191.0 |
| SFANet      | 100.8 | 174.5 |

Table 3: Estimation errors on UCF-QNRF dataset
| Method          | MAE  | MSE  |
|-----------------|------|------|
| Cross-Scene     | 1.60 | 3.31 |
| MCNN[30]        | 1.07 | 1.35 |
| Switch-CNN[21]  | 1.62 | 2.10 |
| ACSCP[23]       | 1.04 | 1.35 |
| CSRNet[14]      | 1.16 | 1.47 |
| SaNet[2]        | 1.02 | 1.29 |
| SFANet          | 0.82 | 1.07 |

Table 4: Estimation errors on UCSD dataset

5.5. Ablation Experiments

Finally, we do ablation experiments to confirm the benefits of attention map path with attention loss. In experiments, we only use VGG backbone and DMP network noted as VGG-DMP. As the comparison result illustrated in Table 5, VGG-DMP also shows its significant performance improvement and surpass the other state-of-the-art methods even without attention map path. The experiment results also confirm a notable effect of attention map path as expected.

| Method          | MAE  | MSE  | MAE  | MSE  |
|-----------------|------|------|------|------|
| CSRNet[14]      | 68.2 | 115.0| 10.6 | 16.0 |
| SaNet[2]        | 67.0 | 107.5| 8.4  | 13.6 |
| VGG-DMP         | 62.7 | 107.0| 7.8  | 12.7 |
| SFANet          | 59.8 | 99.3 | 6.9  | 10.9 |

Table 5: Ablation experiments on the ShanghaiTech dataset

6. Conclusion

We proposed a novel end-to-end model, named SFANet, based on dual path multi-scale fusion with attention mechanism for crowd counting. Multi-scale feature maps are extracted by VGG16-bn backbone, and fused by DMP and AMP. Attention map loss is well designed to emphasize the head regions among noisy background. By taking these two advantages, SFANet shows powerful ability to locate the head regions and regress the head count. Experiments indicate that SFANet achieves the best performance and higher robustness for crowd counting compared with other state-of-the-art approaches.

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