Multi-Resolution Fusion and Multi-scale Input Priors Based Crowd Counting

Usman Sajid†, Wenchi Ma†, Guanghui Wang†‡
†Department of Electrical Engineering and Computer Science, University of Kansas, Lawrence, KS, USA, 66045
‡Department of Computer Science, Ryerson University, Toronto, ON, Canada M5B 2K3
{usajid, wenchima, ghwang}@ku.edu

Abstract—Crowd counting in still images is a challenging problem in practice due to huge crowd-density variations, large perspective changes, severe occlusion, and variable lighting conditions. The state-of-the-art patch rescaling module (PRM) based approaches prove to be very effective in improving the crowd counting performance. However, the PRM module requires an additional and compromising crowd-density classification process. To address these issues and challenges, the paper proposes a new multi-resolution fusion based end-to-end crowd counting network. It employs three deep-layers based columns/branches, each catering the respective crowd-density scale. These columns regularly fuse (share) the information with each other. The network is divided into three phases with each phase containing one or more columns. Three input priors are introduced to serve as an efficient and effective alternative to the PRM module, without requiring any additional classification operations. Along with the final crowd count regression head, the network also contains three auxiliary crowd estimation regression heads, which are strategically placed at each phase end to boost the overall performance. Comprehensive experiments on three benchmark datasets demonstrate that the proposed approach outperforms all the state-of-the-art models under the RMSE evaluation metric. The proposed approach also has better generalization capability with the best results during the cross-dataset experiments.

Index Terms—Crowd counting, crowd-density, patch rescaling module (PRM), multi-resolution fusion, input priors.

I. INTRODUCTION

Crowd counting finds a very important and integral place in the crowd analysis paradigm. Crowd gatherings are ubiquitous and bound to happen frequently at sports, musical, political, and other social events. Automated crowd counting plays an important role in handling and analyzing such events. Crowd counting is an active research area in the computer vision field due to the fact that many key challenges remain yet to be reasonably addressed, such as severe occlusion, huge crowd diversity within and across different regions in the images, and large perspective changes. Moreover, manual human based crowd counting process is unreliable and ineffective due to the tedious and time-consuming nature of this task.

In recent years, computer vision has witnessed great developments in several sub-areas, such as image classification [40], object detection [20], image translation [42] and face recognition [2], with the introduction of convolution neural networks (CNNs). Inevitably, recent state-of-the-art crowd counting methods are overwhelmingly dominated by the CNN based approaches, which generally belong to either direct-regression (DR) [7], [27], [36] based or density-map estimation (DME) [18], [24], [29], [33], [35], [41], [45] based architectures. DR based methods directly regress or estimate the crowd number from the input image or patch. These methods alone do not prove effective for crowd counting due to huge crowd diversity and multi-scale variation in and across different images. The DME based methods perform crowd counting by estimating the crowd-density value per pixel. This type of approaches, in general, also tend to struggle against the above stated major issues and challenges.

Multi-column or multi-regressor CNN based architectures [24], [29], [33], [45] have proved to be very effective for crowd counting task. MCNN [45] is a state-of-the-art three-column density-map estimation based end-to-end crowd counting network, where each CNN based column specializes in handling the specific crowd-density level. At the end of this network, all columns are merged together to yield the crowd estimate after remaining processing. Similarly, multi-column based architectures [18], [29] utilize multiple specialized crowd count regressors to cope with multiple crowd-density scales separately. For example, Switch-CNN [29], a density-map estimation based network, consists of a CNN based switch classifier that routes the input image or patch to one of three crowd count regressors, where each regressor deals with specific crowd level. In addition, many single-column or single-regressor based architectures [17], [30] have also been proposed to address the crowd counting issues and challenges. These methods produce promising results, but still lack the generalization ability for crowd estimation, ranging from low to high crowd-density.

