

Retraction

Retracted: An Improved Image Steganography Framework Based on Y Channel Information for Neural Style Transfer

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] W. Lin, X. Zhu, W. Ye, C. Chang, Y. Liu, and C. Liu, "An Improved Image Steganography Framework Based on Y Channel Information for Neural Style Transfer," *Security and Communication Networks*, vol. 2022, Article ID 2641615, 12 pages, 2022.

Research Article

An Improved Image Steganography Framework Based on Y Channel Information for Neural Style Transfer

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Neural style transfer has effectively assisted artistic design in recent years, but it has also accelerated the tampering, synthesis, and dissemination of a large number of digital image resources without permission, resulting in a large number of copyright disputes. Image steganography can hide secret information in cover images to realize copyright protection, but the existing methods have poor robustness, which is hard to extract the original secret information from stylized steganographic (stego) images. To solve the above problem, we propose an improved image steganography framework for neural style transfer based on Y channel information and a novel structural loss, composed of an encoder, a style transfer network, and a decoder. By introducing a structural loss to restrain the process of network training, the encoder can embed the gray-scale secret image into Y channel of the cover image and then generate steganographic image, while the decoder can directly extract the above secret image from a stylized stego image output by the style transfer network. The experimental results demonstrate that the proposed method can effectively recover the original secret information from the stylized stego image, and the PSNR of the extracted secret image and the original secret image can reach 23.4 and 27.29 for the gray-scale secret image and binary image with the size of 256×256, respectively, maintaining most of the details and semantics. Therefore, the proposed method can not only preserve most of the secret information embedded in a stego image during the stylization process, but also help to further hide secret information and avoid steganographic attacks to a certain extent due to the stylization of a stego image, thus protecting secret information like copyright.

1. Introduction

Nowadays, deep learning technology has made remarkable breakthroughs in computer vision, text processing, clustering [1, 2], and voice recognition with its powerful ability of feature learning. As one of the hot deep learning applications, neural style transfer (NST) not only improves the efficiency and quality of stylization, but also enriches people's lives and brings convenience to art design. However, it also leads to more and more unauthorized digital images being arbitrarily tampered with and synthesized, which seriously damages the rights and interests of copyright owners and the development of related industries. Therefore, how to protect the original image from illegal use in the process of stylization is one of the urgent problems to be solved.

Image steganography is a technique for hiding confidential information from public information. Using the characteristics of image files, we can hide secret image that we want to deliberately hide or prove identity and copyright information into the cover images. The cover image containing secret information is referred to as steganographic (stego) image for normal use or transmission, and its visual effect is almost the same as the original cover image, which would hardly affect the application scene of the cover image [3]. Most traditional methods superimpose secret information directly on a specific area of the image, which may cause great damage to the original image. The emerging deep learning-based methods can make the secret information evenly distributed in the original cover image by automatically learning the deep features of the secret image and

achieve more accurate steganography of the image. For example, the generative adaptive network (GAN) model is used to encode data into images with good results. However, these methods have poor robustness and are difficult to extract effective secret information from stylized stego images [4].

To protect and recover the secret information more effectively, we propose an improved image steganography framework adapting to neural style transfer, consisting of an encoder network, a style transfer network, and a decoder network. By introducing the Y channel information and a novel structural loss to restrain the training of decoder and encoder networks, the encoder can effectively embed the gray-scale secret image into the Y channel of the cover image, and the decoder can directly obtain the original secret information from the stylized stego image. The experimental results demonstrate that the proposed framework can realize better embedding and extraction of the gray-scale secret image before and after the style transfer. The PSNR between the decrypted secret image and the original secret image can reach 23.4, and most of the details and semantics are retained. Therefore, the proposed framework can not only basically maintain most of the hidden information in the stego image during the stylization process, but also better recover the secret image with almost the same visual effect from the stylized stego image. That is, steganography attacks can be better avoided and secret private information such as copyright can be protected to a certain extent.

The rest of this paper is organized as follows. Section 2 presents the state of the art of neural style transfer and deep learning-based image steganography technologies. Section 3 presents the proposed image steganography frameworks for neural style transfer in detail. Then, Section 4 carries out the experiment comparison and analysis. Section 5 gives the conclusion and future research direction.

2. Related Work

2.1. Neural Style Transfer. NST technology is one of the new applications of deep learning proposed by Gatys in 2016. It uses a convolutional neural network (CNN) to separate and fuse the features of a content image and a style image, so as to transfer the particular painting style to the natural content image and generate a novel artistic painting [5]. However, it took a long time due to its iterative processing. Johnson et al. [6] designed a fast style transfer framework based on a feed-forward neural network (FNN), which can train a corresponding stylization model for each style and obtain comparable quality artworks in real time.

To maintain image semantics, Gatys et al. [7] divided the style factors into space, color, brightness, and other perceptual information, and then combined the above information together to achieve effect control of style transfer. Sanakoyeu et al. [8] designed an encoder-decoder network with a style-aware loss function that can generate high-definition stylized images with diverse textures. Liu et al. [9] proposed a depth-aware loss to constrain the training of stylization model, so that the spatial depth features of generated image were consistent with the content image.

