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Generating Images from Small Datasets Using Adaptive Point-wise Grouped Convolutions

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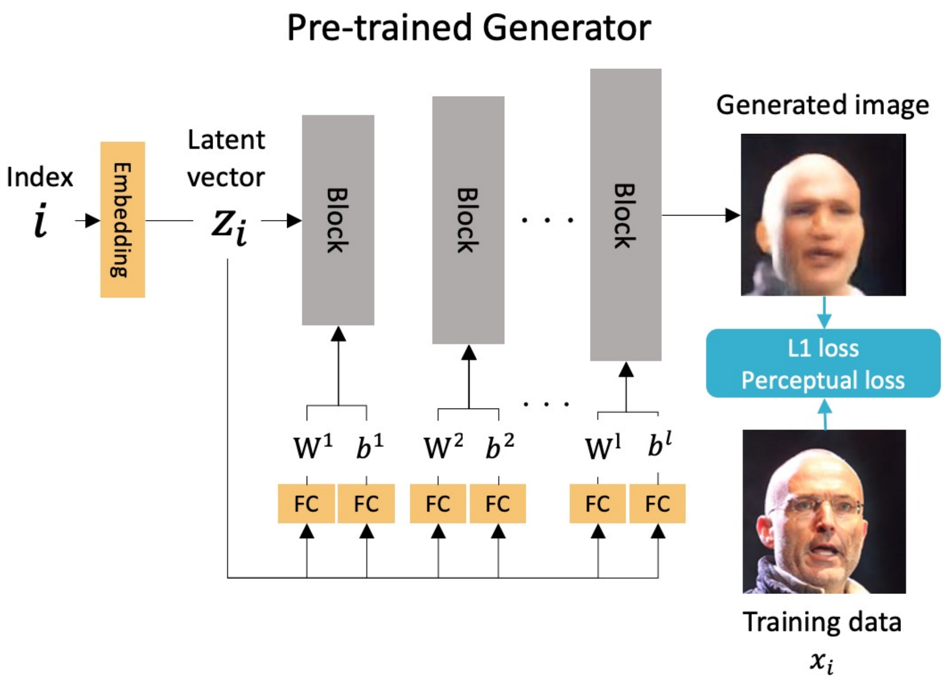
Introduction

- Deep learning models typically use a large amount of data for training.
- However, the construction of large datasets requires a lot of effort.
- For learning with small datasets, the transfer of prior knowledge using pretrained models is effective.
- For deep generative models, a method of transferring prior knowledge to another dataset has also been proposed.
- Noguchi and Harada [12] proposed a new method to generate images from a small data set by transferring a pre-trained generative model.

Objective

Transfer pre-trained generative models to achieve image generation from small datasets.



Related Work — Few-shot GAN—

- In general, GANs require a large number of training samples to produce high-quality images.

- Few-shot GANs require a large image dataset such as ImageNet for pre-training but use a smaller dataset for fine-tuning.

Related Work — Few-shot GAN—

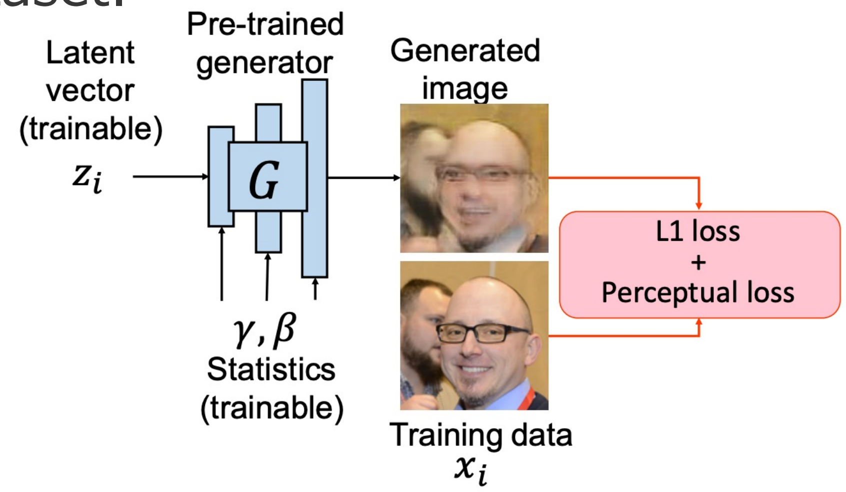
- Noguchi and Harada

  [12] Noguchi, A., Harada, T.: Image generation from small datasets via batch statistics adaptation. ICCV. 2019

  – It is a method for adapting a pre-trained generative model to datasets from different domains.