Recently, Sajid et al. [27], [28] observed that suitable rescaling (down-, no-, or up-scaling) of the input image or patch, according to its crowd density level (low-, medium-, or high-crowd), gives more effective results as compared to the multi-column or multi-regressor based methods. Based on this observation, they also designed a patch rescaling module (PRM) [28] that rescales the input image or patch accordingly based on its crowd-density class label. Although the PRM based single-column proposed schemes [28] empirically prove their observation to be imperative and effective, the PRM module does not fully capitalize on it and thus limits the efficacy of this observation. First, it requires the crowd-density classification label of the original input patch. This additional classification process comes up with its own inaccuracies [27], [28] that compromises the subsequent crowd counting
The contributions of this paper mainly include:

- Compromising and extra crowd-density classification process.
- Priors inclusion fulfills our objective #2 without using any rescaling. In addition, the simple yet effective column-wise input issue (Objective #1) in comparison to recent state-of-the-art methods prove to be more effective in generalizing towards huge crowd variations. The repetitive multi-scale fusions, coupled with column-wise input priors and high-resolution maintenance, prove to maintain the same as its input throughout the column. These repetitive multi-scale fusions, coupled with column-wise rescaled input priors and high-resolution maintenance, prove to be more effective in generalizing towards huge crowd variation issue (Objective #1) in comparison to recent state-of-the-art crowd counting methods as shown in the experiments section V. In addition, the simple yet effective column-wise input priors inclusion fulfills our objective #2 without using any compromising and extra crowd-density classification process.

The contributions of this paper mainly include:

- Better generalization ability: Design a multi-column crowd counting method with better generalization ability towards huge crowd variations.
- Effective input priors: Utilize the input patch rescaling based effective observation [27], [28] (as discussed above) without performing any expensive and compromising crowd-density classification process, and also use all three crowd-density levels (low-, medium, and high-crowd) in a more effective manner than the PRM module [28].

Thus, we propose a new multi-resolution feature-level fusion based end-to-end crowd counting network to achieve the above objectives amid addressing the major crowd counting challenges. The proposed approach works at multiple scales via multi-columns, where each column primarily focuses on the respective scale (low-, medium-, or high-crowd), as shown in Fig. 1. Unlike other state-of-the-art multi-scale or multi-column based methods, the columns also fuse and share the information with each other at a regular basis after every few deep layers (phase). Each column also takes the suitably rescaled version of the original input patch as its input prior without any classification process. Inspired by the success of high-resolution networks [34], [37], each column also serves as a high-resolution sub-network, where the resolution is maintained the same as its input throughout the column. These repetitive multi-scale fusions, coupled with column-wise rescaled input priors and high-resolution maintenance, prove to be more effective in generalizing towards huge crowd variation issue (Objective # 1) in comparison to recent state-of-the-art crowd counting methods as shown in the experiments section V. In addition, the simple yet effective column-wise input priors inclusion fulfills our objective # 2 without using any compromising and extra crowd-density classification process.

The contributions of this paper mainly include:

- We propose a new multi-resolution feature-level fusion based end-to-end crowd counting approach for still images that effectively deals with significant variations of crowd-density, lighting conditions, and large perspective.
- We propose an alternative patch rescaling module by the PRM module [28]. The proposed module fully utilizes all three crowd-density levels without requiring any compromising or additional crowd-density classification process.
- Quantitative experiments demonstrate that the proposed approach outperforms the state-of-the-art methods, including the PRM based schemes, by a large margin with up to 10% improvements.

II. RELATED WORK

Crowd estimation comes up with many key issues including huge crowd-density variation in and across different images, different illumination conditions, large perspective, and severe occlusions. Classical methods belong to either the detection-then-counting or regression-based schemes. Detection-based methods [8], [15], [38], [49] were unable to work in case of high-dense crowd images, where it becomes really difficult to detect the handcrafted features. Regression-based methods [3], [4], [26] learn a transformation function to regress the crowd estimate from the local crowd features. These schemes also prove to be unreliable and ineffective due to the lack of generalization ability.

