Iterative Correlation-based Feature Refinement for Few-shot Counting

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Abstract

Few-shot counting aims to count objects of any class in an image given only a few exemplars of the same class. Existing correlation-based few-shot counting approaches suffer from the coarseness and low semantic level of the correlation. To solve these problems, we propose an iterative framework to progressively refine the exemplar-related features based on the correlation between the image and exemplars. Then the density map is predicted from the final refined feature map. The iterative framework includes a Correlation Distillation module and a Feature Refinement module. During the iterations, the exemplar-related features are gradually refined, while the exemplar-unrelated features are suppressed, benefiting few-shot counting where the exemplar-related features are more important. Our approach surpasses all baselines significantly on few-shot counting benchmark FSC-147. Surprisingly, though designed for general class-agnostic counting, our approach still achieves state-of-the-art performance on car counting benchmarks CARPK and PUCPR+, and crowd counting benchmarks UCSD and Mall. We also achieve competitive performance on crowd counting benchmark ShanghaiTech. The code will be released soon.

1. Introduction

Most existing visual counting methods focus on a specific class at a time, such as people [24, 36, 52, 53], animals [1], and cars [5, 12], while class-agnostic few-shot counting (FSC) counts for any class. As shown in Fig. 1(a), given an image from a novel class and a few labeled exemplars, FSC aims to count objects of the same class as the exemplars, which is a more general and challenging task.

In FSC [28], there are base classes in which both a few labeled exemplars and the locations of all objects are available and novel classes in which only a few labeled exemplars are available. The novel classes share no common classes with the base classes. FSC is expected to learn from base classes and be able to count objects of novel classes with only a few labeled exemplars. To achieve this, recent FSC methods [25, 28] utilize the intuition that the regions more similar to exemplars are more likely to be target objects. These methods firstly calculate the correlation between the image and exemplars, then utilize the correlation to regress the density map, from which the predicted count is obtained by summing all values of the density map. However, there are two main issues about these approaches.

One issue is the coarseness of the correlation. It is shown in Fig. 1(b) that the correlation between the original image feature map and exemplar feature maps (denoted as 1st Correlation) is quite coarse, thus it is difficult to regress a high-quality density map from this coarse correlation. The
coarseness of the correlation is mainly caused by the disturbance of exemplar-unrelated features, such as the features of stones, trucks, and earth in this image.

Another issue is the low semantic level of the correlation. The correlation is just a rough estimate of the similarity between the input image and exemplars, and the semantic information in the correlation is quite poor. In contrast, the CNN-extracted features contain rich semantic information that is beneficial for density regression. However, regressing the density map directly from the feature map suffers from the fact that there are too many disturbing exemplar-unrelated features.

In this paper, considering the vital significance of the exemplar-related features in FSC, we propose an iterative correlation-based feature refinement framework to progressively refine the exemplar-related features and suppress the exemplar-unrelated features. As illustrated in Fig. 1(b), from the 1st to 4th iteration, there are less and less disturbance of the exemplar-unrelated features and the correlation is also iteratively refined. More importantly, since the exemplar-unrelated features have been suppressed, we could regress the density map directly from the semantic-rich refined feature map instead of the semantic-poor correlation. Therefore, our approach solves the above two main issues and achieves state-of-the-art FSC performance, as the FSC results in Fig. 1(a) demonstrate.

The proposed framework is composed of the Correlation Distillation module and the Feature Refinement module as shown in Fig. 1(b). The Correlation Distillation module is used to calculate and normalize the correlation between the image and exemplars. The Feature Refinement module refines the feature map based on the normalized correlation. By doing so, the exemplar-related features, i.e., the features of the regions more similar to the exemplars, would correspond to higher correlation values. These exemplar-related features would also be better refined, boosting the FSC performance which relies more highly on exemplar-related features.

We summarize our contributions as follows:

- We propose a Feature Refinement module to refine exemplar-related features using the normalized correlation, promoting the performance of FSC in which exemplar-related features are more important.
- We propose an iterative FSC framework including a Correlation Distillation module and a Feature Refinement module to iteratively refine the exemplar-related features. The refinement framework allows us to regress the density map directly from the semantic-rich feature map instead of the semantic-poor correlation.
- We propose a Correlation Distillation module to calculate and normalize the correlation between the image and exemplars, obtaining a normalized correlation with proper scales for better feature refinement.
- We propose a Correlation Distillation module for density estimation with foreground-background segmentation and explicit local uncertainty estimation to count penguins. For car counting, [12] proposes LPNs with spatial kernels to simultaneously count and localize cars. However, these methods could count objects of only one specific class at a time.

