DroneNet: Crowd Density Estimation using Self-ONNs for Drones

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Abstract
Video surveillance using drones is both convenient and efficient due to the ease of deployment and unobstructed movement of drones in many scenarios. An interesting application of drone-based video surveillance is to estimate crowd density (both pedestrians and vehicles) in public places. Deep learning using convolution neural networks (CNNs) is employed for automatic crowd counting and density estimation using images and videos. However, the performance and accuracy of such models typically depends upon the model architecture i.e., deeper CNN models improve accuracy at the cost of increased inference time. In this paper, we propose a novel crowd density estimation model for drones (DroneNet) using Self-organized Operational Neural Networks (Self-ONN). Self-ONN provides efficient learning capabilities with lower computational complexity as compared to CNN-based models. We tested our algorithm on two drone-view public datasets. Our evaluation shows that the proposed DroneNet shows superior performance on an equivalent CNN-based model.

1 Introduction
Automatic aerial video surveillance using drones has many potential applications in future smart cities. Due to the ease of deployment, and flexibility to reach anywhere, drones can play a vital role in several scenarios such as crowd surveillance for smart policing in public places e.g., metro stations, stadiums, and political rallies. Simpson [2021], Khan et al. [2023], situational awareness during disasters Sambolek and Ivasic-Kos [2021], traffic monitoring in smart transportation systems Sun et al. [2022], and monitoring of forests and wild life Chandana and Vasavi [2022], Allauddin et al. [2019]. Traditionally crowd counting using images employs handcrafted local features such as full body Topkaya et al. [2014], Tuzel et al. [2008], body parts Li et al. [2008], Felzenszwalb et al. [2010], shapes Lin and Davis [2010], or global features such as texture Chen et al. [2012], edges Wu and Nevatia [2006], foreground Davies et al. [1995] and gradients Dalal and Triggs [2005], Tian et al. [2010] to detect and count people. These methods perform poorly on images of dense crowds with severe occlusions and other variations Khan et al. [2022]. To overcome these challenges, CNN-based crowd counting has been introduced in Zhang et al. [2015], Boominathan et al. [2016]. Several state-of-the-art CNN models are developed over time mainly to improve the accuracy in more challenging scenes Zhang et al. [2016], Zeng et al. [2017], Li et al. [2018], Jiang et al. [2019], Cao et al. [2018], Song et al. [2021]. However, while achieving higher accuracy, the complexity of the

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model is often ignored. Thus, several of these models use popular deep CNN networks as a frontend network to extract fine-grained features. For instance, VGG-16 Simonyan and Zisserman [2015] is used as a front-end in Boominathan et al. [2016], Li et al. [2018], Liu et al. [2019], ResNet He et al. [2016] is used in Peng et al. [2020a], Gu and Lian [2022], and Inception Szegedy et al. [2015] in Wang and Breckon [2022]. Such deep CNN architectures are better suited for applications using powerful GPU servers, but when run on edge devices with low computation power, they incur higher inference delays. Thus, lightweight CNN models are desired for edge-based processing. However, the lower accuracy of lightweight models often precludes the adoption of such models in practical applications.

Recently, authors in Kiranyaz et al. [2020] introduces Operational Neural Networks (ONNs) architectures to achieve higher accuracy with small models consisting of fewer layers. ONNs replace the non-linear convolution operation in neurons with a set of non-linear operations to improve the learning process in more challenging tasks. The Self-organized ONNs (which is an improved version of ONNs) Malik et al. [2021] with even compact architecture show superior performance over conventional CNNs of equivalent or larger sizes in several problems e.g., image restoration Kiranyaz et al. [2020], Malik et al. [2021], video segmentation Hamila et al. [2022], medical imaging Degerli et al. [2021]. Inspired by the improved results of SelfONNs in various tasks, we adopted the SelfONN paradigm in our proposed crowd density estimation model.

