

# Calibrating Uncertainty for Semi-Supervised Crowd Counting

## —Supplementary Material—

Chen Li \* Xiaoling Hu Shahira Abousamra Chao Chen  
Stony Brook University

### A. Appendix

Append. A.1 shows quality results about which high uncertain patches are filtered out.

Append. A.2 shows that our method is reliable even with only 5% labeled samples.

Append. A.3 provides more ablation study results.

Append. A.4 illustrates the implementation details of choosing pseudo-labels.

Method	Ratio	Part A	
		MAE	RMSE
sup.only	5%	88.48	162.42
w/o filtering	5%	111.39	174.87
softmax	5%	94.64	155.65
Ours	5%	<b>74.48</b>	<b>127.51</b>

Table 9: The ablation study results of 5% labeled data.

#### A.1. Illustrate which pseudo-labels were selected and which inaccurate ones were filtered out.

Fig. 6 shows results on unlabeled samples. Green dots are predictions and red rectangles are high-uncertainty patches. On the left, we found a high-uncertainty patch within the sparse region, containing only one false positive (on the traffic light). In the middle and right samples, the high-uncertainty patches contain many false negatives due to occlusion or dark shades.

#### A.2. Is 5% labeled data enough for training reliable uncertainty estimator?

Empirical results show that 5% labeled data is sufficient to achieve superior performance on ShanghaiTech A (main paper Tab. 5 & Tab. 9) and B (Tab. 10) datasets.

#### A.3. Extra ablation study results.

In this section, we show the effectiveness of our method under 5% and 40% labeled images on the ShanghaiTech part-B dataset with extra ablation study experiments. As shown in Tab. 10, our method achieves better performance

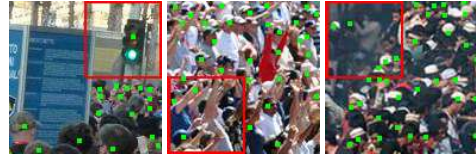


Figure 6: Qualitative results on uncertainty filtering.

under both 5% and 40% labeled image scenarios. This indicates our method can obtain superior performance for semi-supervised crowd counting under various labeled ratios on different datasets.

In Fig. 7, we show additional ablation study results.

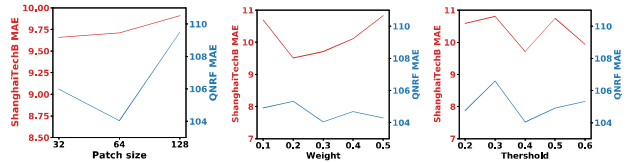


Figure 7: The hyperparameter ablation study results on ShanghaiTech B and UCF-QNRF.

#### A.4. Details of pseudo-labeling

Here we show the details of linearly increasing uncertainty threshold  $u_t$  for choosing pseudo-labels:

$$u_t = startunc + \frac{endunc - startunc}{endep - startep} (t - startep)$$

where  $u_t$  is the uncertainty threshold for choosing image patches, i.e., the image patches with uncertainty estimation higher than  $u_t$  are blanked out, and  $t$  is the current epoch number. The increase of  $u_t$  begins at epoch  $startep$  and ends at epoch  $endep$ . The uncertainty threshold increases from  $startunc$  to  $endunc$ . By using this strategy, we can utilize high-quality model predictions at different training stages properly.

Since it takes several training iterations for multitask model to capture valid crowd and uncertainty information,

\*Email: Chen Li (li.chen.8@stonybrook.edu).

we start leveraging unlabeled information from 10th epoch i.e.  $startep = 10$ . The model predictions on unlabeled images are error-prone, thus uncertainty threshold at the beginning  $startunc$  is 0.1. Besides, we have  $endep = 130$  and  $endunc = 0.6$ .

Method	Type	Ratio	Part B	
			MAE	RMSE
MT [4]	SSL	5%	19.3	33.2
L2R [2]	SSL	5%	20.3	27.6
GP [3]	SSL	5%	15.7	27.9
PA [5]	PAL	5%	16.50	25.28
DAccount [1]	SSL	5%	<u>12.6</u>	<u>22.8</u>
ours	SSL	5%	<b>11.03</b>	<b>20.93</b>
MT [4]	SSL	40%	15.9	25.7
L2R [2]	SSL	40%	16.8	25.1
DAccount [1]	SSL	40%	<u>9.6</u>	<u>14.6</u>
Ours	SSL	40%	<b>7.79</b>	<b>12.70</b>

Table 10: The ablation study results of labeled ratio on the ShanghaiTech part-B dataset.

### A.5. Implementation details

In practice, for the convenience of implementation, we use (1 - batch normalized ASM) as a surrogate to train the

uncertainty branch, and the model confidence output will be used to filter out unreliable patches.

### References

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