2. Related Work

Object counting approaches could be roughly divided into class-agnostic ones and class-specific ones.

Class-agnostic counting approaches aim to count objects of different classes. IEP Counting [37] divides images into several regions, then regresses the count by inclusion-exclusion principle. PDEM [9] proposes Soft-IoU and EM-Merger, helping object detection and counting in densely packed scenes. In [17], a localization-based counting loss is proposed, formulating counting as a segmentation problem. However, [9, 17, 37] could only work on close-set benchmarks where the classes in the test set are the same as those in the training set, which does not fulfill the requirements of FSC. GMN [25] and FamNet [28] both utilize the correlation to regress the density map for FSC. However, after pre-trained on ILSVRC dataset [31], GMN still needs to be re-trained with dozens or hundreds of annotated images for adaption when used for new classes. Also, the coarseness and low semantic level of correlation decrease the performance of GMN and FamNet, as described in Sec. 1.

Class-specific counting approaches count objects of a specific class at a time, such as people [24, 36, 52, 53], animals [1], cars [5, 12], among which crowd counting has been widely researched. For crowd counting, traditional methods [18, 38, 43] count the crowd number in an image by detecting persons, which does not work well for images with high crowd density. Recent methods mainly use a deep neural network to predict the density map [42] from the crowd image, where the sum over the density map is the crowd count [19]. Various crowd counting approaches have been proposed to handle perspective distortion [47, 49], to address scale variation [2, 53], to refine the predicted density map [27, 32, 33], and to encode context information [34, 46], continuously improving the crowd counting performance. A cross-scene crowd counting method is proposed in [50] to improve the generalization ability. FamNet uses a detector and a regressor to estimate the crowd count and proposes a DecisionNet to merge the two predicted results. Recently, [36, 41] propose novel loss functions that predict quite accurate position of each person, highly improving the crowd localization ability. For animal counting, [1] augments density estimation with foreground-background segmentation and explicit local uncertainty estimation to count penguins. For car counting, [12] proposes LPNs with spatial kernels to simultaneously count and localize cars. However, these methods could count objects of only one specific class at a time.
Few-shot approaches are also highly related with our work. Few-shot classification [8, 44], detection [6, 45], and segmentation [48, 51] aim to complete corresponding tasks on images of novel classes given a few exemplars. For classification, MAML [8] learns parameters which can adapt to novel classes at test time by few gradient descent steps. FRN [44] formulates few-shot classification as a reconstruction problem in latent space. For detection, [6] exploits the similarity between the input image and the exemplars to detect novel objects while suppressing false detection in the background. [45] generates multi-scale positive samples as object pyramids and refines the prediction at various scales. For segmentation, [51] proposes a two-branch dense comparison module performing multi-level feature comparison between the input image and the exemplars, and the segmentation results are iteratively refined. [48] aims to alleviate the problem of feature undermining and enhance the feature embedding of latent novel classes. However, researches for few-shot counting are still limited.

3. Method

In this section, we first briefly introduce the preliminaries for few-shot counting (FSC) in Sec. 3.1. Then the proposed iterative feature refinement framework is described in Sec. 3.2, following the detailed architectures of the Correlation Distillation module and the Feature Refinement module in Sec. 3.3. Finally, we provide a theoretical comparison between our method and the transformer in Sec. 3.4. The overall framework of our approach is shown in Fig. 2.

3.1. Few-shot Counting Preliminaries

In FSC [28], object classes are divided into base classes \( C_b \) and novel classes \( C_n \), where \( C_b \) and \( C_n \) have no intersection. For each image from \( C_b \), both a few corresponding exemplars and the locations of all target objects are provided. While, for the images from \( C_n \), only their corresponding exemplars are available. FSC aims to count target objects from \( C_n \) with only a few annotated exemplars by leveraging the generalization knowledge from \( C_b \). Denote the number of exemplars per image as \( K \), the task is called \( K \)-shot FSC.