The contribution of the paper is as follows: We propose a compact crowd counting and density estimation model using Self-ONN Malik et al. [2021] architecture. To our knowledge, the use of SelfONN in crowd density estimation has not been proposed earlier. The proposed model is tested on benchmark crowd datasets containing images taken with drones. The performance is compared with an equivalent CNN model as well as other existing state-of-the-art crowd counting models over various metrics to show significant performance improvement.

2 Related Work

CNN-based crowd counting and density estimation was first proposed in Zhang et al. [2015] using a single-column CNN network that consists of six layers. Following the success of CNNs, several other works proposed different CNN architectures in attempts to achieve better accuracy over benchmark datasets. The major architectural changes introduced over time include multi-column networks Zhang et al. [2016], Boominathan et al. [2016], Sam et al. [2017], Sindagi and Patel [2017], modular networks Zeng et al. [2017], Cao et al. [2018], Wang and Breckon [2022], encoder-decoder models Jiang et al. [2019], Gao et al. [2019], and models using transfer learning Li et al. [2018], Liu et al. [2019], Aich and Stavness [2018], Tang et al. [2022]. Small-sized models with single-column architectures (e.g. Zhang et al. [2015] typically suffers from low accuracy when the images have scale variations. Scale variations arise from the camera perspective distortions i.e., objects closer to the camera are bigger than those far from the camera. Thus, multi-column networks with filters of different receptive fields in each column are used to capture these scale variations. For instance, the multi-column CNN (MCNN) proposed in Zhang et al. [2016] uses a three-column architecture with filters of variable sizes (9 × 9, 7 × 7, 5 × 5, and 3 × 3) in different columns. The switching-CNN Sam et al. [2017] uses three CNN networks (regressor networks) dynamically selected by another CNN network (classifier or switch). The input image is thus passed through only one column (regressor) based on the image crowd density determined by the classifier. A drawback of multi-column CNNs is that their capability to adapt to scale variations is limited by the number of columns. Thus, the model size will significantly increase when there are large-scale variations in the dataset. An alternative solution is to use modular networks which use single-column architecture with special scale-adaptive modules. These models are inspired by the Inception model Szegedy et al. [2015]. Another category of crowd counting models is the encoder-decoder models Jiang et al. [2019], Gao et al. [2019] inspired from the UNet architecture Ronneberger et al. [2015], where an encoder network learns and extracts features from the network and a decoder network then uses these features to predict the density map. Encoder-decoder models are good when high-quality density maps are desired. Crowd counting can become more challenging when applied to very dense and congested scenes. Thus, a large number of research works propose the use of transfer learning i.e., a pretrained image classification model such as VGG Simonyan and Zisserman [2015], ResNet He et al. [2016] or Inception Szegedy et al. [2015] as a front-end to extract features and then a small CNN network uses these features to estimate the
crowd density. Transfer-learning based approaches are generally more accurate and faster to train. However, these models incur longer inference delays and require more memory to store and execute.

3 Proposed Scheme

In aerial crowd surveillance applications using drones, we aim at designing a lightweight architecture that can run faster on low-end processors and provide sufficient accuracy. We developed a lightweight model following a similar architecture of MCNN Zhang et al. [2016] but replacing the convolution layers with the SelfONN layers. To keep the model size compact for the intended application, we do not use transfer learning.

3.1 The DroneNet Architecture

The architecture of our proposed network (DroneNet) is shown in Fig. 1. Like MCNN, it is a three-column CNN architecture with the same number of layers in each column. The difference is that all convolution layers in the three columns are replaced with SelfONN layers except the last (1 × 1) convolution layer after columns concatenation. We used Tanh activation layers after each SelfONN layer except the last convolution layer which is proceeded by a Relu activation layer.

![Figure 1: Architecture of DroneNet.](image)

3.2 Hyper-parameters Settings

A SelfONN layer uses an additional hyper-parameter $q$ which introduces non-linearity in the neurons. We set the value of $q = 3$ in the first layer of each column, whereas all the remaining SelfONN layers use $q = 5$. The last standard convolution layer does not use $q$.