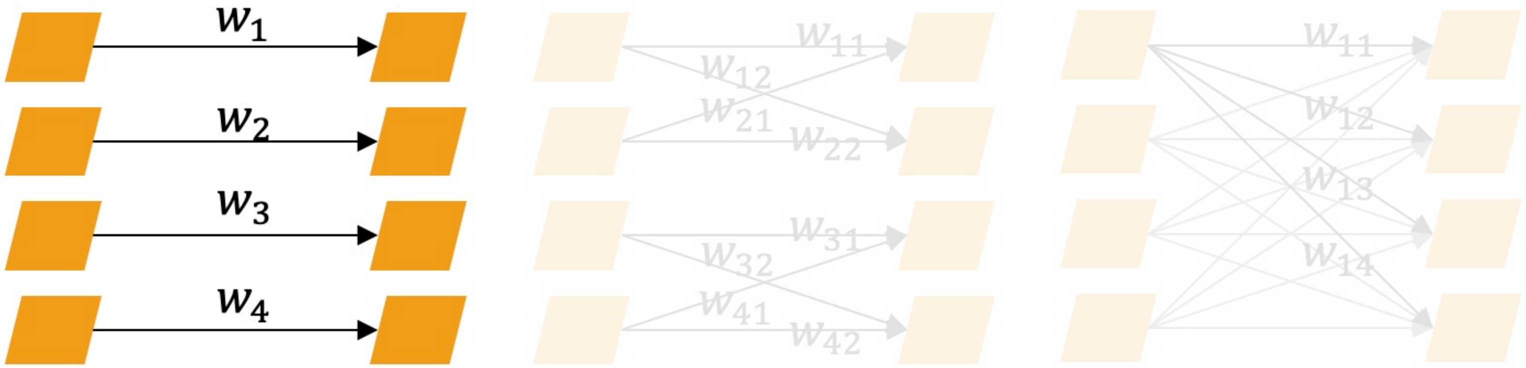
  – To effectively use the pre-learned knowledge, the weights of the convolutional layers of the generator are all fixed during fine-tuning.

  – Adapt only the scale and shift parameters of the batch normalization (BN) layer to a small dataset.



Method — Adaptive Point-wise Grouped Convolution —

- Extending the work of Noguchi and Harada (a), we introduce an Adaptive point-wise grouping convolution for more flexible domain adaptation.



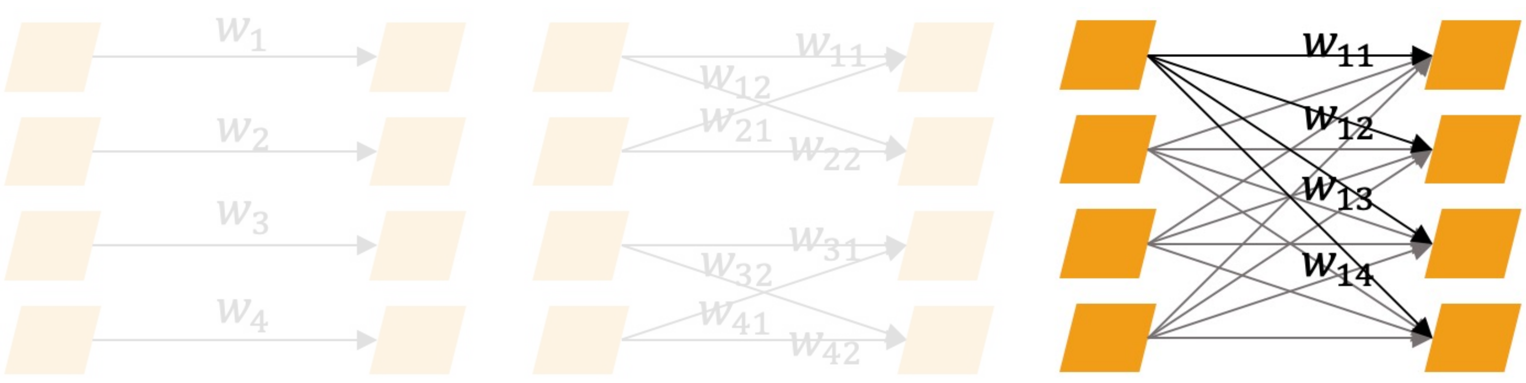
(a) Channel-wise modulation (Noguchi and Harada[10])

