

Supplementary Materials of the paper “Cover-separable Fixed Neural Network Steganography via Deep Generative Models”

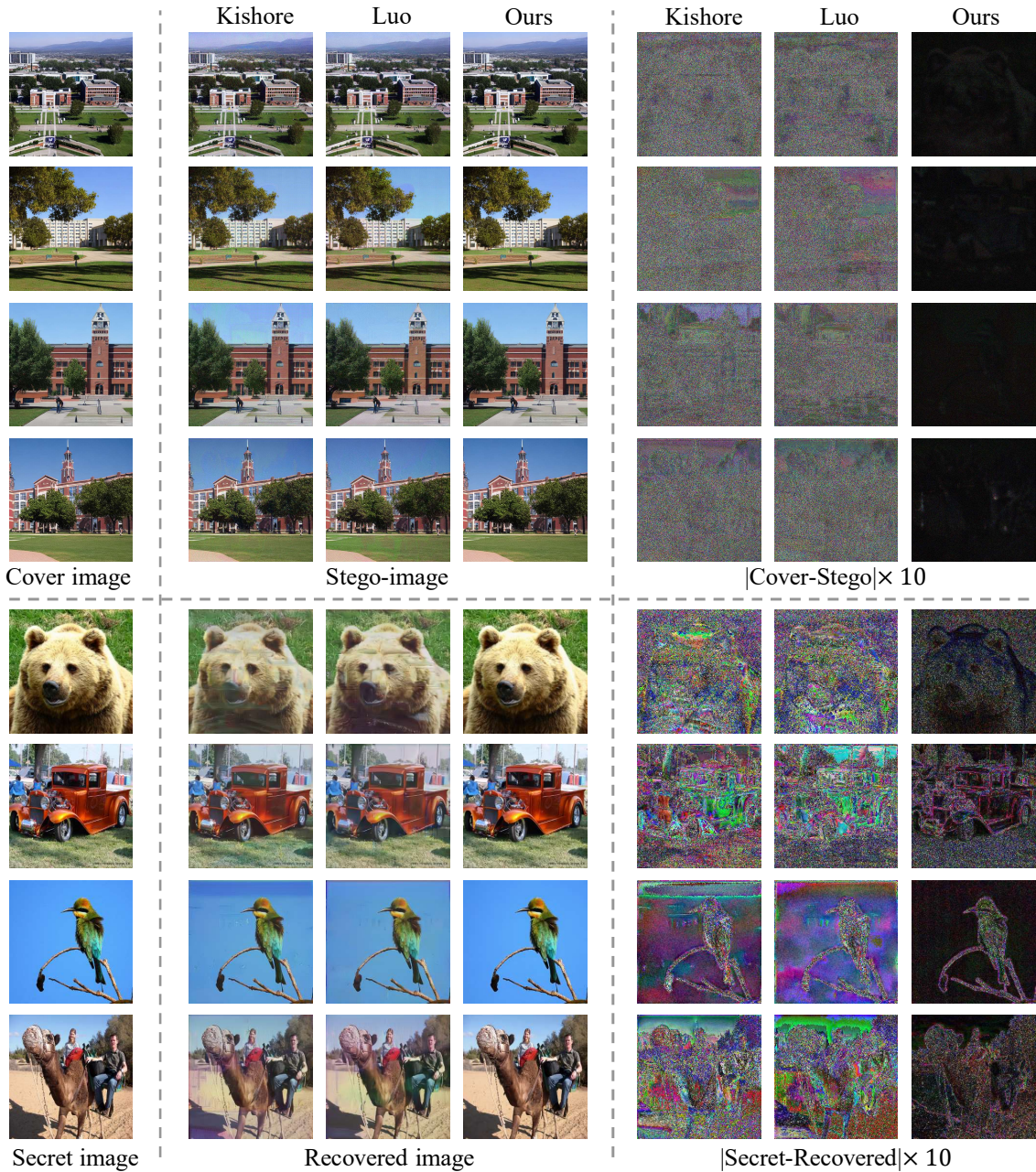


Figure S1: Visualization of the stego and recovered images generated using different FNNS methods.

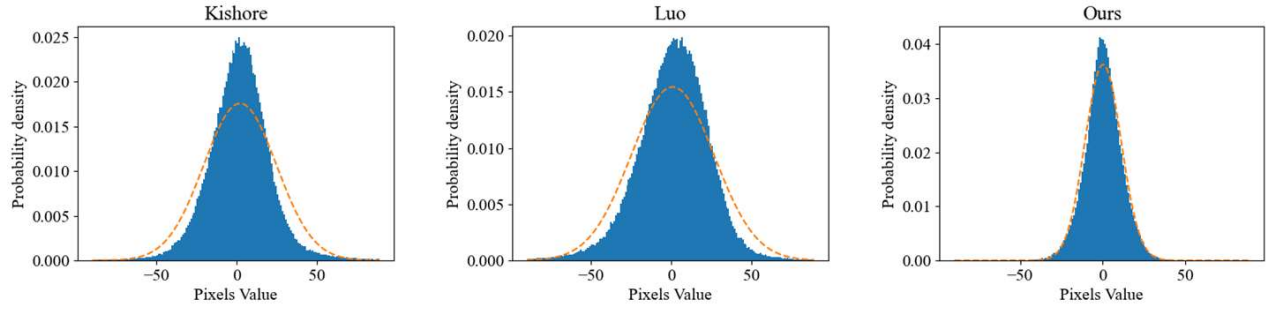


Figure S2: Histogram of pixels in the residuals between the original secret image and its decoded versions obtained using different FNNS methods. The orange dash curve in the figure is the corresponding Gaussian distribution with mean value and standard deviation estimated from the pixels.

Table S1: Visual quality of the recovered images generated using different FNNS schemes before/after the denoising.

Methods	ImageNet		
	PSNR(dB)↑	SSIM↑	LPIPS↓
Kishore <i>et al.</i> [23]	20.31/22.79	0.5780/0.7827	0.2899/0.1763
Luo <i>et al.</i> [30]	18.64/21.20	0.4979/0.7413	0.3649/0.2288
Ours	27.79/33.01	0.7326/0.9156	0.1372/0.0390

Post-processing of Decoded Secret Images. When using FNNS schemes with random decoding networks, we empirically observe the presence of regular errors (i.e., Gaussian noise) in their decoded secret images, As shown in Fig. S2. The Gaussian noise, fortunately, could be easily removed by existing denoising algorithms. Here, we recommend the receiver use a lightweight denoising algorithm [47] to process the decoded secret images. On the ImageNet and Campus-I datasets, we test the visual quality of the recovered images before and after the denoising and report the results in Table S1. As can be seen, denoising processing can effectively improve the visual quality of the recovered images for all FNNS methods.