Luan et al. [10] presented a novel high-fidelity style transfer method. By introducing regularization terms to constrain the change range of style transfer, the satisfying real image style transformation can be achieved in various scenes such as delayed transformation, weather, season, art style, and so on. Liu et al. [11] retained salient semantic and emotional information of the original image in combination with saliency prediction technology. To deal with multistyle transfer, Dumoulin et al. [12] realized multistyle transfer on a single network model, which can simultaneously learn and integrate 32 different styles, thus relieving the problem of large space consumption. Chen et al. [13] proposed an arbitrary style transfer method named StyleBank, to separate content and style by building a forward encoder-decoder network. Tian et al. [14] implemented a patch-level network model to achieve multistyle transfer by reconstructing image in style-swap layer. Huang et al. [15] realized the fast arbitrary stylization by introducing a novel adaptive instance normalization (AdaIN) layer. Li et al. [16] designed a WCT (white-color transform) layer to train different decoders to achieve arbitrary and real-time diversified stylization.

2.2. Deep Learning-Based Image Steganography.

Compared with traditional methods, image steganography based on deep learning has attracted extensive attention due to its improved performance and more flexible application scenarios [17, 18]. Qian firstly proposed a novel Gaussian neuron CNN (GNCNN) model in 2015 [19] for secret data hiding, which processed the image by using KV kernel of traditional algorithm and CNN network. Xu et al. [20] added a deeper network model based on GNCNN and different activation functions to significantly improve the hiding effect. To better avoid steganography, Jian et al. [21] presented a new CNN model that incorporates high-pass filters and truncated linear unit (TLU) activation functions into the spatially rich model (SRM). Their model showed good performance because it can pass most steganography tests.

Baluja [22] proposed a deep encoder-decoder model using CNN network, which can embed a secret color image into a cover image of the same size. Volkhonskiy et al. [23] constructed an improved deep convolutional generative adversarial network (DCGAN) model to avoid steganography detection and improve the capacity of embedding. Zhu et al. [24] also trained an encoder-decoder network combined with a novel noise layer (called as HiDDeN), which can well hide and extract secret information and generate a stego image that is visually indistinguishable from the cover image. Inspired by QR code, Tancik et al. [25] proposed a hyperlink embedding and extraction technique based on an encoder-decoder model. The encoder realized the hidden embedding of hyperlinks, and the decoder can be loaded into hardware like mobile phones to extract the hidden hyperlinks by taking photos of stego image. Image steganography is also used in combination with style transfer techniques in various scenarios [26]. Chen et al. [27] proposed a two-stage model and an end-to-end model for retaining the input content image information during style transfer process through steganography technology,

effectively eliminating artifacts introduced in the reconstruction of stylized images. Zhong et al. [28] designed an image steganography technology combined with style transfer, which generated two different stylized images for content images, one for steganographic embedding and the other for steganographic analysis comparison, so as to improve the resistance of model steganographic analysis. To further improve the antisteganography algorithm, Li et al. [29] proposed an image steganography method based on style transfer and quaternion exponent moments (QEM). The arithmetic invariance of QEM is used to embed the secret information, and then, the stego image is style transferred. Finally, the secret image is extracted while the content image is reconstructed. Zhang et al. [30] proposed an image conversion network CSST-Net based on arbitrary style transfer, which can constrain style transfer by encoding secret information into adaptive steganography matrix, while directly synthesizing stylized images embedded with secret information during style transfer. Although the embedded information of deep learning-based method is still not high enough, its appearance greatly enriched the application scenarios of image steganography, which reflected that deep learning could not be limited to improving the embedding capacity and quality, and could have strong robustness.

2.3. Analysis and Summary. Most existing stylization methods tend to improve the efficiency of stylization and the quality of artworks, but their lack of consideration to effectively protect images involved in style transfer increases the risks of these images being arbitrarily modified, integrated, and disseminated, which make it difficult to protect the legal rights of the copyright owner. The deep learning-based image steganography technique extends the types of secret information that can be embedded, not only binary-coded character information, but also any image information. Most of the existing methods can embed secret images well, but they cannot effectively extract secret information from stylized stego images, because the structure of the original stego image is seriously disturbed or even lost in the process of style transfer, which ultimately leads to the inability to maintain the hidden secret information.

3. The Improved Image Steganography Framework for Neural Style Transfer

As the above analysis, the existing stylization methods fail to provide effective protection for the secret information of original content images. At the same time, the existing steganographic methods have poor robustness to stylized stego images. To solve the above problem, we propose an improved image steganography framework adapting to neural style transfer by introducing Y channel information and a structural loss. Figure 1 shows the structure of the proposed framework including an encoder network, a style transfer network, and a decoder network.

The encoder network generates a stego image by embedding a secret image into Y channel of a cover image; the

decoder network extracts the secret image from the stylized stego image. Similar to the model in [18], the architecture of encoder/decoder network is composed of five convolutional layers with 50 convolution kernels of $\{3 \times 3, 4 \times 4, 5 \times 5\}$, as shown in Figure 2.

The neural style transfer network shown in Figure 3 transfers specific style to the stego image, which is a fast image transformation network used in [11], consisting of 3 convolutional layers, 4 residual blocks, 2 deconvolutional layers, and a final output layer. And the tanh function is adopted to constrain the pixel values of an output image to be between 0 and 255.