Recently, CNN based models are widely used due to their superior performance. Broadly, they belong to one of three types: Detection-based, regression-based, and density-map estimation methods. Detection-based methods [16], [30] follow the principle of detection-then-counting, and use advance CNN detectors (e.g. Faster-RCNN [9], YOLO [25]) to detect persons in the images. Li et al. [16] used the contextual information based adaptive head detection method for crowd count. Shami et al. [30] first detected persons using the CNN based head detectors, followed by the weighted average and final crowd count estimation. These methods seem impractical for high-dense crowd images due to the small head or person size. Regression-based methods learn a transformation function to map the input image to its crowd count. Wang et al. [30] deployed the AlexNet [14] based architecture to perform crowd estimation on the input image. Fu et al. [7] first classified the input 5-way based on the crowd-level, and then used two cascaded CNNs, where one improves the weaker crowd estimation being made by the other CNN as a boosting strategy. These methods alone fail to comprehend the hugely varying crowd-density scale. Sajid et al. [27], [29] proposed regression-based methods that use deep networks and smartly and accordingly rescaled input to estimate the crowd count. But the rescaling process first requires the expensive crowd-density classification process that comes with its own inaccuracies.

Density-map estimation based methods [18], [24], [29], [33], [35], [41], [45] generate crowd density-maps, with density value per pixel, and the final image crowd count is obtained by the summation of all pixels density estimations. Most recent state-of-the-art methods are the members of this category. Zhang et al. [45] proposed a multi-column crowd counting network (MCNN), that uses three columns with different filter sizes to account for the respective crowd scale. Sindagi et al. [33] designed a cascaded end-to-end network
The proposed network. The original $128 \times 128$ input patch ($I_2$ or $P$) is used to produce the new up-scaled ($I_1$) and down-scaled ($I_3$) input priors, which go through their respective stems ($stem_1$, $stem_2$, $stem_3$). The resultant initial channels ($IC_1$, $IC_2$, $IC_3$) then pass through the phase-based main network, containing three deep columns/branches with the residual modules ($RM$). Multi-resolution fusion regularly occurs between these columns, followed by passing through the auxiliary ($RH_1$, $RH_2$, $RH_3$) and the final ($RH_{f\text{inal}}$) crowd regression heads to yield the respective crowd counts ($cc_{p(1)}$, $cc_{p(2)}$, $cc_{p(3)}$, and $cc_{f\text{inal}}$). The final crowd count for the input patch ($I_2$) is the weighted average of these crowd estimates. The MN maintains the channels ($C$) resolution throughout each column. (In this paper, we used both terms ($I_2$ and $P$) interchangeably for the same original input patch. Similarly, multi-scale and multi-resolution fusion are interchangeable here.)

Fig. 2. The Residual Module (RM) consists of either only 2- or 3-layers \cite{10} based four residual units (RU).

that simultaneously calculates the crowd-density 10-way for the input and uses this classification as input prior to the next part of the network. Switch-CNN \cite{29} uses a CNN-based switch to route the input patch to one of three specialized crowd regressors based on the crowd-density level. Ranjan et al. \cite{24} designed the two-branch network, where the low-resolution branch have been combined with a high-resolution branch to generate the final density-map. Liu et al. \cite{18} proposed a hybrid approach that coupled both detection and density-map estimation techniques, and used the appropriate counting mode based on the crowd-density. Recently, Wan et al. \cite{35} used support image density-map to predict the input image density-map by the residual regression based difference between the two density-maps. Xu et al. \cite{41} first grouped patch-level density-maps into several density levels, followed by the automatic normalization via an online learning strategy with a multipolar center loss. One major issue with these methods is to find the optimal Gaussian kernel size, which depends on many related factors. They also do not generalize well on the huge crowd-variation challenge.

Thus, we propose a new multi-resolution feature-level fusion based end-to-end crowd counting network aiming to address the major crowd counting challenges and recent state-of-the-arts limitations.