3.2. Iterative Feature Refinement Framework

Given an image \( I \in \mathbb{R}^{C_I \times H_I \times W_I} \), a frozen ImageNet pre-trained ResNet-18 [11] is applied to extract features. The feature maps from layer1 to layer3 are selected. These feature maps are firstly resized to the same size \( H \times W \), then concatenated together to form a multi-layer image feature map \( f_I \in \mathbb{R}^{C \times H \times W} \). The feature maps of the exemplars are calculated by ROI Pooling [30] on the corresponding multi-layer image feature map. Then the feature maps of all exemplars are concatenated together to obtain the exemplar feature map \( f_e \in \mathbb{R}^{K \times C \times H_e \times W_e} \), where \( K \) is the number of exemplars, \( H_e, W_e \) are manually selected size.

In the Correlation Distillation module, the correlation \( A \) between the image feature map \( f_I \) and the exemplar feature map \( f_e \) is firstly calculated. Then we propose exemplar normalization (EN) and spatial normalization (SN) to respectively normalize the correlation \( A \) among different exemplars and spatial positions, providing a normalized cor-
The Feature Refinement module firstly calculates the correlation feature map $f_c$ based on the normalized correlation $A_n$. Here the name “correlated feature map” means that the features in this feature map are highly related to the normalized correlation $A_n$. Specifically, the features corresponding to larger correlation values are better retained. Then this module fuses the correlated feature map $f_c$ with the input image feature map $f_i$ to obtain the refined feature map $f_i'$. In essence, the feature refinement is instructed by the normalized correlation $A_n$. The features of the positions whose correlation values are large, i.e., the exemplar-related features, would be better refined. This boosts the performance of FSC in which the exemplar-related features are more crucial. The Correlation Distillation module and the Feature Refinement module are detailed in Sec. 3.3.

The refined feature map $f_i'$ could serve as the inputs to the next iteration. The $N$ iterations would progressively refine the exemplar-related features and suppress the exemplar-unrelated features. Without the disturbance of the exemplar-unrelated features, we could regress the density map $D_\in\mathbb{R}^{H_i\times W_i}$ directly from the semantic-rich refined feature map instead of the semantic-poor correlation. The regression head is composed of iterative convolution, ReLU activation, and bi-linear up-sample. Its detailed architecture is given in the Supplementary Material.

The annotations of most counting datasets are dots, indicating the object positions. However, it is difficult to train a network with the dot annotations directly. Most existing methods generate ground truth (GT) density maps for training. Following [28], we utilize the Gaussian smoothing with adaptive window size to generate the GT density maps. The GT density map for image $I$ is denoted as $D_{gt} \in \mathbb{R}^{H_i\times W_i}$. Our model is trained with MSE loss $\mathcal{L}$ as follows,

$$\mathcal{L} = \text{MSE}(D - D_{gt}).$$  \hfill (1)

The training configuration is detailed in Sec. 4.

### 3.3. Module Architecture

The scales of correlation values should be normalized to better refine features, for which we propose Exemplar Normalization (EN) and Spatial Normalization (SN). EN aims to seek the normalization among different exemplars, while SN improves the performance significantly.

The ablation study of normalization in Sec. 4.5 indicates that both EN and SN improve the performance significantly.

**Feature Refinement module** firstly calculates the correlation feature map based on the normalized correlation, then obtains the refined feature map by feature fusion. In our design, the correlated feature map should be highly related to the normalized correlation. Namely, the larger the correlation value of a specific position is, the more related to exemplars its corresponding feature is, the better this feature should be maintained. Therefore, the values of the normalized correlation $A_n$ are regarded as weights of combining the exemplar feature map $f_e$ to acquire the correlated feature map $f_c$. The combination process is illustrated as follows. First, the exemplar feature map $f_e$ is flipped horizontally and vertically. Then, we convolute the normalized correlation $A_n$ with the flipped exemplar feature map as the convolution kernel to obtain the correlated feature map $f_c$. Here the convolution is done independently with each exemplar, then the results are summed to acquire the correlated feature map $f_c$. The formula is

$$f' = (A_n \odot f_c) \in \mathbb{R}^{K \times H \times W},$$

$$f_c = \text{sum}(f', \dim = 0) \in \mathbb{R}^{C \times H \times W},$$ \hfill (6)

where $\text{sum}(\cdot, \dim = 0)$ is the sum over the $\dim$-th dimension. Additionally, $\text{sum}(\cdot, \dim = 0)$ is computed for $f'$ to acquire the output $f_c$.
The refined feature map \( f \) shortcut connection, convolution and LN, as shown in Fig. 2. The flip helps the correlated feature map retain consistent spatial structure as the exemplar feature map, whose advantages are verified in the ablation study in Sec. 4.5.