We use a novel structural loss and a perceptual loss to train the above three networks as a whole to hide and recover secret information efficiently under the situation of style transfer and improve the robustness of image steganography model. Specifically, the above two kinds of losses are applicable to constrain the training of the encoder and the decoder, and the transfer network is a pretraining model used to generate stylized stego images as the input of decoder.

3.1. Perception Loss. According to [11], the Y channel contains rich semantic information. Thus, to improve the image quality after embedding secret image I_s , we propose to embed the I_s into the Y channel of a cover image I_c to obtain a stego image I_{s+c} ; then, the stylized stego image I_{s+c}^s is obtained by the style transfer network with the input of I_{s+c} ; at last, the hidden secret image I_s^o is decoded by the decoder network with the input of I_{s+c}^s .

So as to constrain the network training process and keep the stego image similar to cover image encoded by encoder network, and the original secret image similar to the decrypted image decoded by the decoder network, we take the weighted sum of 1-norms of the original secret image and the decrypted image, and the weighted sum of 1-norms of the cover image and the stego image as the final perceptual loss. The calculation of perceptual loss is shown as follows:

$$\ell_{\text{perc}}(I_c, I_{s+c}, I_s, I_s^o) = \alpha I_c - I_{s+c} + \beta I_s - I_s^o, \quad (1)$$

where I_c, I_{s+c}, I_s and I_s^o refer to the cover image, the stego image, the original secret image, and the decrypted secret image obtained by the decoder, respectively, α and β are the weight parameters, and ℓ_{perc} refers to the perceptual loss.

3.2. Structural Loss. The larger the SSIM value (between 0 and 1), the more similar the structure of the two images. Similar to the literature [31], SSIM value is used to measure the structure similarity of two images. Thus, a structural loss is constructed by calculating the SSIM value between the original secret image I_s and the decrypted secret image I_s^o , which can better keep the structure information of the secret image. The calculation of structural loss is shown as follows:

$$\ell_{\text{stru}} = \ell_{\text{stru}}(I_s, I_s^o) = \sigma\phi(I_s) - \phi(I_s^o)^2 + \rho(1 - \text{SSIM}(I_s, I_s^o)), \quad (2)$$

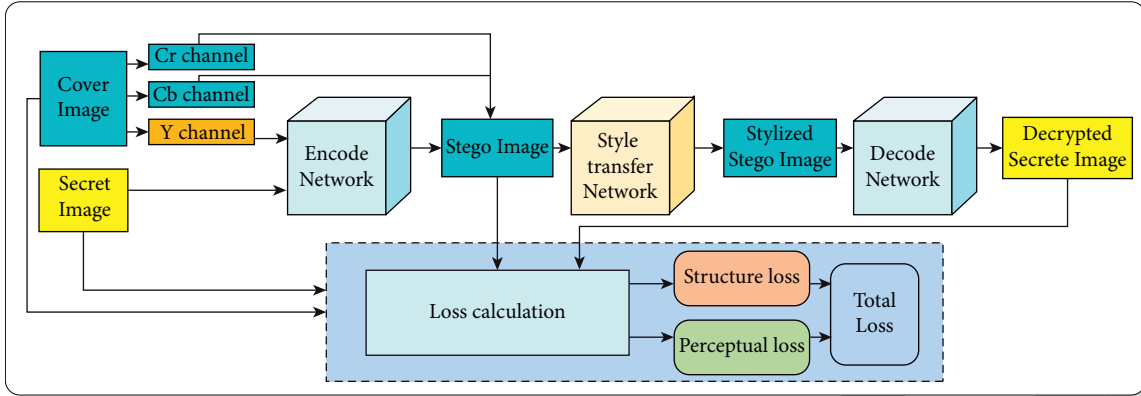


FIGURE 1: The structure of the proposed framework.

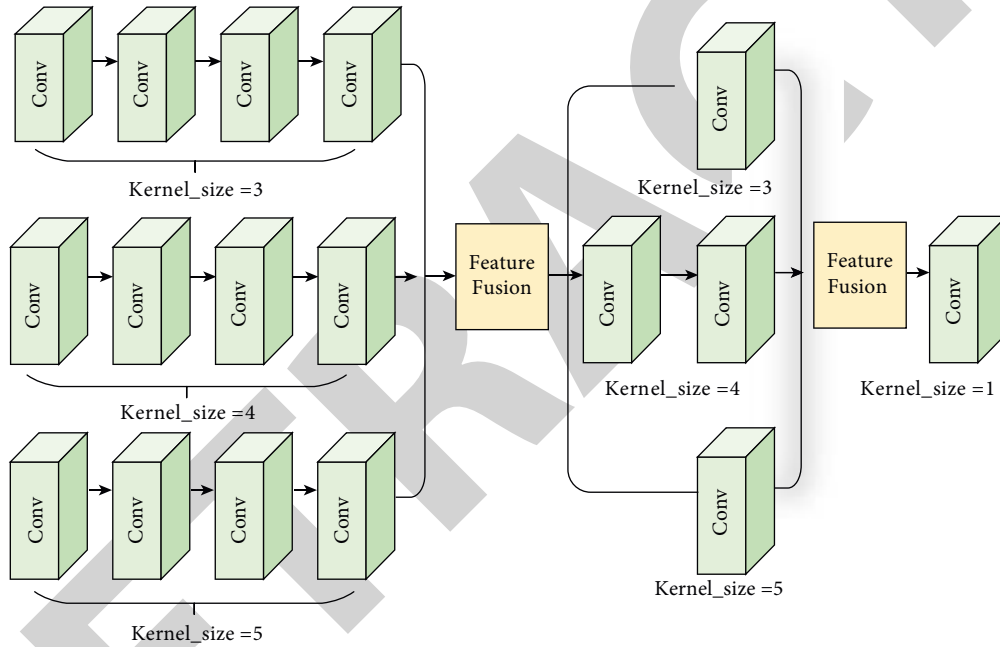


FIGURE 2: The structure of encoder/decoder network.