III. PROPOSED APPROACH

The paper proposes a multi-column and multi-resolution fusion based end-to-end crowd counting network to achieve the two set objectives in Sec. I amid addressing the major crowd counting challenges including huge crowd variation in and across different images, large perspective, and severe occlusions. The proposed scheme is shown in Fig. 1 where the input image is first divided into $128 \times 128$ non-overlapping patches. Each resultant patch then goes through the proposed network for the patch-wise crowd count. Finally, the image crowd estimate is computed by the sum of the crowd count of all patches. The $128 \times 128$ input patch is used to generate the new $256 \times 256$ and $64 \times 64$ size input priors by $2 \times$ times up- and down-scaling, respectively. These multi-scale input priors pass through the respective stems ($Stem_1$, $Stem_2$, $Stem_3$) to generate three separate initial channels ($IC_1$, $IC_2$, $IC_3$), which act as the corresponding input to three columns/branches in the
main network (MN). The MN regularly fuses feature maps in between these branches. At the end of the main network, the resultant feature maps from three branches pass through the final regression head ($RH_{final}$) to yield the input patch crowd estimate. The MN also outputs into three auxiliary crowd estimating regression heads ($RH_1, RH_2, RH_3$) that helps in improving the input patch final crowd count. In the following, we will discuss three main components in detail.

A. Input priors and respective stems

We up- and down-scale the original $128 \times 128$ size input patch ($I_2$ or $P$) by $2 \times$ to generate its rescaled versions ($256 \times 256$ and $64 \times 64$ respectively). These input priors ($I_1$, $I_2$, $I_3$) pass through their respective stems ($Stem_1$, $Stem_2$, $Stem_3$) to produce initial feature channels ($IC_1$, $IC_2$, $IC_3$). These stems, as shown in Table I, also decrease the input priors resolution to $1/4$, and the resultant initial feature maps resolution becomes half in the subsequent lower column. The upscaled input prior ($I_1$) helps in handling highly dense crowd regions by zooming in and observing the original input ($I_2$) in detail to avoid huge crowd under-estimation. Similarly, the input prior ($I_3$) uses a smaller scale, especially helpful for the low-crowd regions in the images that may otherwise cause significant crowd over-estimation. Empirically, it has been observed that coupling these simple yet effective rescaled input priors ($I_1, I_3$) with the original input ($I_2$) yields better crowd estimates, and consequently avoid huge crowd under- or over-estimation, as shown in the ablation study in Sec. V-E.

B. Main Network (MN)

The main network is composed of three deep columns/branches, each with its own input prior feature maps, and also caters the respective crowd-density scale. The main network is divided into three phases from left to right, where each phase consists of one or more columns/branches. The total number of columns in a phase is equal to its phase number. All branches in a phase fuse feature maps with each other after each Residual Module (RM). At the end of each phase, the MN also feeds its lowest-resolution output into the auxiliary crowd regression heads ($RH_1, RH_2, RH_3$), as detailed in the next subsection III-C. Each branch in the main network maintains its original input resolution throughout the branch, unlike other state-of-the-art multi-scale crowd

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**Table I**

| Name | Output size | Filters (F) Operation |
|------|-------------|-----------------------|
| $I_1$ | $3 \times 256 \times 256$ | 64 | $\times 256$ |
| $I_2$ | $3 \times 128 \times 128$ | (3 × 3) conv, stride 2, padding 1, 64F |
| $I_3$ | $3 \times 128 \times 128$ | (3 × 3) conv, stride 2, padding 1, 64F |
| $IC_1$ | $256 \times 64 \times 64$ | (1 × 1) conv, stride 1, padding 0, 256F |
| $IC_2$ | $64 \times 32 \times 32$ | (3 × 3) conv, stride 2, padding 1, 64F |
| $IC_3$ | $128 \times 16 \times 16$ | (3 × 3) conv, stride 2, padding 1, 128F |

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**Table II**

| Configuration | Output Size | Filters (F) Operation |
|--------------|-------------|-----------------------|
| $v1$ (Highest-resolution) | $32 \times 64 \times 64$ | (3 × 3) conv, stride 2, padding 1, 64F |
| $v2$ (Middle-column) | $64 \times 32 \times 32$ | (1 × 1) conv, stride 1, padding 0, 64F |
| $v3$ (Lowest-resolution) | $64 \times 8 \times 8$ | (2 × 2) Avg Pooling, stride 2 |