The correlated feature map \( f' \) is fused with the input image feature map \( f_I \) to obtain the refined feature map \( f' \) by shortcut connection, convolution and LN, as shown in Fig. 2. The refined feature map \( f' \) could serve as the inputs to the next iteration for further feature refinement. The iterative refinement framework gradually refines the exemplar-related features, promoting the performance of FSC where the exemplar-related features are more significant.

### 3.4. Comparison with Transformer

Essentially, our method is closely related to the self-attention module in transformer [39], which is defined as,

\[
\text{Attention}(q, k, v) = \text{softmax} \left( \frac{q \cdot k}{\sqrt{d_k}} \right) v, \tag{7}
\]

where \( q, k, v \) are respectively the query, key, and value, \( d_k \) is the channel number of tokens. The dot multiplication between \( q \) and \( k \) can be taken as correlation calculation. The division by \( \sqrt{d_k} \) and the softmax can be seen as correlation normalization. The multiplication with \( v \) can be seen as calculating the correlated feature map with normalized correlation. Also, transformer has shortcut connections and feedforward networks for feature fusion. The difference lays in that our method is based on convolution and keeps the spatial structure of feature maps, while transformer splits feature maps into independent tokens resulting in the loss of spatial structure. The ablation study in Sec. 4.5 shows that keeping the spatial structure brings a large improvement.

### 4. Experiments

#### 4.1. Evaluation Metrics

We choose Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to measure the performance of object counting approaches following [9, 24, 28]:

\[
\text{MAE} = \frac{1}{N_I} \sum_{i=1}^{N_I} |C_i - C_i^{GT}|, \tag{8}
\]

\[
\text{RMSE} = \sqrt{\frac{1}{N_I} \sum_{i=1}^{N_I} (C_i - C_i^{GT})^2}, \tag{9}
\]

where \( N_I \) is the number of images, \( C_i \) and \( C_i^{GT} \) are the predicted and ground truth count of the \( i^{th} \) image, respectively.

### 4.2. Datasets

**FSC-147** [28] is a multi-class FSC dataset with 147 classes and 6135 images. The number of objects per image varies extremely from 7 to 3701 with an average of 56. Each image has 3 exemplars for counting. It is worth noting that FSC-147 is an open-set counting benchmark. The training set contains 89 classes, while the validation set and test set both contain another disjoint 29 classes. In addition, the images collected from COCO [22] dataset in the validation and test set of FSC-147 are named as Val-COCO and Test-COCO, which comprise of 277 and 282 images, respectively. These two COCO subsets are also used as an FSC evaluation benchmark, especially for the comparison with detection-based approaches considering that COCO is a widely adopted object detection benchmark.

**Car counting datasets.** **CARPK** [12] is a car counting dataset with 1448 images and nearly 90,000 cars from a drone perspective. These images are collected in various scenes of 4 different parking lots. The training set contains 3 scenes, while another scene is used for testing. **PUCPR+** [5, 12] is a camera-shot car counting dataset with 125 images and nearly 17,000 cars. The number of cars per image varies extremely from 0 to 331. The training set contains 100 images and the rests are used for test.

**Crowd counting datasets.** **ShanghaiTech** [53] contains 1198 annotated images with 330, 165 persons in total. This dataset consists of two parts as PartA containing 482 images with highly congested scenes downloaded from the Internet and PartB including 716 images with relatively sparse crowd scenes taken from streets in Shanghai. **UCSD** [3] is a dataset of 2000 frames captured by surveillance cameras. These scenes contain sparse crowds varying from 11 to 46 persons per image. **Mall** [4] contains over 60,000 pedestrians in 2000 video sequences taken in a mall. For both UCSD and Mall, 800 frames are employed for training and the remaining 1200 frames are used for testing.