3.3 Model Training

The DroneNet model is trained over the DroneRGBT dataset Peng et al. [2020b]. The DroneRGBT dataset has 1807 RGB and thermal image pairs in the train set. Each image has a spatial resolution of 512×640 pixels. We split the train set into a ratio of (70% : 30%) for training and validation. The dataset covers several scenes (e.g., campus, streets, public parks, car parking, stadiums, and plazas) and contains diverse crowd densities, illumination, and scale variations. The dataset provides the head locations of people (called dot annotations). To train the model, the dot annotations are converted to density maps that serve as ground truth for the images. The density map is generated by convolving a delta function $\delta(x - x_i)$ with a Gaussian kernel $G_\sigma$, where $x_i$ is a pixel containing the head position.

$$D = \sum_{i=1}^{N} \delta(x - x_i) * G_\sigma$$  \hspace{1cm} (1)

where, $N$ is the total number of annotated points (i.e., the total count of heads) in the image. We empirically determined a fixed value of $\sigma = 7$ that provides a good estimation of the head sizes. We employ full image-based training instead of patch-based training for simplicity and speed. To avoid
model overfitting, data augmentation techniques including horizontal flipping, and random brightness and contrast are applied. We use Adam optimizer Kingma and Ba [2015] with a base learning rate of 0.0001. The loss function used is pixel-wise Euclidean distance between the target and predicted density maps which are defined in Eq. 2.

$$L(\Theta) = \frac{1}{N} \sum_{i=1}^{N} ||D(X_i; \Theta) - D_{gt}^i||^2_2$$ (2)

where $N$ is the number of samples in training data, $D(X_i; \Theta)$ is the predicted density map with parameters $\Theta$ for the input image $X_i$, and $D_{gt}^i$ is the ground truth density map. The model was trained on two GPUs (Nvidia RTX-8000) using PyTorch deep learning framework.

4 Evaluation and Results

4.1 Evaluation Metrics

We evaluated the performance of DroneNet using eight (8) metrics including mean absolute error (MAE) and Grid Average Mean Error (GAME), Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), model size (MB), Giga Multiply-Accumulate operations (GMACs), inference time (milli-second), and throughput (frames per second).

MAE and GAME provide the accuracy of the model and are calculated as 3 and 4, respectively:

$$MAE = \frac{1}{N} \sum_{n=1}^{N} (e_n - g_n)$$ (3)

where, $N$ is the total number of images in the dataset, $g_n$ is the ground truth (actual count) and $e_n$ is the prediction (estimated count) in the $n^{th}$ image.

$$GAME = \frac{1}{N} \sum_{n=1}^{N} \left( \sum_{l=1}^{4} |e_{n}^l - g_{n}^l| \right)$$ (4)

We set the value of $L = 4$, thus each density map is divided into a grid size of $4 \times 4$ creating 16 patches.

The SSIM and PSNR metrics measure the quality of predicted density maps as compared to ground truth density maps and are calculated as follows 5 6:

$$SSIM(x, y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_x \sigma_y C_2)}{\left(\mu_x^2 \mu_y^2 + \sigma_x^2 \sigma_y^2 + C_1\right)(\mu_x^2 \mu_y^2 + C_2)}$$ (5)

where $\mu_x, \mu_y, \sigma_x, \sigma_y$ represent the means and standard deviations of the actual and predicted density maps, respectively.

$$PSNR = 10 \log_{10} \left( \frac{Max(I^2)}{MSE} \right)$$ (6)

where $Max(I^2)$ is the maximal in the image data. If it is an 8-bit unsigned integer data type, the $Max(I^2) = 255$.