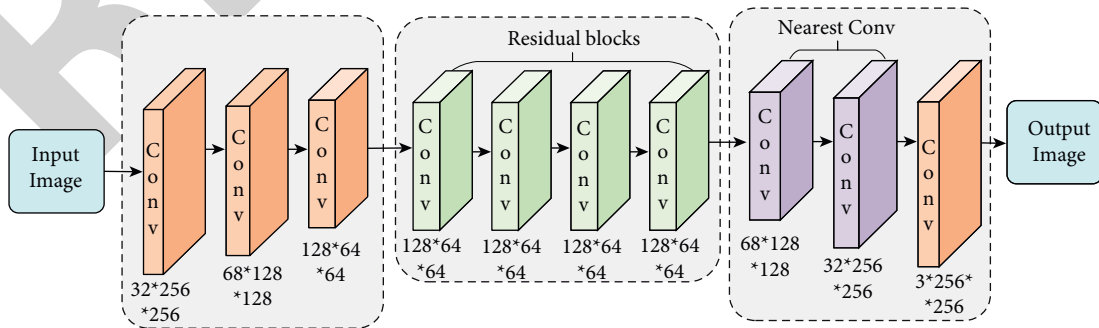


FIGURE 3: Neural style transfer network.

where $\phi(I_s)$ and $\phi(I_o^s)$ are the pixel matrix of the original secret image and the decrypted secret image, and σ and ρ are the weight parameters, respectively.

3.3. *Total Loss.* The total loss of the proposed network consists of cover loss ℓ_{cover} and secret loss ℓ_{secret} , and both of them are equal to the weighted sum of perceptual loss and

structural loss, calculated as follows, where γ and δ are adjustable weight values.

$$\ell_{\text{cover or } \ell_{\text{secret}}} = \gamma \ell_{\text{perc}} + \delta \ell_{\text{stru}}. \quad (3)$$

Finally, the weighted sum of the cover loss ℓ_{cover} and secret loss ℓ_{secret} is calculated as the total loss ℓ_{total} of the overall network shown in the following equation, where λ and η are the weight parameters of the cover loss and the secret loss.

$$\ell_{\text{total}} = \lambda \ell_{\text{cover}} + \eta \ell_{\text{secret}}. \quad (4)$$

4. The Experimental Analysis

In this paper, we design the training process of the proposed method shown in Figure 1. In each forward calculation, a cover image and a secret image are preprocessed and input to the encoder network. After the encoder network completes the embedding of secret image, stego image is output. The stego image is input into the pretrained style transfer network to obtain the stylized stego image, which can be processed by the decoder network to decode the embedded secret image. At this point, the corresponding perceptual loss and structural loss are calculated. In back propagation, the proposed method carries out back propagation according to the loss value and updates the parameters of the encoder and the decoder network. After many times of forward calculation and back propagation, the optimized encoder and decoder are obtained.

4.1. Platform and Dataset. In the experiments, 53228 images are randomly selected from Microsoft CoCo2017 [32], among which 26614 images are used as cover images, and the rest is secret images for model training. All images are resized into 256×256 pixels before training.

In the experiment, the graphics card is NVIDIA Tesla P40 GPU with a memory of 16GB, and the CPU is Intel(R) Xeon(R) CPU E5-2620 v4 with memory of 128G. And the deep learning software is PyTorch 0.4.0 with CentOS 7 operating system and Python 3.7 platform. The learning rate is set to 1×10^{-3} , and the Adam function is used to optimize the network. For the weight parameters, we set the $\alpha:\beta$ in Equation (1) to 1:1, the $\sigma:\rho$ in Equation (2) to 3:10, the $\gamma:\delta$ of cover loss and secret loss in Equation (3) to 7:10 and 1:1, and the $\lambda:\eta$ in Equation (4) to 2:1, according to our experience.

Peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) are used as the evaluation indexes. PSNR is adopted to evaluate the quality of a compressed image compared with the original image, and the higher the value, the less distortion in the compressed image. SSIM is usually used for measuring image similarity in terms of three aspects of structure, brightness, and contrast [11]. The larger the value, the more similar the structure of the two images.

4.2. The Color Image and the Gray-Scale Image Regarded as Secret Images, Respectively. To explore the robustness of encoder-decoder model proposed by Baluja et al. [20] for

neural style transfer, we use color images as secret images in this subsection. As shown in Figure 4, the third and fifth rows are original stego images and stylized stego images, and the fourth and sixth rows are the corresponding extracted secret images.

As observed in Figure 4, the original secret images can be completely extracted from the stego images by the decoder model, but they can hardly be decoded from the stylized stego images, which are almost distorted with basically cluttered noise point composition. This is because the color image has a large amount of information, and the stylization process destroys more embedded information, which makes it difficult to decode effective information from the stylized image. Thus, Baluja's method is not effective enough and has poor robustness in the scenario of neural style transfer.