### 4.3. Class-agnostic Few-shot Counting

The class-agnostic FSC performance of our approach is evaluated on the FSC-147 [28] dataset.

**Setup.** The sizes of the image, the multi-layer feature map, and the exemplar feature map are selected as
512 × 512, 128 × 128, and 3 × 3, respectively. The number of iterations is set as 4. The model is trained with Adam optimizer [14] for 200 epochs with batch size 4 on 4 Tesla V100 GPUs. The hyper-parameter $\epsilon$ in Adam optimizer is set as $2e-5$ initially, and it is dropped by 0.25 every 80 epochs.

**Quantitative results** are given in Table 1. Our approach is compared with baselines employed in [28]: FR few-shot detector [13], FSOD few-shot detector [7], Pre-trained GMN [25], GMN [25], MAML [8], FamNet [28]. Our approach outperforms all counterparts with a quite large margin. For example, our method surpasses the SOTA few-shot detector method FSOD by 21.08 MAE and 67.80 RMSE on the validation set, 18.21 MAE and 55.11 RMSE on the test set. We also excel the SOTA FSC method FamNet by 8.47 MAE and 21.87 RMSE on the validation set, 7.76 MAE and 14.00 RMSE on the test set. These significant advantages demonstrate the effectiveness of our method.

**Quantitative results on COCO subsets** [22,28] are provided in Table 2. Our approach is compared with COCO pre-trained object detection methods: Faster RCNN [30], RetinaNet [21], Mask RCNN [10], and FSC approach FamNet [28]. Note that these detection networks are pre-trained on the COCO dataset containing thousands of exemplars, while our approach needs only 3 exemplars. Our approach still surpasses Mask RCNN with a quite large margin (29.66 MAE and 108.88 RMSE on the validation set, 22.43 MAE and 56.32 RMSE on the test set). Moreover, our method significantly outperforms FSC method FamNet by 16.97 MAE and 44.80 RMSE on the validation set, 9.63 MAE and 22.24 RMSE on the test set.

**Qualitative results** are shown in Fig. 4. For both round objects (e.g. Polka Dots) and square objects (e.g. Stamps, Comic Books), both vertical strip objects (e.g. Books) and horizontal strip objects (e.g. Shirts), both small objects (e.g. Keyboard Keys) and large objects (e.g. Chairs), both gathered objects (e.g. Apples) and scattered objects (e.g. Elephants), our approach counts objects exactly with only a few exemplars. In particular, for Bottle Caps where the background is quite complex with lots of disturbance, our method still successfully counts target objects exactly. This verifies that our method can gradually refine the exemplar-related features and suppress exemplar-unrelated features.

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Table 1. **The few-shot counting performance on FSC-147.** We significantly surpass all baseline approaches by a large margin.

| Method                      | Val Set      | Test Set     |
|-----------------------------|--------------|--------------|
|                             | MAE ↓ RMSE ↓ | MAE ↓ RMSE ↓|
| FR few-shot detector [13]   | 45.45        | 112.53       |
| FSOD few-shot detector [7]  | 36.36        | 150.00       |
| Pre-trained GMN [25]        | 60.56        | 137.78       |
| GMN [25]                   | 29.66        | 89.81        |
| MAML [8]                   | 25.54        | 79.44        |
| FamNet [28]                | 23.75        | 69.07        |
| **Ours**                   | **15.28**    | **47.20**    |

Table 2. **The few-shot counting performance on COCO subsets.** We remarkably outperform three COCO pre-trained object detectors and FamNet.

| Method                      | Val-COCO Set | Test-COCO Set |
|-----------------------------|--------------|---------------|
|                             | MAE ↓ RMSE ↓ | MAE ↓ RMSE ↓ |
| Faster RCNN [30]            | 52.79        | 172.46        |
| RetinaNet [21]             | 63.57        | 174.36        |
| Mask RCNN [10]            | 52.51        | 172.21        |
| FamNet [28]                | 39.82        | 108.13        |
| **Ours**                   | **22.85**    | **63.33**     |

Figure 4. **Few-shot counting results on FSC-147.** From top to down: images and the predicted density maps. The objects marked by the red rectangles are the exemplars.
Table 3. The car counting performance on CARPK and PUCPR+. Though designed for general class-agnostic few-shot counting, our method still surpasses all baselines.

