Large-capacity and Flexible Video Steganography via Invertible Neural Network

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Sharing the SAME model & SAME parameters

Background-The Task of Steganography



1

Background-Invertible Neural Network

Invertible Block



Z split Z_1, Z_2

D Invertible Neural Network



Forward:





2

4



Overview



Contributions:

- ✓ Large hiding capacity
- $\checkmark\,$ Hiding a scalable number of secret videos into one video
- $\checkmark\,$ Different receivers can recover different secret videos through a specific key
- ✓ Invertible



D Network Structure



O2 Proposed Method

□ Scalable Design



- Customize the convolution kernel
- > All convolution kernels share a parent matrix

□ Key-controllable Design





Loss Function:

- > Forward hiding:
- $\mathcal{L}_f = ||\mathbf{X}_{st \circledast j}[I_c] \mathbf{X}_{co \circledast j}[I_c]||_2^2,$
- > Backward recovering (w/o key control): $\mathcal{L}_{b} = \sum_{n=1}^{N_{s}} ||\hat{\mathbf{X}}_{se \circledast j}(n)[I_{c}] - \mathbf{X}_{se \circledast j}(n)[I_{c}]||_{2}^{2} + ||\hat{\mathbf{X}}_{co \circledast j}[I_{c}] - \mathbf{X}_{co \circledast j}[I_{c}]||_{2}^{2},$
- Backward recovering (w key control):
- $\mathcal{L}_{b} = ||\frac{1}{N_{s}} \sum_{n=1}^{N_{s}} \hat{\mathbf{X}}_{se \circledast j}(n)[I_{c}] \mathbf{X}_{se \circledast j}(n_{key})[I_{c}]||_{2}^{2} + ||\hat{\mathbf{X}}_{co \circledast j}[I_{c}] \mathbf{X}_{co \circledast j}[I_{c}]||_{2}^{2}.$
 - Final loss:

 $\mathcal{L} = \mathcal{L}_f + \lambda \mathcal{L}_b,$





Comparison on One-video Hiding:

Table 1. Quantitative comparison (PSNR/SSIM) on Vimeo-T200. The best and second-best results are highlighted and underlined. Our Table 2. Multiple videos steganography comparison (PSNR) of LF-VSN achieves the best performance in stego and secret quality with acceptable complexity.

	Weng et al. [43]	Baluja [4]	ISN [32]	HiNet [21]	RIIS [47]	PIH [11]	LF-VSN (Ours)
Stego	29.43/0.862	34.14/0.860	42.08/0.965	42.09/0.962	43.50/0.951	-	45.17/0.980
Secret	32.08/0.899	35.21/0.931	42.11/0.984	44.44/0.991	44.08/0.964	36.48/0.939	48.39/0.996
Params.	42.57M	<u>2.65</u> M	3.00M	4.05M	8.15M	0.67 M	7.40M

Comparison on Multiple-video Hiding:

our LF-VSN, ISN [32], and PIH [11] on Vimeo-T200 test set. Our LF-VSN can hide/recover 7 videos with promising performance.

	Videos	2	3	4	5	6	7
Z	Stego	37.60	36.41	32.56	31.46	-	-
IS	Secret	41.47	38.76	33.42	33.39	-	-
HIH	Stego	-	12	1	-	-	-
	Secret	35.95	34.96	34.20	-	-	-
urs	Stego	40.97	38.55	37.55	36.57	35.68	35.01
Õ	Secret	44.24	42.27	40.21	38.88	36.94	35.71





Figure 7. Visualization of our LF-VSN in 7 videos steganography, showing promising performance in such an extreme case.

Figure 6. Visual comparison between our LF-VSN, ISN [32], and PIH [11] in 4 videos Steganography. We present the secret reconstruction results of video 2 and video 4. Our LF-VSN produces better result with intact color and details.



□ Key-controllable Video Steganography:



Key 2* recovered Key 4* recovered Key 6* recovered Figure 8. Visualization of our key-controllable scheme in 6 videos steganography. In the second and third rows, we use the correct and wrong (*) keys of 2, 4, 6 to recover secret videos, respectively.

Given Scalable Video Steganography:



Figure 9. Performance comparison between our scalable and fixed design in multiple videos steganography.



Given Steganographic Analysis:



Figure 10. Statistics-based steganalysis by StegExpose [7]. The closer the detection accuracy is to 50%, the higher the security is.

Learning-based steganalysis:



Figure 6. Deep-learning steganalysis results, which are produced by the latest Size-Independent-Detector (SID) steganalysis method [9]. The closer the detection accuracy is to 50%, the higher the steganography security is.



□ Ablation Study:

Table 4. The ablation study of different components in our LF-VSN. It includes the sliding window size, number of invertible blocks (IB), frequency concatenation (FreqCat), and redundancy prediction module (RPM).

Num. videos	1	2			4			6	2		3		3	3
Window size	1	3	5	1	3	5	1	3	5	3	3 (ours)	3	3	3
Num. IB	16	16	16	16	16	16	16	16	16	12	16	20	16	16
FreqCat	1	\checkmark	~	\checkmark	\checkmark	\checkmark	×							
RPM	~	\checkmark	\checkmark	\checkmark	~	\checkmark	×	\checkmark						
Stego	39.64	40.97	41.08	36.41	37.55	37.86	34.47	35.46	35.96	38.03	38.55	38.91	38.28	36.85
Secret	42.97	44.24	44.43	37.67	40.21	40.42	35.11	36.83	39.97	41.99	42.27	42.40	41.69	40.36

□ Real-world Application:

Table 1. The impact of video compression. PSNR is presented.

qp	Video size	HiNet[21]	Ours 1 video	Ours 3videos	Ours 5videos	Ours 7videos	
0	100MB	32.04	44.15	39.55	37.11	32.05	
5	80.1MB	23.05	35.23	34.32	32.47	29.87	
10	35.7MB	18.61	31.25	29.49	28.30	26.94	
15	21.6MB	13.45	23.55	21.78	20.97	19.80	
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Figure 1. Visualization of secret quality after video compression.

ffmpeg -s 1280x720 -i <input> -c:v libx264 -qp <qp> <output>



- ✓ We propose a large-capacity video steganography method, which can hide/recover multiple (up to 7) secret videos in/from a cover video. Our hiding and recovering are fully reversible via a single INN.
- ✓ We propose a key-controllable scheme with which different receivers can recover particular secret videos from the same cover video via specific keys.
- ✓ We propose a scalable embedding module, utilizing a single model and a single training session to satisfy different requirements for the number of secret videos hidden in a cover video.
- ✓ Extensive experiments demonstrate that our proposed method achieves state-of-theart performance with large hiding capacity and flexibility.



Thanks for Your Attention!



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Code: <u>https://github.com/MC-E/LF-VSN</u>