4.3. Gray-Scale Image and Y Channel Information Embedding. After style transfer, the structure and color of steganographic images are fused and updated accordingly with style features of style image. Therefore, the original semantic information of stego images is damaged to varying degrees, leading to the disruption and destruction of the embedded secret information.

The rapid style transfer network has great ability of semantic preservation, which shows that the Y channel of images contains more semantic information [23]. Thus, we compare the extraction ability of two different embedding schemes for embedding secret images. Scheme 1 embeds a gray-scale image into the cover image. Scheme 2 encodes a gray-scale image into the Y channel of the cover image.

As shown in Figure 5, both schemes can embed secret gray-scale images well and generate stego images with similar quality, and their stylized effects are also good. As observed from Scheme 1, the decoder can basically extract the outline information of the secret images from the stylized stego images, but most of the detailed contents and textures are still lost, and the extraction quality still needs to be improved. In Scheme 2, the decoder can more clearly decode the main content information of the secret image from the stylized stego image. For example, the edges and textures such as faces, clothes, umbrellas, and road signs in the images can be clearly distinguished. Compared with Scheme 1, Scheme 2 has better steganography performance and greatly reduced the distortion of the secret information.

4.4. Combining Y Channel Embedding and Structural Loss to Optimize the Decoder Model. To further improve the clarity of the decrypted secret image, we construct a structural loss to constrain the decoder model training. The first, second, third, and fourth columns are the gray-scale secret image, cover image, stego image, and stylized stego image, respectively; the fifth, sixth, and seventh columns are three different schemes proposed in this paper, in which Scheme 1 and Scheme 2 are in subsection 4.3.2 and Scheme 3 proposed in this subsection.

As shown in Figure 6, the quality of the secret image extracted by Scheme 3 is significantly improved compared to Scheme 2, and most of the detailed texture and structures in



FIGURE 4: The effects of Baluja's method using color images.

the images are maintained, which is not visually distinguishable from the original image. For example, the edges of umbrellas and clothes, and the markings of giraffes are smoother and clearer, without obvious mosaics. In addition, it can be seen from the residual images of the secret images extracted by each method and the original secret images that the extraction quality of Scheme 1 is the worst, and most of the information is wrong. Scheme 3 can recover most information better with less error bits.

To quantitatively analyze the experimental results, we randomly select 30 pairs of secret images and cover images and use two different style models to evaluate the proposed methods in this paper. The PSNR and SSIM values between the cover image and the corresponding stego image, and the secret images and the decrypted images are calculated, respectively. Then, the mean values of PSNR and SSIM of each scheme are calculated as shown in Table 1.

As observed in Table 1, Scheme 3 better balances the quality between the stego image and the decrypted secret image, which also can make the distortion of the stego image relatively small. The other two schemes can produce stego

images with better quality because the secret images are directly embedded in the cover images without constraint. However, due to the stylization processing, the visual gap of stego images generated by various methods is not too obvious, which will not affect its subsequent use. Furthermore, the effect of secret images extracted by them is poor, which is difficult to be applied in actual scenes.

Figure 7 shows the total loss curve, secret loss curve, and cover loss curve of the network model in this paper in training process. The size of secret image and cover image is 256×256 . The total loss curve reflects that the network model is close to convergence during the 21st epoch iteration training. As can be seen from the figure, encoder network loss and decoder network loss, which constitute the total loss, also converge at this point, and their convergence values are different due to the different weighted weights of them.

4.5. Comparison and Analysis of Existing Methods. In this subsection, MNIST dataset is used as secret images, and the influence of the size of embedded secret images on model's