| Method          | CARPK [12] | PUCPR+ [5, 12] |
|-----------------|------------|----------------|
| MAE ↓ RMSE ↓    |            |                |
| YOLO [29]       | 48.89 57.55 | 156.00 200.42  |
| Faster RCNN [30]| 47.45 57.39 | 111.40 149.35  |
| Small RPN [12, 30]| 24.32 37.62 | 39.88 47.67    |
| RetinaNet [21]  | 16.62 22.30 | 24.58 33.12    |
| LPN [12]        | 23.80 36.79 | 22.76 34.46    |
| One Look [26]   | 59.46 66.84 | 21.88 36.73    |
| IECCN [37]      | 51.83      | 15.17          |
| GMN [25]        | 7.48 9.90  | -               |
| PDEM [9]        | 6.77 8.52  | 7.16 12.00     |
| FamNet [28]     | 18.19 33.66| 14.68 20.87    |
| Ours            | 5.33 7.04  | 2.42 3.55      |

† Trained and evaluated by ourselves with the official code.

Figure 5. Car counting results on CARPK and PUCPR+. From top to down: the exemplars and the predicted density maps.

4.4. Class-specific Counting

Our approach is designed to be a general class-agnostic FSC approach, counting objects of novel classes with only a few exemplars. Nonetheless, we also evaluate our method on class-specific counting tasks to further testify its superiority. The setup is detailed in the Supplementary Material.

Car counting tasks are conducted on CARPK [12] and PUCPR+ [5, 12]. The quantitative results are shown in Table 3. We sample 5 exemplars from the training set. Note that these exemplars are fixed for both training and test. Our method is compared with classical object detectors: YOLO [29], Faster RCNN [30], Small RPN [12, 30], RetinaNet [21], car counting methods: LPN [12], One Look [26], and general counting approaches: IECCN [37], GMN [25], PDEM [9], FamNet [28]. Our approach surpasses all the compared methods considerably. Specifically, our approach surpasses PDEM by 1.44 MAE and 1.48 RMSE on CARPK, and outperforms PDEM by 4.74 MAE and 8.45 RMSE on PUCPR+. The qualitative results are shown in Fig. 5, demonstrating that our method has the ability to accurately localize and count cars.

Table 4. The crowd counting performance (MAE ↓) on UCSD, Mall, and PartA and PartB of ShanghaiTech. Our method surpasses all general counting methods, and achieves competitive performance on par with specific crowd counting methods.

| Type         | Method     | UCSD [3] | Mall [4] | PartA [53] | PartB [53] |
|--------------|------------|----------|----------|------------|------------|
| Crowd        | Crowd CNN [50] | 1.60     | -        | 181.8      | 32.0       |
| Counting     | MCNN [53]  | 1.07     | -        | 110.2      | 26.4       |
|              | Switch-CNN [2] | 1.62     | -        | 90.4       | 21.6       |
|              | CP-CNN [35] | -        | -        | 73.6       | 20.1       |
|              | CNN-boost [40] | 1.10     | 2.01     | -          | -          |
|              | MoC-CNN [16] | -        | 2.75     | -          | -          |
|              | CRSNet [20] | 1.16     | -        | 68.2       | 10.6       |
|              | RPNet [49]  | -        | -        | 61.2       | 8.1        |
|              | GLF [41]    | -        | -        | 61.3       | 7.3        |
| General      | GMN [25]    | -        | -        | 95.8       | -          |
| Counting     | LC-FCN8 [17]| 1.51     | 2.42     | -          | 13.14      |
|              | LC-PSPNet [17]| 1.01     | 2.00     | -          | 21.61      |
|              | FamNet [28] | 2.70 †   | 2.64 †   | 159.11 †   | 24.90 †    |
| Ours         | 0.98 1.69   | 73.70    | 9.98     |

† Trained and evaluated by ourselves with the official code.

Figure 6. Crowd counting results on ShanghaiTech. From top to down: the exemplars and the predicted density maps.
4.5. Ablation Study

Extensive ablation studies are conducted on FSC-147 [28] to illustrate the effectiveness of the model architecture, correlation normalization, and flip operation.