(b) Adaptive Point-wise Grouped Convolution (Ours)

(c) Adaptive Point-wise Convolution

Method — Adaptive Point-wise Grouped Convolution —

- The 1×1 convolutional layer, called point-wise convolution (c), constructs new features by computing linear combinations of input channels.
- However, point-wise convolution has the problem of too many parameters.



(a) Channel-wise modulation (Noguchi and Harada[10])

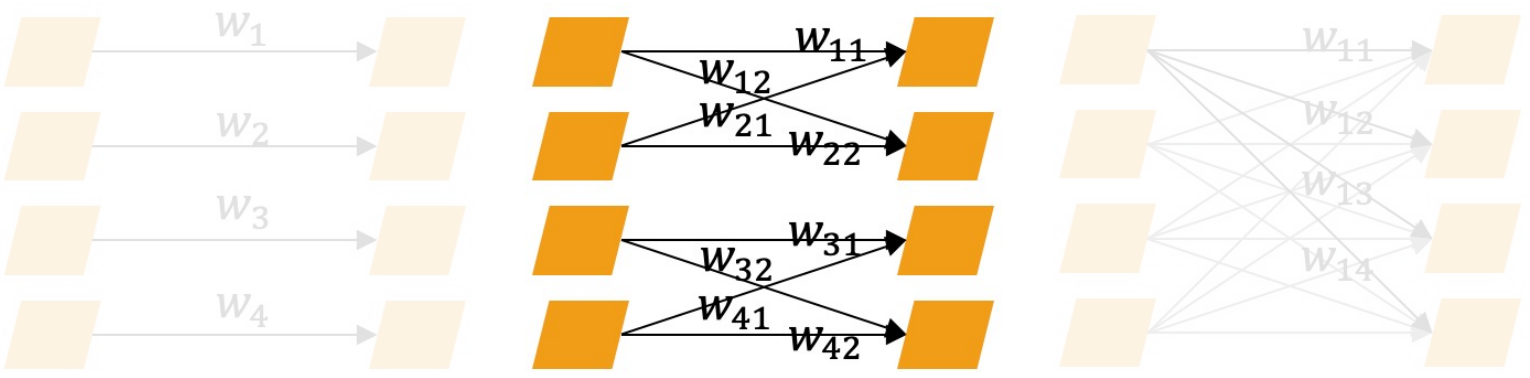
(b) Adaptive Point-wise Grouped Convolution (Ours)

(c) Adaptive Point-wise Convolution

Method ― Adaptive Point-wise Grouped Convolution ―

- The idea of grouping convolution is also applied to Adaptive point-wise convolution (b) as a way to reduce the number of parameters.

- In grouped convolution, the input feature maps are grouped in the channel direction, and convolution operations are applied between each group.
  → The number of parameters can be reduced.