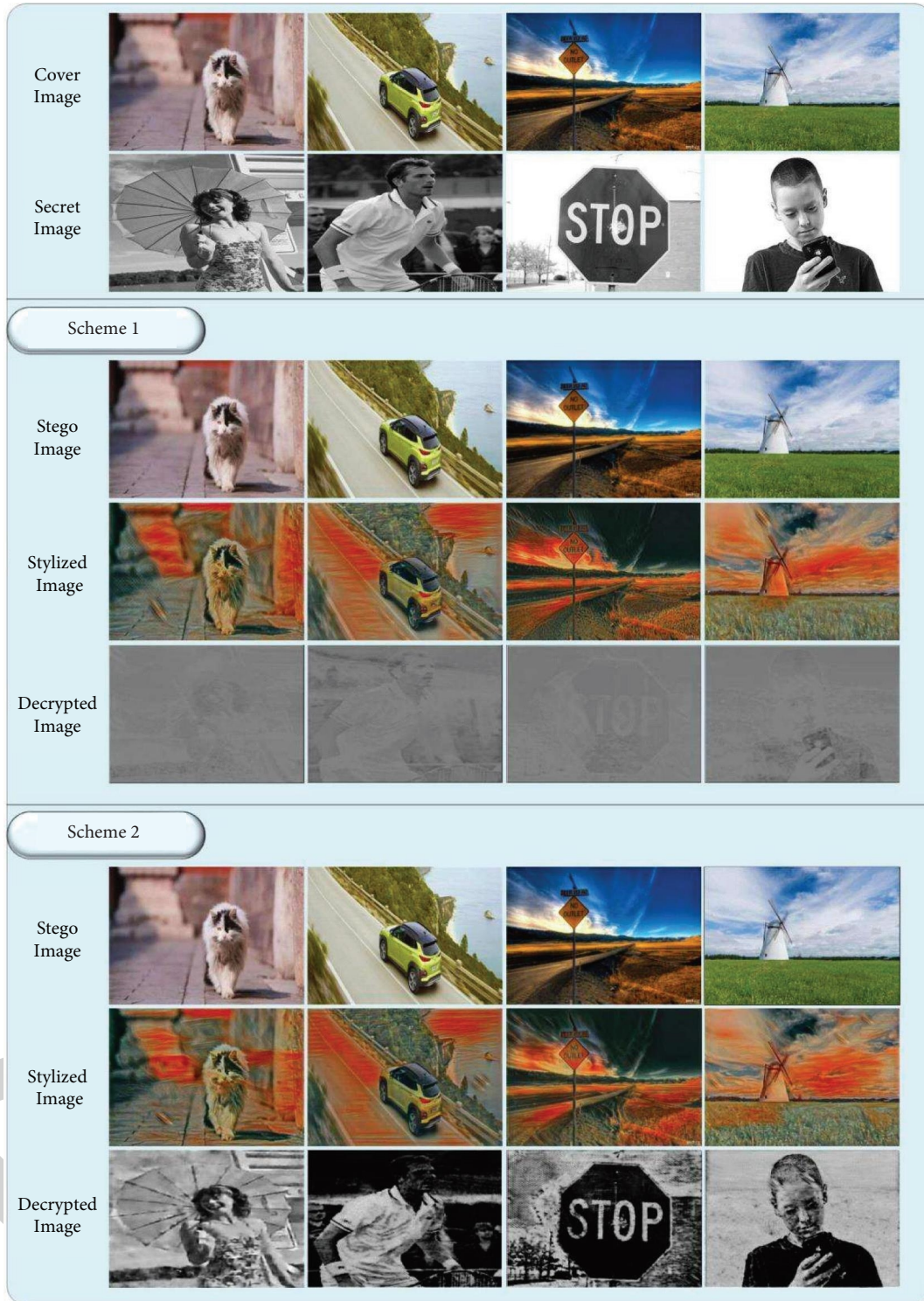


FIGURE 5: The extracted effects by different schemes.

results is analyzed and compared with Li's method [26]. Specifically, we embedded and extracted 50 secret images of different sizes, including 256×256 , 128×128 , 32×32 , and 28×28 , respectively. The size of the cover image is 256×256 . Figure 8 shows the corresponding effects.

As observed from Figure 8, as the size of the embedded secret image decreases, the encoder can better embed the secret image into the cover image, the visual effect of the stylized stego image is also good, and the secret image extracted by the decoder is getting better and better.