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**Fig. 3.** Concatenation-based crowd regression head (v4) concatenates the lower-resolutions with the highest-level channels using the bilinear up-sampling, whereas the summation-based head (v5) adds the lower-resolution feature maps, before proceeding through the several deep layers to finally yield the crowd estimate (single neuron).
estimation methods. The lower columns resolution and total channels in any phase depend on the highest-resolution branch \((i = 1)\). Let \(C_i\) and \(R_i\) be the total channels and their resolution respectively in the highest-resolution column. Then, the remaining columns \((i = 2, 3)\) follow the below principle for their \(C_i\) and \(R_i\) in a given phase [34], [37].

\[
C_i = 2C_{i-1}, R_i = \frac{R_{i-1}}{2} \quad (1)
\]

Residual Module: It consists of four residual units, where each unit is formed by either only 2-layer or 3-layer based residual block [10], as shown in Fig. 2. The 2-layer based residual block [10] contains two \(3 \times 3\) convolution layers. Similarly, the 3-layer residual channel [10] starts with a bottleneck layer, followed by one \(3 \times 3\) convolution layer and a bottleneck layer. Each convolution operation in these units is followed by the batch Normalization (BN) [13] and the nonlinear ReLU activation [22]. After applying the operation is followed by the Batch Normalization (BN) [13] and the nonlinear ReLU activation [22]. After applying the regularizer, total residual modules in each column of a specific phase remain the same.

Recurring Multi-resolution Fusions: The primary purpose of the multi-resolution fusion is to exchange the information between different resolutions/columns, so as to enhance the generalization ability of the proposed scheme towards huge crowd diversity in and across different images. We utilize one or more \(3 \times 3\) convolution operations to fuse higher-resolution feature maps into the lower-resolution channel. To fuse the lower-resolution feature maps into the higher-level channels, bilinear upsampling followed by the bottleneck layer (to adjust the number of channels) have been deployed. Let \(Ch_i\) be the fusion source channels from column at index \(i\) \((i = 1, 2\) or \(3)\), \(Ch_j\) be the fusion target column at index \(j\) \((j = 1, 2\) or \(3)\), and \(f(.)\) be the transformation function. If \(i < j\), then \(f(Ch_i)\) downsamples the \(Ch_i\) channels by 2\((j - i)\) times via \((j - 1)\) stride-2 \(3 \times 3\) convolution(s). For example, fusing \(3\)-column channels \((Ch_1)\) into \(2\)-column channels \((Ch_2)\) first requires one stride-2 \(3 \times 3\) convolution \((f(Ch_1))\) for \(2 \times 2\) downsampling. Similarly, \(Ch_1\) fusion into \(Ch_2\) requires 2 stride-2 \(3 \times 3\) convolutions for \(4 \times 4\) downsampling before the fusion operation. If \(i = j\), then \(f(Ch_i) = Ch_i\), i.e., no transformation is done. If \(i > j\), then \(f(Ch_i)\) transformation upscales the \(Ch_i\) using the bilinear upsampling, followed by the bottleneck layer to adjust the number of channels accordingly before the fusion process. Each convolution operation is followed by the Batch Normalization (BN) [13] and the nonlinear ReLU activation [22]. After applying the appropriate transformation(s) and channels alignment(s) as discussed above, the summation based fusion operation finally outputs the sum of these transformed representations.

C. Crowd Regression Heads

The proposed approach contains three phase-wise crowd regression heads \((RH_1, RH_2, RH_3)\) and the final regression head \((RH_{final})\).

Phase-wise Regression Heads: One of the primary purpose of phase based organization of the main network is to introduce auxiliary crowd regression heads \((RH_1, RH_2, RH_3)\) at the end of each phase. The last lowest-resolution output of each phase serves as the input to its respective regression head. These heads mainly consist of several convolution based deep layers, followed by optional average pooling operation and one or more fully connected (FC) layers as detailed in Table II. Finally, the single neuron \((1D, FC)\) at the end of each head gives the corresponding crowd counts \((cc_{P(1)}, cc_{P(2)}, cc_{P(3)})\) for the input patch \((P)\).

