A REAL-TIME DEEP NETWORK FOR CROWD COUNTING

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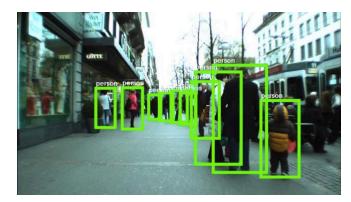


- Introduction and Motivation
- Framework
- Experiments
- Conclusion

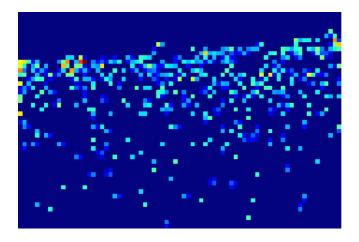
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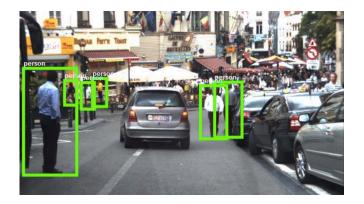
Background

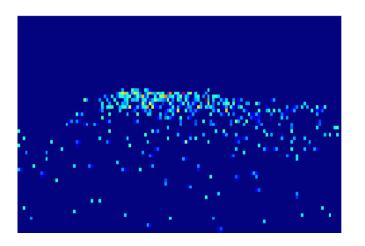
- Crowd counting
 - Count-oriented Approaches



• Density-oriented Approaches







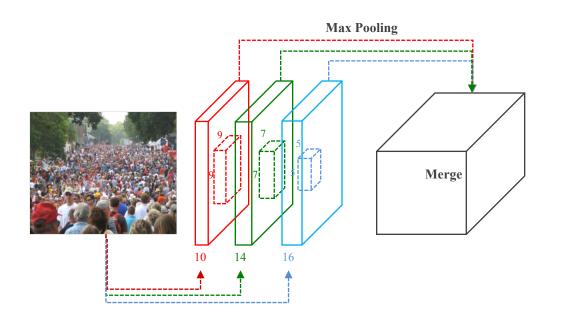
Challenges

- Occlusions, high clutter, scale and perspective
- limited computing resources in practical applications
- High requirement to the processing speeds





Motivation



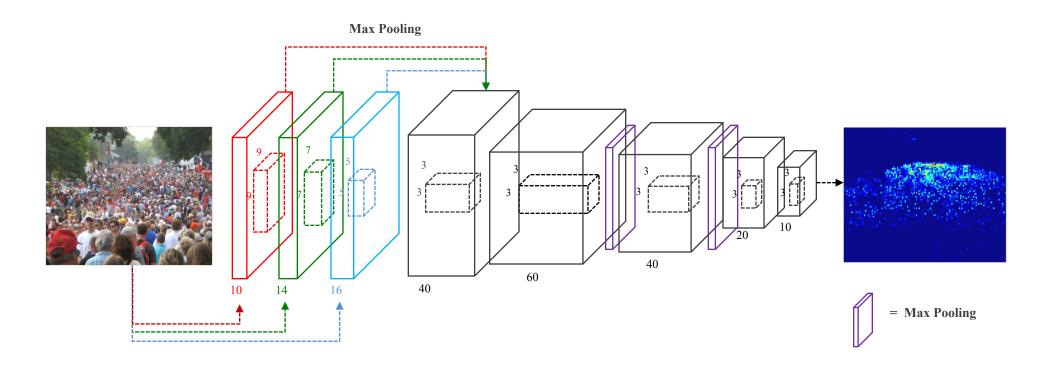
- to deal with the problem as bellow:
 - sub-optimal and timeconsuming problem.
 - need to store a large amount of parameters

Y. Zhang, D. Zhou, S. Chen, S. Gao, and Y. Ma. Single-image crowd counting via multi-column convolutional neural network. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 589–597, 2016.

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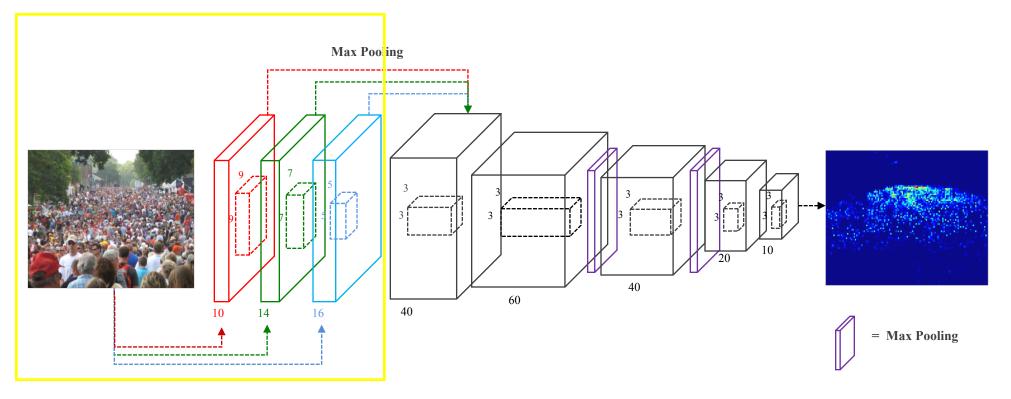
Framework

- two components:
 - The parallel convolution layer with different kernels
 - The convolution with pooling layers that followed.