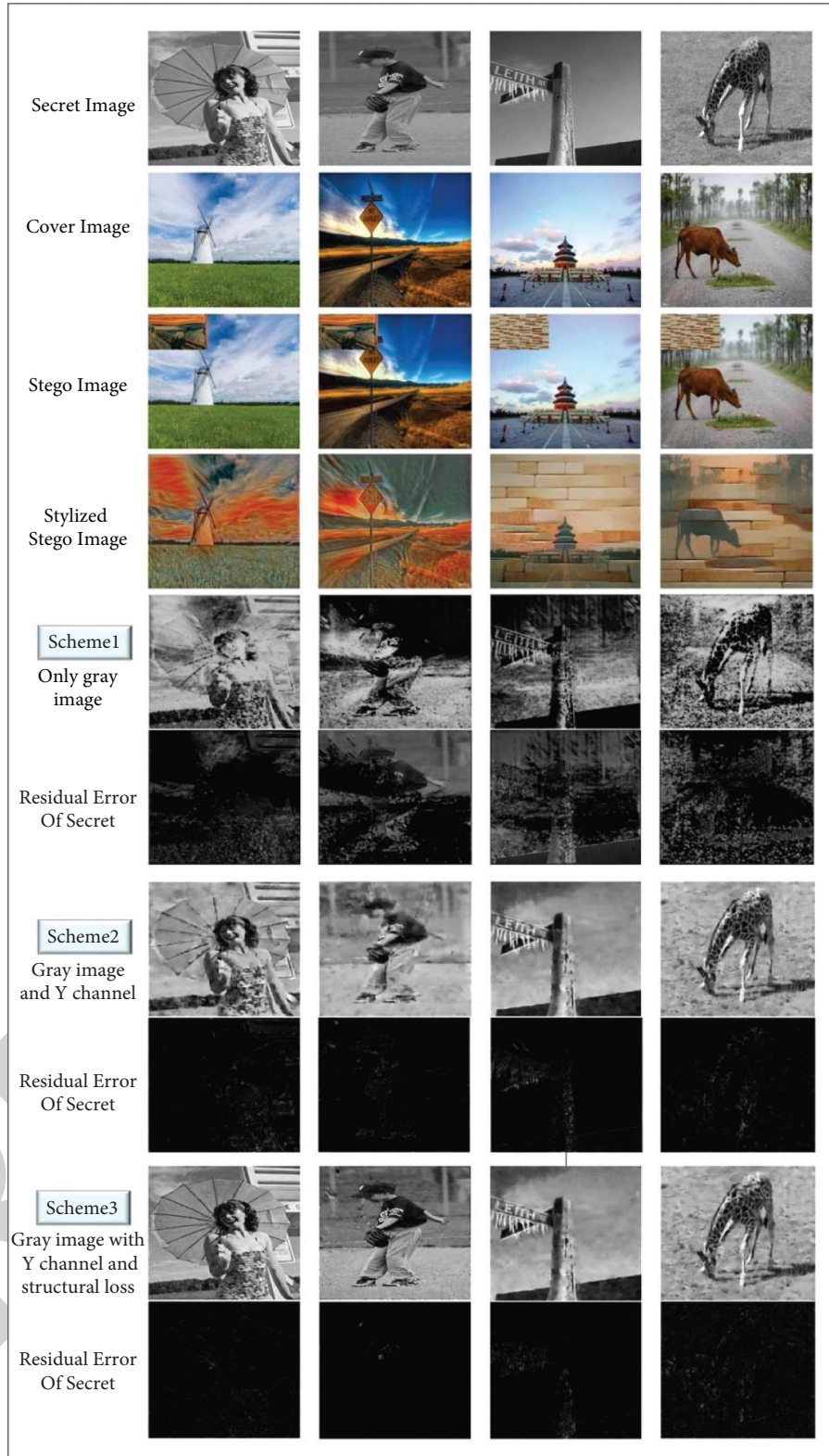


FIGURE 6: The visual effects of secret images extracted by different proposed schemes.

TABLE 1: The mean values of PSNR and SSIM of each scheme.

Evaluation indexes		Scheme 1 (only gray-scale image)	Scheme 2 (gray-scale image and Y channel)	Scheme 3 (gray-scale image with Y channel and structural loss)
Between original secret images and extracted images	PSNR	11.4829	13.0054	24.1432
	SSIM	0.5438	0.7529	0.8027
Between cover images and stego images	PSNR	31.7026	31.3511	26.0245
	SSIM	0.8976	0.8150	0.7850

The bold fonts indicate that the corresponding schemes have the highest PSNR and SSIM values, that is, the secret images extracted by Scheme 3 are most similar to the original images. And the values between cover images and stego images of Scheme 1 is the highest, but the visual effects of three schemes are acceptable since the stylized stego images are almost the same to each other.

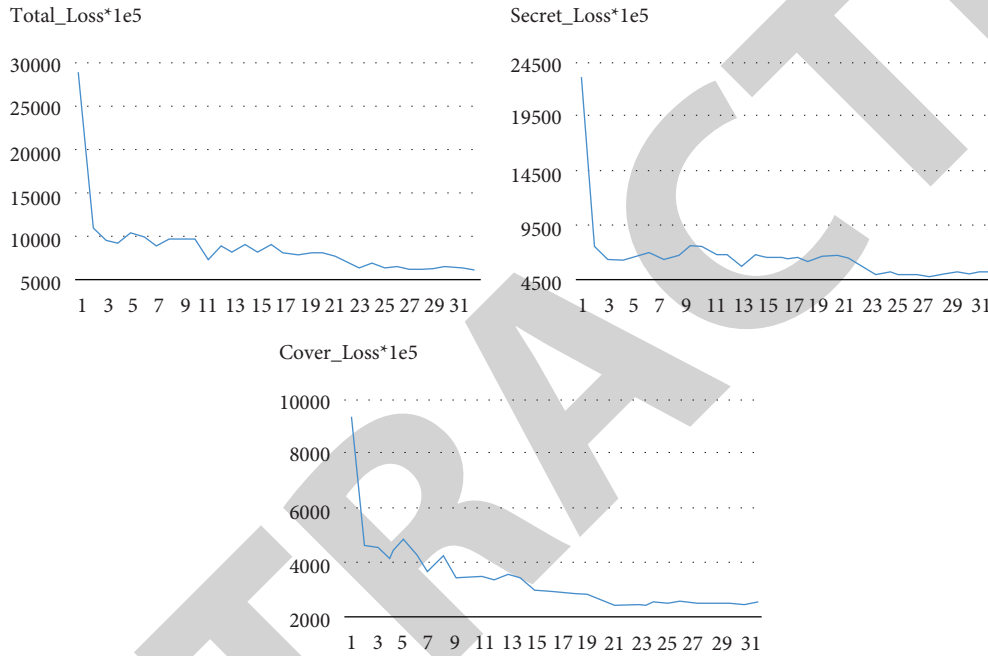


FIGURE 7: Convergence of loss curve. (a) Total loss. (b) Secret loss. (c) Cover loss.

However, with the increase of the size of the embedded secret image, more noises appear in the decrypted secret image.

To make quantitative analysis of the above effects, we calculate the PSNR and SSIM between original secret image and decrypted secret image with different sizes, and the results are shown in Table 2. The effect of the method proposed in this paper is far better than that of

Li's method [29], the PSNR is 31.35, SSIM is 0.96, and BER is 0.06 in case of secret images of 32×32 . This is because the proposed method can directly extract the secret image from the stylized stego image, while Li's method needs to extract the secret image from the destylized stego image relying on training an additional destylization network, thus losing more original secret information.