**Ablation study regarding architecture** is conducted and the results are shown in Table 5. (a) Transformer is a 2-encoder, 2-decoder network revised based on [39], in which the exemplar features serve as \( k \), \( q \), \( v \) and the image features serve as \( q \), \( q \), \( k \), \( v \) are all split into tokens. The density map is predicted using the decoder outputs. (b) Raw Correlation is similar to FamNet [28] without the test-time adaptation, predicting the density map directly from the raw correlation. (c) Raw Correlation + CRF is used to compare our refinement method with DenseCRF [15], which is a classical refinement method widely used in semantic segmentation. The raw correlation is firstly refined by DenseCRF. Then the refined correlation and the original correlation are concatenated to serve as the inputs for the density map regression. (d) The rest five methods follow our designed architecture, where \( i \)-iter Correlation and \( i \)-iter Feature mean the density maps are predicted using the correlation and the refined feature map of the \( i \)th iteration, respectively.

Several conclusions could be drawn from Table 5. First, by comparing Raw Correlation with 1-iter Feature and 4-iter Correlation with 4-iter Feature, it is obvious that predicting density map from features is significantly better than predicting from correlation, because features contain much richer semantic information than correlation. Second, the performance is stably improved with the increase of the iteration number, suggesting that the exemplar-related features are gradually refined during the iterations. Third, 4-iter Feature obviously surpasses 4-layer Transformer, indicating that keeping spatial information brings substantial improvement. Fourth, our refinement modules (\( i \)-iter Feature) significantly surpass Raw Correlation + CRF. The reason can be illustrated by Fig. 7, showing that our approach is more sensitive to independent objects, while DenseCRF cannot distinguish independent objects in the gathered scene though it can derive quite clear region boundaries.

| Architecture     | Val Set MAE ↓ | Val Set RMSE ↓ | Test Set MAE ↓ | Test Set RMSE ↓ |
|------------------|---------------|---------------|----------------|-----------------|
| Transformer      | 20.45         | 55.22         | 20.21          | 93.47           |
| Raw Correlation  | 24.36         | 74.61         | 23.65          | 108.77          |
| Raw Correlation + CRF | 22.50       | 65.35         | 20.40          | 107.81          |
| 4-iter Correlation | 19.74        | 64.30         | 18.70          | 99.34           |
| 1-iter Feature   | 16.23         | 55.34         | 16.46          | 92.62           |
| 2-iter Feature   | 16.04         | 54.53         | 15.36          | 87.35           |
| 3-iter Feature   | 15.78         | 53.39         | 14.74          | 88.22           |
| 4-iter Feature   | **15.28**     | **47.20**     | **14.32**      | **85.54**       |

**Table 5. Ablation study regarding architecture on FSC-147.**

![Figure 7. Comparison between our refinement approach and DenseCRF refinement.](image)

**Ablation study regarding correlation normalization and flip operation on FSC-147.**

| EN | SN | Flip | Val Set MAE ↓ | Val Set RMSE ↓ | Test Set MAE ↓ | Test Set RMSE ↓ |
|----|----|------|---------------|---------------|----------------|-----------------|
| X  | X  | ✓    | 22.19         | 66.52         | 20.48          | 99.74           |
| ✓  | ✓  | ✓    | 16.55         | 51.87         | 15.14          | 85.65           |
| X  | ✓  | ✓    | 16.58         | 51.26         | 16.40          | 93.97           |
| ✓  | ✓  | X    | 16.78         | 57.47         | 15.35          | 93.59           |
| ✓  | ✓  | ✓    | **15.28**     | **47.20**     | **14.32**      | **85.54**       |

**Table 6. Ablation study regarding correlation normalization and flip operation on FSC-147.**

5. Conclusion

In this paper, we propose an iterative few-shot counting framework including a Correlation Distillation module and a Feature Refinement module to gradually refine the exemplar-related features. The density map is predicted from the final refined feature map. We conduct extensive experiments on the few-shot counting benchmark FSC-147, car counting benchmarks CARPK and PUCPR+, and crowd counting benchmarks UCSD, Mall, and ShanghaiTech. Our approach achieves state-of-the-art performance on FSC-147, CARPK, PUCPR+, UCSD, and Mall. We also achieve competitive performance on ShanghaiTech, though our approach is de facto a general class-agnostic FSC method.
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