Final Regression Head \((RH_{final})\): Phase 3 outputs three blocks of feature maps, each from the respective column with varying resolution. These blocks have been exploited in different ways for possible and effective \(RH_{final}\) head configuration, as discussed below.

Standalone Single-Column Output based \((v1, v2, v3)\): Here, we only use one of three phase-3 outputs for the \(RH_{final}\) configuration [34], [37]. Subsequent configurations are shown in Table II and named as v1 (highest-resolution), v2 (middle-column), and v3 (lowest-resolution), respectively. These representations consist of several deep layers, followed by the 1024 dimensional fully connected (FC) layer and the final single neuron to directly regress the crowd count.

Concatenation-based \((v4)\): The lower-resolution feature maps concatenate at the highest-resolution branch, with configuration shown in Fig. 3a [34], [37].

Summation-based \((v5)\): The higher-level feature maps are summed up into the subsequent lower resolution feature maps after respective downsampling, as shown in Fig. 3b [34], [37].

Employing one of the above configurations, the \(RH_{final}\) yields its crowd count \((cc_{final})\) for the input patch \(P\). The final crowd count \((CC_P)\) for the original input patch \(P\) is computed using all regression heads weighted crowd estimates as follows:

\[
CC_P = w \ast cc_{P(1)} + x \ast cc_{P(2)} + y \ast cc_{P(3)} + z \ast cc_{final} \quad (2)
\]

Where \(w = x = y = 0.1\) and \(z = 0.7\). The mean squared error (MSE) has been used as the loss function for each of the four regression heads \((RH)\), given as follows:

\[
L_{RH} = \frac{1}{N} \sum_{i=1}^{N} (F(x_i, \Theta) - y_i)^2 \quad (3)
\]

where \(N\) represents the total training patches per batch, \(y_i\) denotes the ground truth crowd count for the input image patch \(x_i\), and \(F(.)\) represents the transformation function that learns the \(x_i\) to crowd count mapping with learnable weights \(\Theta\). Finally, the total loss for the input patch \(P\) is the weighted accumulation of all four regression head losses as below:

\[
L_P = w \ast L_{RH_1} + x \ast L_{RH_2} + y \ast L_{RH_3} + z \ast L_{final} \quad (4)
\]
**TABLE III**

| Method          | ShanghaiTech MAE | ShanghaiTech RMSE | UCF-QNRF MAE | UCF-QNRF RMSE |
|-----------------|------------------|-------------------|-------------|---------------|
| MCNN            | 110.2            | 173.2             | 277         | 426           |
| CMTL            | 101.3            | 152.4             | 252         | 514           |
| Switch-CNN      | 90.4             | 135.0             | 228         | 445           |
| SaCNN           | 86.8             | 139.2             | -           | -             |
| IG-CNN          | 72.5             | 118.2             | -           | -             |
| ACSCF           | 75.7             | 102.7             | -           | -             |
| CSRNet          | 68.2             | 113.0             | -           | -             |
| CL              | -                | -                 | 132         | 191           |
| CFF             | 65.2             | 109.4             | 93.8        | 146.5         |
| RRSP            | 63.1             | 96.2              | -           | -             |
| CAN             | 62.3             | 100.0             | 107         | 183           |
| L2SM            | 64.2             | 98.4              | 104.7       | 173.6         |
| BL              | 62.8             | 101.8             | 88.7        | 154.8         |
| ZoomCount       | 66.6             | 99.5              | 126         | 201           |
| PRM-based (5)   | 67.8             | 86.2              | 94.5        | 141.9         |
| v1/v2 (ours)    | 71.4/70.1        | 85.7/85.3         | 103.1/100.6 | 139.6/136.3   |
| v3/v4 (ours)    | 69.8/69.7        | 84.7/81.9         | 101.7/98.4  | 137/135.1     |
| v2 (ours)       | 67.1             | 81.0              | 96.9        | 130.1         |

**IV. IMPLEMENTATION DETAILS**

We employ the following two standard metrics, namely Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), for the evaluation and comparison of the proposed scheme with other state-of-the-art methods.

\[
MAE = \frac{1}{T} \sum_{t=1}^{T} |CC_t - \hat{CC}_t|, \quad RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (CC_t - \hat{CC}_t)^2}
\]

where \( T \) represents the total test images in a dataset, and \( CC_t \) and \( \hat{CC}_t \) denote the actual and estimated crowd counts respectively for the test image \( t \).

