Neural Spectral Decomposition for Dataset Distillation

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In the Supplementary Material, we will further analyze and, secondly, we will show some other visualization results.

Fig. 1: Visualization results of synthetic images with (CFIAR10, Ratio=0.2) on MTT.

We further visualize other synthetic images, Figure 1 shows the visualization results of MTT on CIFAR10, our method can make better use of the information between the spectra and can make use of the high-frequency information compared to MTT.

We visualize our synthetic dataset in Figure 2, the synthetic dataset is the result on CIFAR10 with IPC=10 by three methods. Figure 2a shows the synthetic dataset distilled by Discrete Wavelet Transform, each line represents a category, because we randomly sampled some high-frequency information and low-frequency information each time for fusion in the process of distillation us-

Fig. 2: Visualization results of synthetic images generated by using different kernel form. (a) DWT, (b) LDCT and (c) ours on CIFAR10 with IPC=10.

ing DWT, so it makes the distillation process can be better learned the high-frequency information, and the visualization result proves this. Figure 2b shows the results of the synthetic dataset distilled by the Learnable Discrete Cosine Transform (LDCT). Compared with DWT, the LDCT pays more attention to the high-frequency information, which further argues that the high-frequency information is very conducive to the learning of the synthetic dataset. Figure 2c shows the visualization results of our spectral decomposition method, and it can be found that our method not only focuses on the low-frequency information well but also makes better use of the high-frequency information, which makes the synthetic dataset better acquire the information on different frequency bands. Figure 3 shows the visualization results of SVD and LSVD on CIFAR10, respectively, and Figure 4, Figure 5, Figure 6 shows the visualization results of our method on CIFAR100, TinyImageNet, ImageNet Subset respectively, which clearly further demonstrates that our method can make better use of the spectral information and improve the compression rate at the same time. It is worth noting that our synthesized data is difficult to identify which category it belongs to, and thus can be well applied to privacy protection.

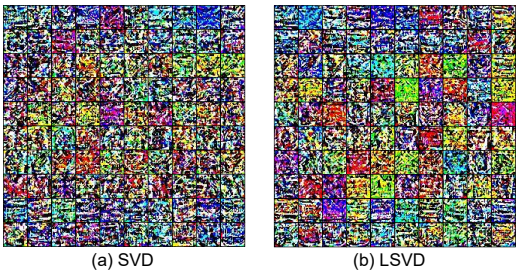

Fig. 3: Visualization results of synthetic images generated by using different kernel form. (a) SVD, (b) LSVD on (CIFAR10, Ratio=0.02)

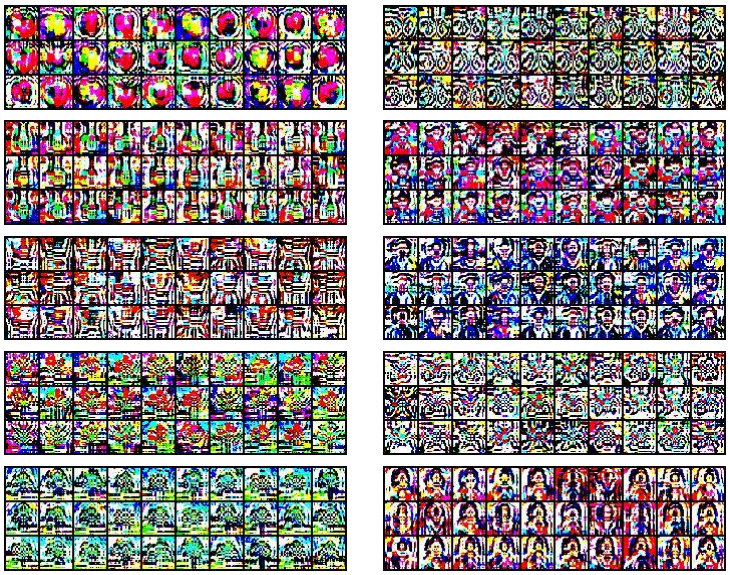

Fig. 4: Visualization results of synthetic images with (CFIAR100, Ratio=0.2).