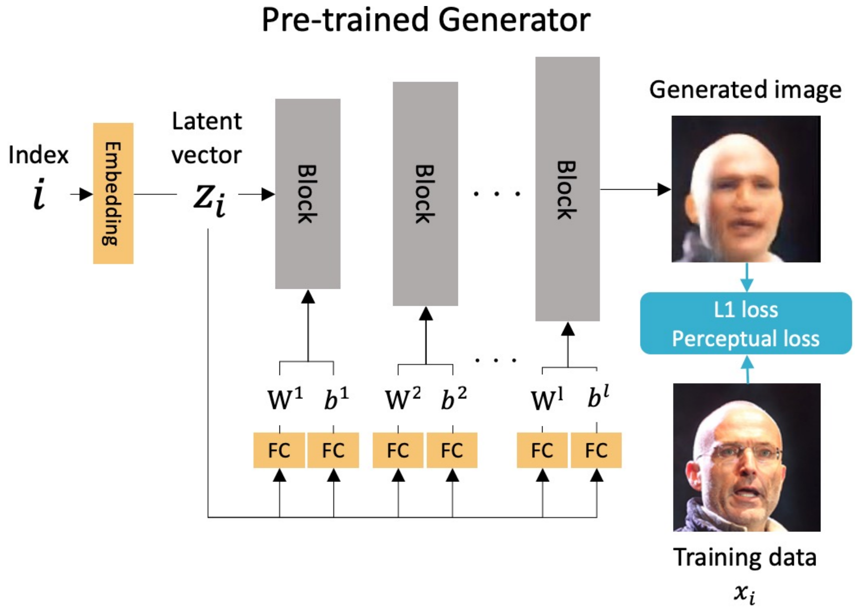
(a) Channel-wise modulation (NoguchiとHarada[10])

(b) Adaptive Point-wise Grouped Convolution (Ours)

(c) Adaptive Point-wise Convolution

Method — Training and Inference —

- The generator is first pre-trained on a large dataset such as ImageNet.
- Then, an Adaptive Point-wise Grouped Convolutional layer with corresponding FC layers is inserted immediately after all the batch normalization layers and fine-tuned on a small dataset.
- During inference, a randomly sampled vector z based on the standard normal distribution is fed into the generator to generate a random image.



Experiments — Experiment setup—

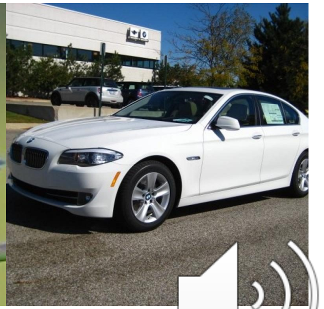
- Model
  - BigGAN-128
- Dataset
  - Human face（FFHQ Dataset）
  - Passion flower（Oxford 102 flower Dataset）
  - African firefinch（260 Bird Species Dataset）
  - BMW（Cars Dataset）
- Evaluation metric
  - KMMD

    Evaluation metric when the number of test images is small


Human face


Passion flower


African firefinch

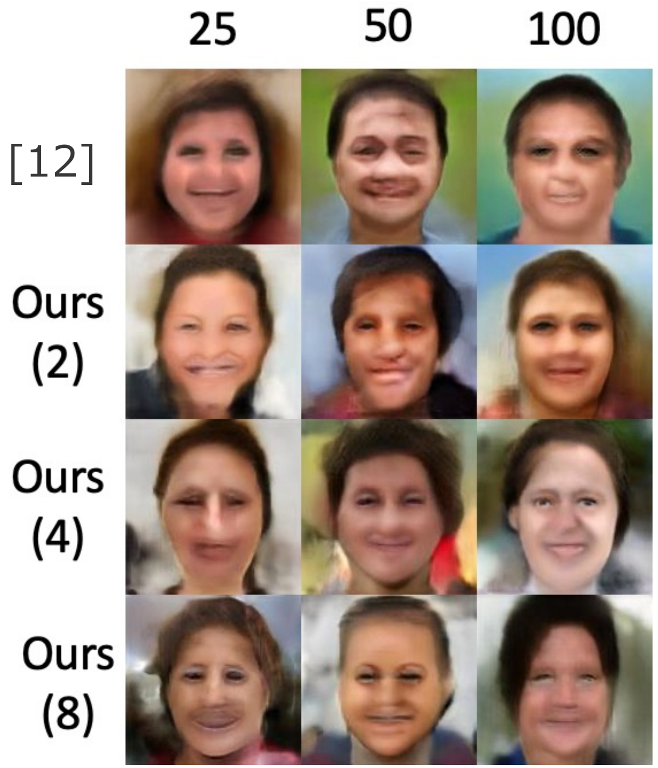

BMW

Experiment1 — Comparison with the baseline —

- We compared the quality of the generated images when the number of groupings was changed based on Noguchi and Harada.