**Training Details:**

We randomly extract 60,000 patches of 256 × 256, 128 × 128, and 64 × 64 sizes with varying crowd number from the training images. Horizontal flip based data augmentation is then used to double the training samples quantity. We trained the proposed model for 100 epochs, used SGD optimizer with a weight decay of 0.0001 and a Nesterov momentum value of 0.9. Multi-step learning has been employed that initially starts at 0.001 and decreases by half after every 25 epochs. As per the standard literature convention, 10% data from the predefined training set has been separated for the model validation purpose.

**V. EXPERIMENTAL RESULTS**

In this section, we first perform standard quantitative analysis on three benchmark datasets: UCF-QNRF [12], ShanghaiTech [45], and AHU-crowd [11]. These benchmarks pose a great collective challenge for the proposed scheme to prove its effectiveness, as they vary significantly with each other in terms of average image resolution, average crowd number per image, total images, and lighting conditions. Next, we discuss the ablation experiments findings and the cross-dataset evaluation, followed by the qualitative evaluation. For comparison with other state-of-the-art methods, we evaluate all five versions of the proposed method (v1, v2, v3, v4, v5) as being the best of them quantitatively.

**A. Experiments on UCF-QNRF Dataset**

UCF-QNRF [12] is one of the most diverse, realistic, and challenging dataset. It consists of 1,535 free-view images with a predefined train/test division of 1,201/334. It contains images with relatively very small (300 × 377) and very large (6666 × 9999) resolutions, with 1,251,642 total people

**TABLE IV**

| Method                  | MAE   | RMSE  |
|-------------------------|-------|-------|
| Haar Wavelet            | 407.0 | -     |
| DPM [6]                 | 395.4 | -     |
| BOW-SVM [5]             | 218.8 | -     |
| Ridge Regression [4]    | 207.4 | -     |
| Hu et al. [11]          | 137   | -     |
| DSRM [45]               | 81    | 129   |
| ZoomCount [27]          | 74.9  | 111   |
| CC-2P (PRM-based) [28]  | 66.6  | 101.9 |

**TABLE V**

| RM Modules Quantity Effect | MAE   | RMSE  |
|----------------------------|-------|-------|
| 1                          | 79.3  | 111.4 |
| 2 (our default)            | 67.1  | 81.0  |
| 3                          | 75.8  | 104.7 |

**Input Priors Effect**

| Method                  | MAE   | RMSE  |
|-------------------------|-------|-------|
| w/o (I1, I2)            | 77.1  | 108.8 |
| w/o (I2)                | 75.9  | 106.5 |
| w/o (I2)                | 73.8  | 101.4 |
| only (I1) with original input size (256 × 256) | 80.1 | 124.5 |
| with (I1, I2, I3) (our default) | 67.1 | 81.0 |

**Auxiliary Regression Heads Effect**

| Method                  | MAE   | RMSE  |
|-------------------------|-------|-------|
| w/o RH1                 | 76.2  | 107.0 |
| w/o RH2                 | 71.4  | 115.2 |
| w/o RH3                 | 73.9  | 103.1 |
| w/o (RH1, RH2, RH3)     | 78.5  | 120.7 |
| with (RH1, RH2, RH3) (our default) | 67.1  | 81.0 |
annnotations that show its crowd complexity and diversity. We compare the proposed approach with the state-of-the-art methods (including the PRM based approach [28]) in Table III. As shown, the proposed scheme (v5) outperforms the state-of-the-arts under the RMSE evaluation metric by ∼8.3% (from 141.9 to 130.1), amid performing reasonably well for the MAE.

