Supplementary Material of Counting Crowds in Bad Weather

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https://awccnet.github.io/

1. More Experimental Results

1.1. Quantitative Evaluation

We evaluate our method with more methods including MCNN [19], CSR-Net [5], SA-Net [1], and NoisyCC [14] on the ShanghaiTech [20], UCF-QNRF [4], JHU-Crowd++ [13], and NWPU-CROWD [17] datasets. The results are demonstrated in Table 1. The proposed AWCC-Net can achieve the best performance in UCF-QNRF and JHU-Crowd++ while conducting comparable performance in the ShanghaiTechA and NWPU-CROWD datasets. Moreover, we present the density maps under different adverse weather and clear scene predicted by the AWCC-Net and other algorithms in Figure 1. The results show that the AWCC-Net can predict the more accurate density distribution and counts of crowds under bad weather and clear scenes.

2. Implementation Details

In Table 1 of the regular paper, we compare our methods with several baselines. The results of 'BL-U', 'BL-UF', 'GL', 'GL-U' and 'GL-UF' are retrained based on their original setting and official implementation since they do not provide pre-trained weights on the JHU-Crowd++ dataset. The results of other methods are directly reported from their original papers or the paper of the JHU-Crowd++ dataset [13].

* indicates equal contribution.

Dataset	ShanghaiTechA		UCF-QNRF		JHU-Crowd++		NWPU-CROWD	
Method	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
MCNN [19]	110.2	173.2	277.0	426.0	188.9	483.4	232.5	714.6
CSRNet [5]	68.2	115.0	-	-	85.9	309.2	121.3	387.8
SANet [1]	67.0	104.5	-	-	91.1	320.4	190.6	491.4
SFCN [18]	64.8	107.5	102.0	171.4	77.5	297.6	105.7	424.1
BL [9]	62.8	101.8	88.7	154.8	75.0	299.9	105.4	454.2
LSCCNN [11]	66.5	101.8	120.5	218.2	112.7	454.4	-	-
CG-DRCN-VGG16 [13]	64.0	98.4	112.2	176.3	82.3	328.0	-	-
CG-DRCN-Res101 [13]	60.2	94.0	95.5	164.3	71.0	278.6	-	-
DM-Count [16]	59.7	95.7	85.6	148.3	-	-	88.4	388.6
NoisyCC [14]	61.9	99.6	85.8	150.6	-	-	96.9	534.2
UOT [10]	58.1	95.9	83.3	142.3	60.5	252.7	87.8	387.5
S3 [7]	57.0	96.0	80.6	139.8	59.4	244.0	83.5	346.9
GL [15]	61.3	95.4	84.3	147.5	59.9	259.5	79.3	346.1
ChfL [12]	57.5	94.3	80.3	137.6	57.0	235.7	76.8	343.0
CLTR [6]	56.9	95.2	85.8	141.3	59.5	240.6	**74.3**	333.8
MAN [8]	56.8	90.3	77.3	131.5	53.4	209.9	76.5	**323.0**
GauNet [3]	**54.8**	**89.1**	81.6	153.7	58.2	245.1	-	-
AWCC-Net	56.2	91.3	**76.4**	**130.5**	**52.3**	**207.2**	74.4	329.1

Table 1. **Quantitative comparison on the ShanghaiTech A [20], UCF-QNRF [4], JHU-Crowd++ [13], and NWPU-CROWD [17] datasets with existing methods.**

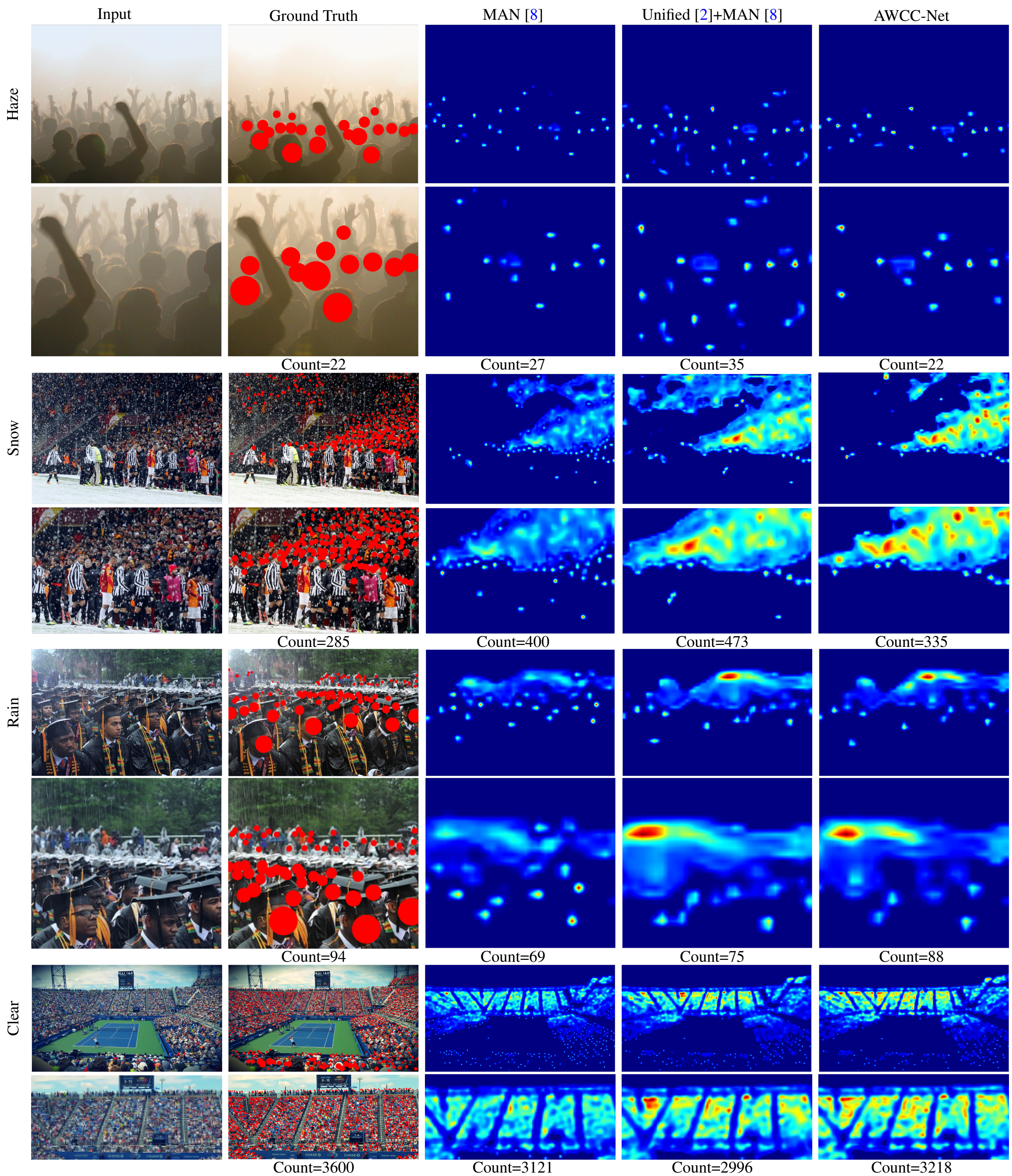

Figure 1. **Comparison of density maps of the proposed method and other methods in the adverse weather (i.e., haze, snow, rain) and clear scene.** The proposed method can compute more accurate density maps compared to the results estimated by other strategies.

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