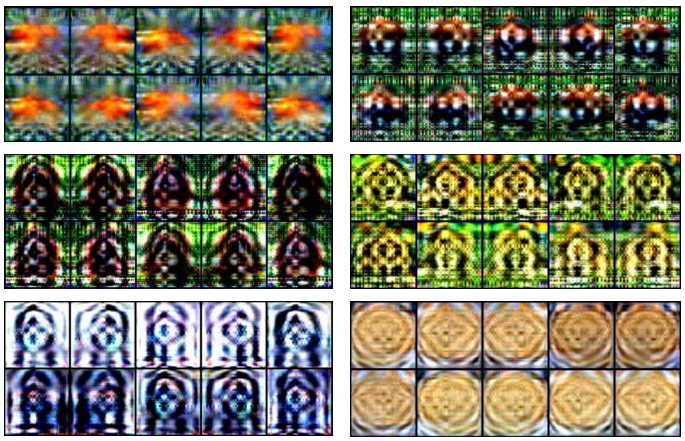

Fig. 5: Visualization results of synthetic images with (TinyImageNet, Ratio=0.2).

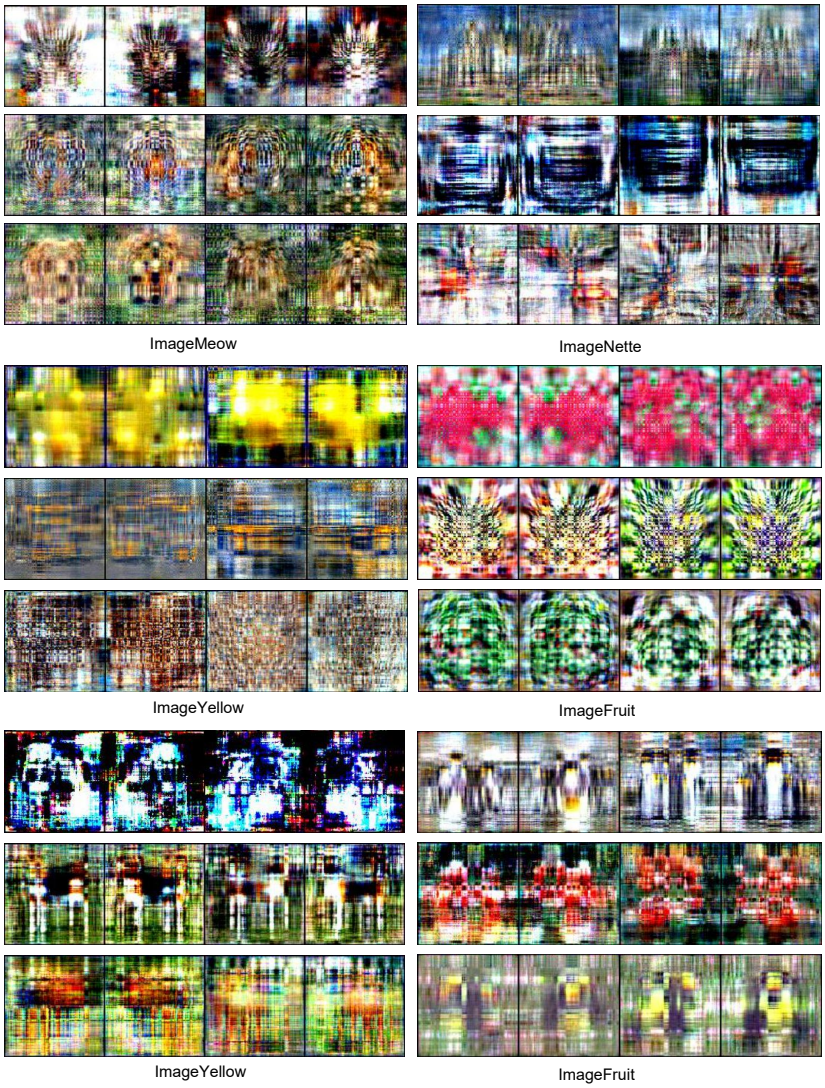

Fig. 6: Visualization results of synthetic images with (ImageNet Subset, Ratio=0.1).