B. Experiments on ShanghaiTech Dataset

The ShanghaiTech Part-A benchmark [45] is another diverse and free-view crowd counting benchmark. It contains 482 images (predefined train/test division of 300/182) with a total of 241,677 people annotations and average image resolution of 589×868. Based on the quantitative comparison with the state-of-the-art methods (including the PRM based methods [28]) as shown in Table III, the proposed approach (v5) decreases the RMSE error by ∼6% (from 86.2 to 81.0). For the MAE metric, our schemes give reasonable and comparable results. The lowest RMSE value also demonstrates that our method is less susceptible to huge crowd over- and under-estimation.

C. Experiments on AHU-Crowd Dataset

The AHU-Crowd [11] dataset contains 107 crowd images with 58 to 2,201 people annotations per image and 45,807 annotations in total. As per the standard evaluation process, we perform 5-fold cross-validation, and final (MAE, RMSE) results are obtained by computing their average. Evaluation and comparison results are shown in Table VII where our scheme (v5) outperforms other state-of-the-arts under both evaluation metrics with significant improvements i.e., the MAE error decreases by ∼9.6% (from 66.6 to 60.2) and the RMSE improves by ∼10% (from 101.9 to 91.7).

D. Effect of RM Modules Quantity

In this ablation study, we examine the effect of the number of RM modules in the Phase-2 and 3 of the proposed scheme.

E. Effect of Input Priors (I1, I2, I3)

This section reveals the quantitative importance of the input priors. We remove these input priors in different experimental settings to analyze their effectiveness. In the first three separate experiments, we only use (I1), (I1, I2) and (I1, I2, I3) input prior(s) respectively. While, in the last setting, we only deployed the I1 input, but with the original 256×256 input size without any rescaling. The consequent ablation results are shown in Table VII from which we can see that removing these input priors significantly decreases the overall network performance (with minimum MAE, RMSE errors increase of 9.1%, 20.1% respectively). Thus, all three input priors are critical for the proposed method effectiveness.

F. Effect of Auxiliary Crowd Regression Heads

In this experiment, we analyze the quantitative effect of employing the auxiliary crowd regression heads (RH1, RH2, RH3) in the proposed scheme. During this ablation study, we removed each auxiliary head one by one and evaluate the network (v5) on the ShanghaiTech Part-A [45] dataset. As shown in Table V, the performance decreases significantly after removing these heads (RH1, RH2, RH3). For instance, without using the RH1 head, the MAE error increases the most with a jump of 11.9%. Similarly, the RMSE error is being affected the most by the RH2 head removal with a 29.7% increase in error.

G. Cross-Dataset Evaluation

To analyze the generalization ability of the proposed method, we carried out the cross-dataset validation. During the experiment, all methods have been trained and tested on the ShanghaiTech Part-A [45] and the UCF-QNRF [12] datasets respectively. As shown in Table VII the proposed method demonstrates better generalization capability as compared to the state-of-the-art methods (including the PRM-based scheme [28]) with MAE, RMSE errors decrease by 8.2% (from 219...
to 201) and 8.9% (from 305 to 278) respectively. Similar to the previous experiments, the proposed approach version (v5) appears to be the most effective cross-dataset validation scheme with the lowest MAE, RMSE values.

H. Qualitative Evaluation

In this section, we demonstrate some qualitative results as shown in Fig. 4. We also compare our scheme with the PRM-based [25] and density-map estimation (DME) [12] based recent state-of-the-art methods. In comparison, it can be observed that the proposed scheme yields the best performance of all on these actual test images with hugely varying crowd-density, lighting condition, and image resolution.

VI. CONCLUSION

To address the major crowd count challenges, we proposed a new multi-resolution fusion based end-to-end crowd counting network for the still images in this work. We also deployed a new and effective PRM substitute that uses three input priors, and proves to be much more accurate than the PRM. Both quantitative and qualitative results have revealed that the proposed network outperforms the state-of-the-art approaches under the RMSE evaluation metric. Cross-dataset evaluation also demonstrates better generalization capability of our approach towards new datasets.

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