The other metrics such as the size of the model can be useful to know the required storage space (especially when a device does not have external memory and has limited on-chip memory), GMACs can be an indication of the model time complexity as well as can be used to estimate the model energy consumption. Similarly, the inference time and throughput are both related to the execution speed and can be used in application configuration (e.g., frame capturing rate of the camera, etc.).
4.2 Results

The DroneNet is trained using the aforementioned method and hyper-parameter settings and evaluated over various metrics. The performance of the DroneNet is compared over eight (8) metrics against five (5) other crowd counting models namely CrowdCNN Zhang et al. [2015], MCNN Zhang et al. [2016], CMTL Sindagi and Patel [2017], CSRNet Li et al. [2018], and SANet Cao et al. [2018]. The results are graphically illustrated in Fig. 2.

The analysis shows that DroneNet achieves better accuracy (MAE and GAME) than CrowdCNN, MCNN, CMTL, and SANet and is very close to that CSRNet. Importantly, the DroneNet using Self-ONN achieves higher accuracy than the equivalent CNN-based model (MCNN). In addition, DroneNet also achieves equal or slightly better SSIM and PSNR values than MCNN. In terms of model size, DroneNet has a higher size than MCNN. However, the size is still of the order that can be easily stored in on-chip memory as compared to the deep models such as CSRNet (which is about 25× higher). The inference-time comparison also shows that DroneNet achieves a throughput closer to that of MCNN and much higher than all other models.

Figure 2: Performance evaluation of DroneNet over various metrics.

Fig. 3 shows sample predictions using DroneNet and other CNN-based networks.

Figure 3: Sample Predictions: The first column shows images from the test set. The second column shows the ground truth for the given images. The third and fourth columns show predictions using MCNN Zhang et al. [2016] and proposed DroneNet.
4.3 Ablation Study

To validate the accuracy of DroneNet, we further investigated its performance over two other benchmark datasets used in crowd counting studies i.e., ShanghaiTech Part-B Zhang et al. [2016] and CARPK Hsieh et al. [2017]. The trained DroneNet is trained using the same hyper-parameter settings with different values of $\sigma$ for ground truth density-map generation. We use $\sigma = 15$ for both datasets as in Li et al. [2018], Ma et al. [2019]. Our evaluation shows that DroneNet achieves better accuracy (low MAE and GAME values) than MCNN over both datasets Zhang et al. [2016].

Table 1: Ablation Study on ShanghaiTech Part-B Zhang et al. [2016] dataset.

| Model            | ShanghaiTech Part-B | CARPK         |
|------------------|---------------------|---------------|
|                  | MAE  | GAME | MAE  | GAME |
| MCNN Zhang et al. [2016] | 26.4 | 55.2 | 10.1 | 43.4 |
| DroneNet (ours)  | 22.4 | 41.9 | 9.0  | 40.1 |

The counting errors (i.e., actual count - predicted count) for the CARPK dataset Hsieh et al. [2017] are plotted in Fig. 4.

Figure 4: Counting errors in DroneNet over CARPK Hsieh et al. [2017] dataset.

It can be observed that the model performs much better on a large number of images with low to medium densities. On high-density images ($< 150$ per image), the errors are relatively larger. High-density images are typically more challenging due to overlapping and occlusion effects.

5 Conclusion

In this paper, we propose a novel deep learning model i.e., DroneNet using the Self-ONN learning paradigm instead of the commonly used CNN networks. DroneNet is lightweight, efficient, accurate, and is potentially a suitable choice for deployment over drones with limited computing resources on board. The performance of DroneNet is tested on benchmark datasets and the results report significant improvement over the equivalent CNN network (MCNN). Furthermore, the accuracy performance is very close to the CSRNet network exacerbates in terms of computational complexity and memory requirement. The DroneNet can run over edge devices much faster than CSRNet and almost at equal
speed at equivalent deep architectures. In future work, we aim to test DroneNet on other benchmark datasets. We also aim to use Self-ONNs for designing dense crowd counting models for fine-grained counting in other applications.

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