- The quality of the proposed method improved as the number of parameters increased.
  →Adaptive point-wise convolution increased the variation of feature channels.

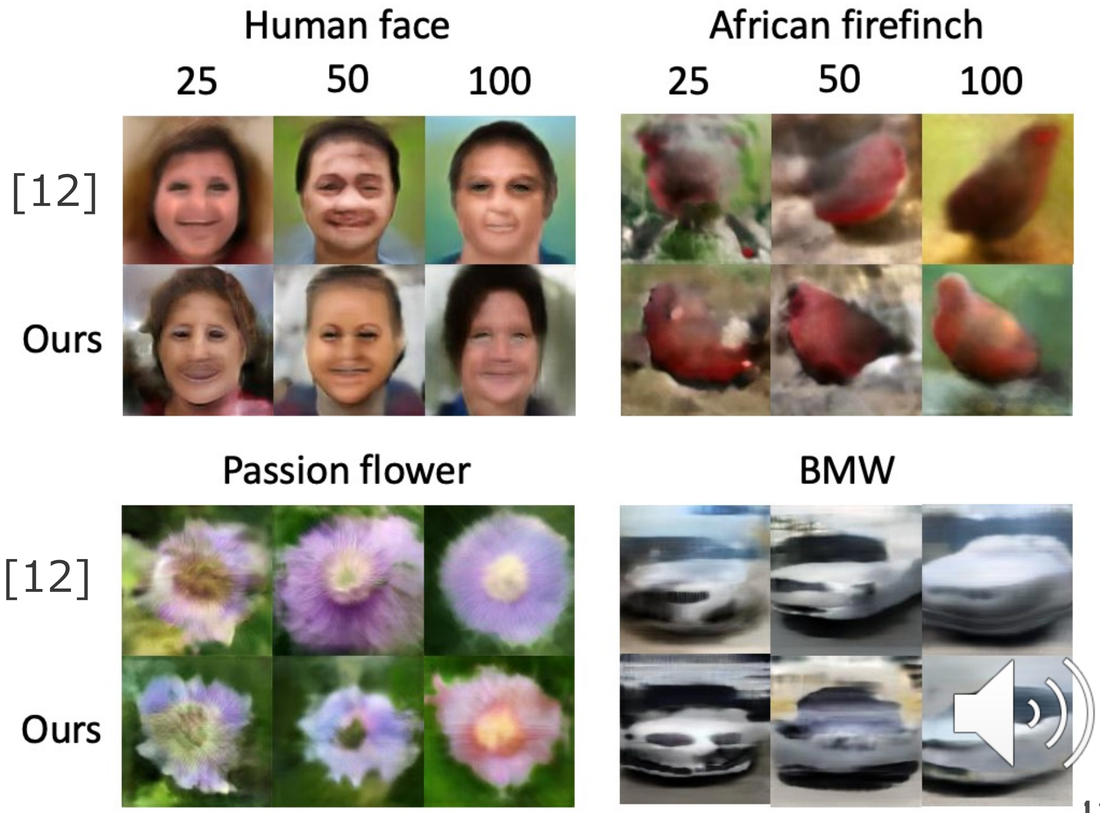
Model	Parameter ratio	Number of data	KMMD(↓)
Noguchi and Harada	1	25 50 100	2.966 2.507 2.509
Ours	2	25 50 100	2.944 2.496 2.493
	4	25 50 100	2.942 2.491 2.490
	8	25 50 100	**2.928** **2.485** **2.487**