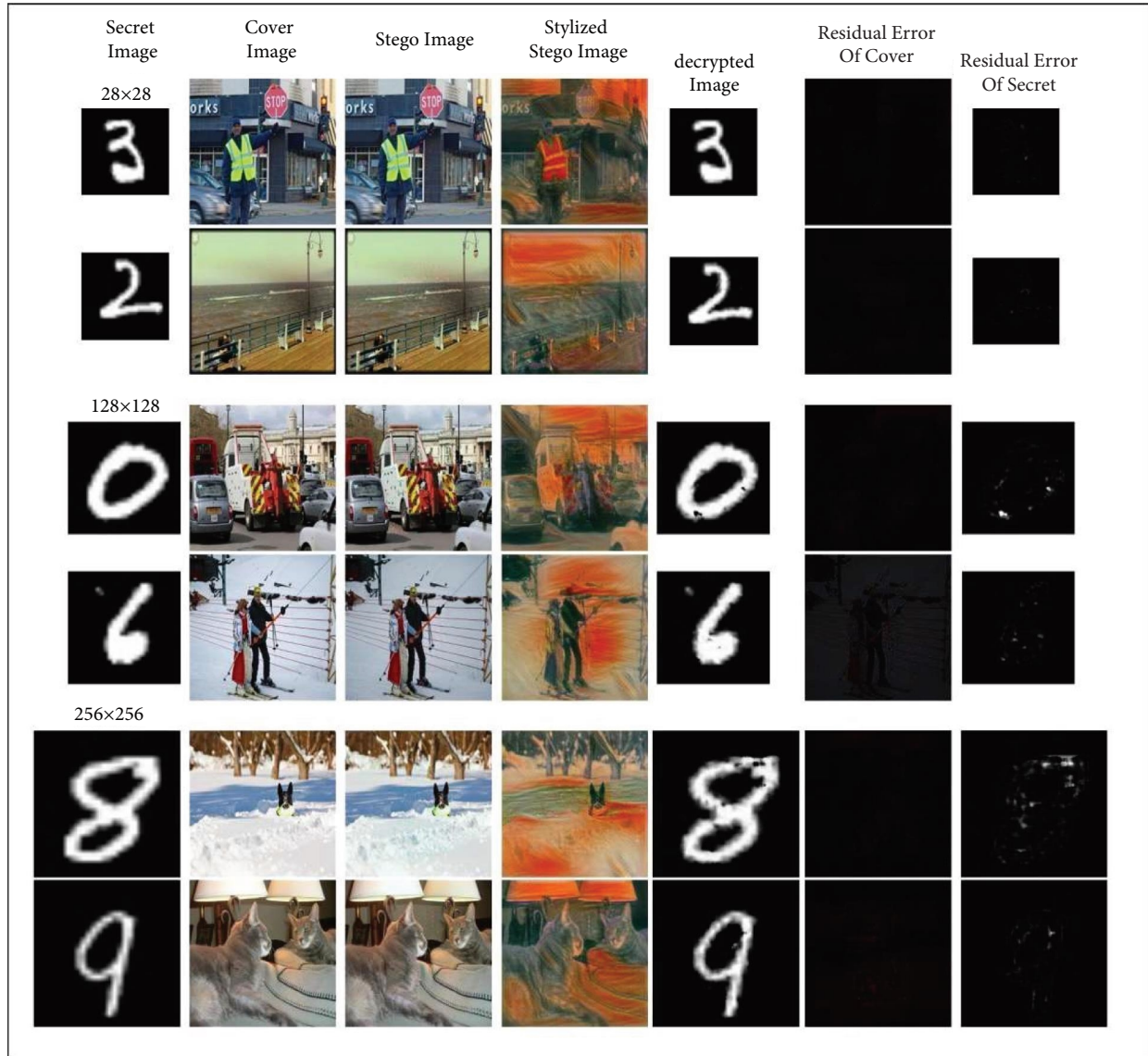


FIGURE 8: The visual effects for embedding secret images of different sizes.

TABLE 2: The mean PSNR and SSIM values of cover images and secret images.

Size of cover image	Size of secret image	PSNR		Secret image SSIM		BER	
		Our	Li [29]	Our	Li [29]	Our	Li [29]
256×256	28×28	31.35	—	0.96	—	0.04	—
	32×32	30.21	—	0.94	—	0.06	0.09
	128×128	27.43	—	0.85	—	0.17	—
	256×256	27.29	—	0.82	—	0.22	—

5. Conclusion and Future Works

In this paper, we attempt to explore the combination of image steganography and style transfer techniques, and to study how to effectively maintain the secret information of the stego image (referred to the content image) before and after stylization, so as to achieve better protection of private information like copyright. Thus, we proposed a novel

steganography framework for neural style transfer by introducing the Y channel information and a structural loss, which enables the secret information to be efficiently embedded into the cover image and directly recovered from stego images or stylized stego images with high quality. The experimental results show that the proposed method has high robustness to the stylization and expands the application scenarios of image steganography.

However, this technology still has a large space for optimization. For instance, the structure of encoder-decoder network can be further optimized to improve the image quality of encrypted and decrypted images. The capacity of embedded secret information needs to be increased, so that the model can embed the color images and then can decode the original secret information with high quality from stego images processed or disturbed by different techniques. That is, we can expand the application of image steganography technology in different situations, such as image conversion, coloring, generation, etc., to achieve more expansion and improvement.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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