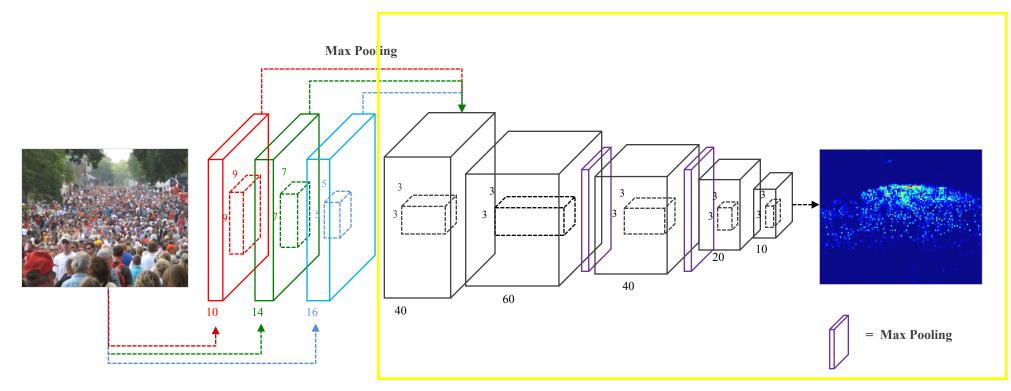
Framework

- In the front part:
 - using three filters different receptive fields in one layer (red/green/blue).
 - the feature maps are merged directly after receptive fields.



Framework

- In the latter part:
 - consists of 6 convolutional layers specifically.
 - last convolution layer aggregate the feature maps into a density map.



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- Dataset
 - ShanghaiTech dataset
 - The WorldExpo'10 dataset
- Evaluation
 - MAE & MSE







• Result & Comparing

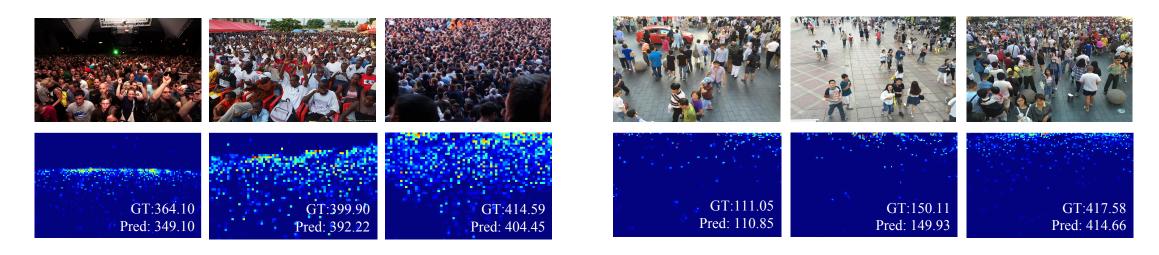
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Method	Part A		Part B		Parameter
Methou	MAE	MSE	MAE	MSE	size
CMTL [18]	101.3	152.4	20.0	31.1	2.36M
Zhang <i>et al.</i> [17]	181.8	277.7	32.0	49.8	0.62M
MCNN [7]	110.2	173.2	26.4	41.3	0.15M
TDF-CNN [19]	97.5	145.1	20.7	32.8	0.13M
C-CNN	88.1	141.7	14.9	22.1	0.07M
ACSCP [20]	75.7	102.7	17.2	27.4	5.10M
Switching CNN [1]	90.4	135.0	21.6	33.4	15.30M
CSRNet [21]	68.3	115.0	10.6	16.0	16.26M
SaCNN [22]	86.8	139.2	16.2	25.8	24.06M
CP-CNN [2]	73.6	106.4	20.1	30.1	68.40M

Table1. Comparison on ShanghaiTech dataset

-		-					
Method	S 1	S2	S 3	S 4	S5	Avg.	Params
Zhang <i>et al.</i> [17]	9.8	14.1	14.3	22.2	3.7	12.9	0.62M
MCNN [7]	3.4	20.6	12.9	13.0	8.1	11.6	0.15M
TDF-CNN [19]	2.7	23.4	10.7	17.6	3.3	11.5	0.13M
C-CNN(ours)	3.8	20.5	8.8	8.8	7.7	9.9	0.07M
CSRNet [21]	2.9	11.5	8.6	16.6	3.4	8.6	16.26N
SaCNN [22]	2.6	13.5	10.6	12.5	3.3	8.5	24.06N
CP-CNN [2]	2.9	14.7	10.5	10.4	5.8	8.86	68.40N

Table2. Comparison on WorldExpo'10 dataset

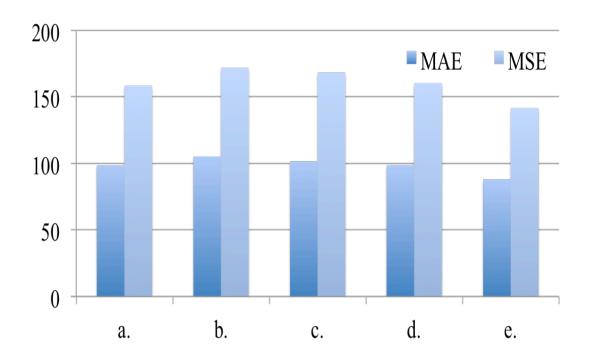
• Results demonstration



(b) ShanghaiTech Part B

(a) ShanghaiTech Part A

• Ablation Experiments & Speed Comparison



Method	CMTL [18]	MCNN [7]	C-CNN
FPS	8.37	64.52	104.16

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Conclusion

- A compact CNN for crowd counting is proposed to deal with the lack of real-time performance of existing methods.
- Utilizes three filters with different sizes of local receptive field in one layer and directly targeting a merged feature map at once.
- Compared with the baseline approaches, the proposed model obtains an improvement significantly.

Thanks!