Experiment2 ― Experiments with additional datasets ―

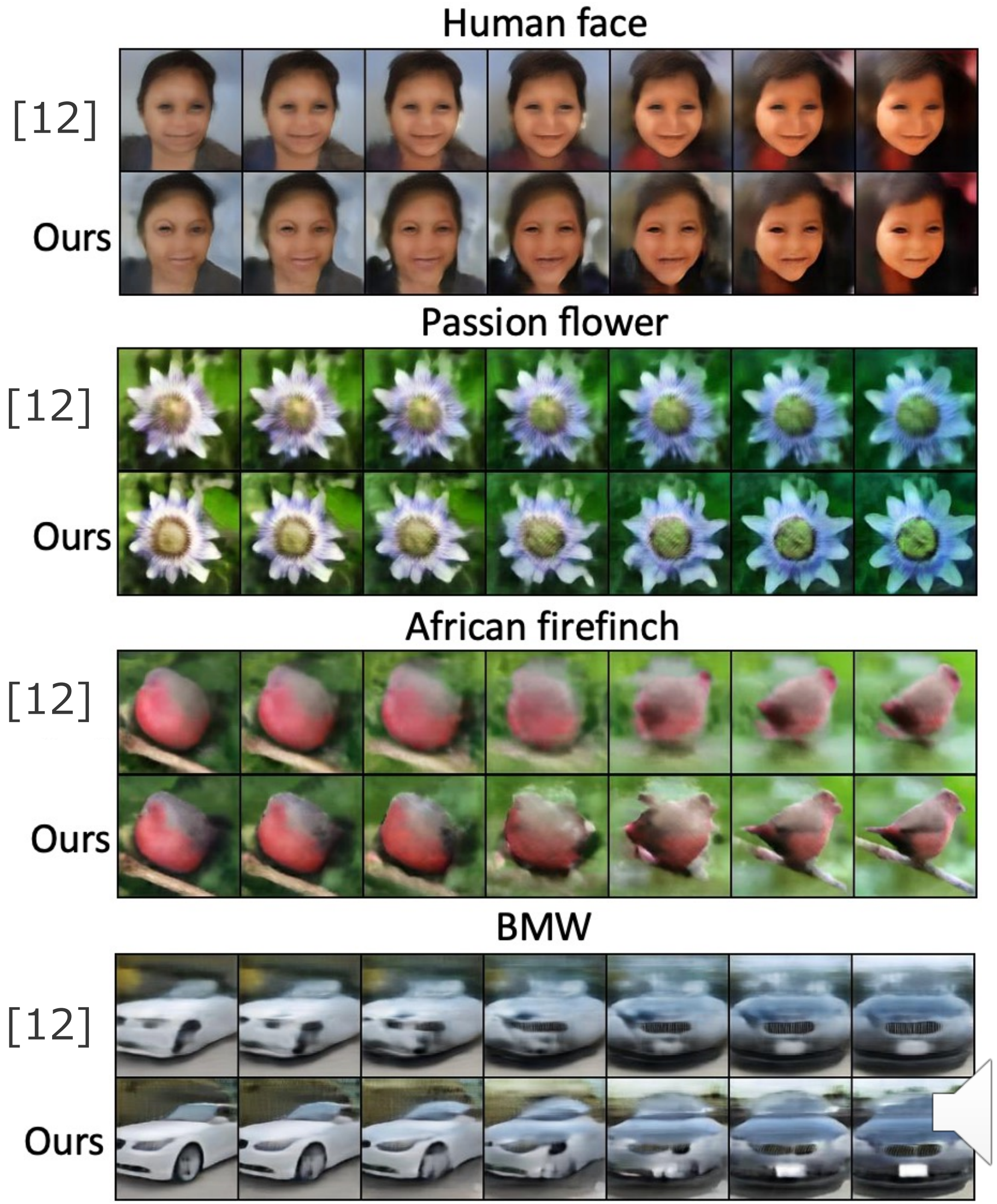
- We used 25, 50, and 100 images sampled from each of the four datasets and compared the proposed method with the baseline.
- The proposed method can produce more detailed and higher-quality images than the baseline.

Dataset	Model	Number of data	KMMD(↓)
Passion flower	Noguchi and Harada	25 50 100	2.976 2.977 2.965
	Ours	25 50 100	**2.955** **2.960** **2.954**
African firefinch	Noguchi and Harada	25 50 100	2.965 2.531 2.532
	Ours	25 50 100	**2.937** **2.493** **2.506**



Experiment2 — Experiments with additional datasets —

- The results of interpolation between two randomly generated latent vectors are shown.
- The proposed method shows clear, smooth, and stable completion.



Conclusion

- In this work, we proposed a simple and effective method for generating images from small datasets.

- By updating only the parameters of Adaptive Point-wise Grouped Conv, a new image can be generated from a small number of images.

- In the future, the method may be used to generate higher-quality images from smaller datasets.

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