Generative Steganography with Kerckhoffs' Principle based on Generative Adversarial Networks

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Abstract—The distortion in steganography that usually comes from the modification or recoding on the cover image during the embedding process leaves the steganalyzer with possibility of discriminating. Faced with such a risk, we propose generative steganography with Kerckhoffs' principle (GSK) in this letter. In GSK, the secret messages are generated by a cover image using a generator rather than embedded into the cover, thus resulting in no modifications in the cover. To ensure the security, the generators are trained to meet Kerckhoffs' principle based on generative adversarial networks (GAN). Everything about the GSK system, except the extraction key, is public knowledge for the receivers. The secret messages can be outputted by the generator if and only if the extraction key and the cover image are both inputted. In the generator training procedures, there are two GANs, Message- GAN and Cover-GAN, designed to work jointly making the generated results under the control of the extraction key and the cover image. We provide experimental results on the training process and give an example of the working process by adopting a generator trained on MNIST, which demonstrate that GSK can use a cover image without any modification to generate messages, and without the extraction key or the cover image, only meaningless results would be obtained.

Index Terms—Information security, generative steganography, generative adversarial networks (GAN), Kerckhoffs' principle

I. INTRODUCTION

Steganography aims at sending out secret messages by embedding them into an innocent cover. The goal of steganography is to conceal the hidden channel by the public channel. However, there appear to be two hidden drawbacks deserving further research that mainly lie in 1) the insufficient resistibility to steganalysis and 2) the system security that relies on the secrecy of the design or implementation of data hiding.

The first drawback is derived from the modification or recoding on covers. There is always modification or recoding on the cover after embedding, which is designed to appear as innocent as possible to ensure the existence of the hidden channel undetected. Such changes in the covers leave the steganalyzer with possibility of discriminating, because it brings in distortion that might be measured by establishing a distortion function. Since Syndrome-Trellis Codes (STC) was

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proposed [1], steganography minimizing a heuristically-defined embedding distortion has been widely used, making the design of distortion functions the only focus. With the evaluation dimensions growing higher, the construction getting more complex, and deep-learning algorithms introduced in steganalysis [2][3], it appears that any change of the cover might be a hidden risk to expose the presence of data hiding.

The other drawback lies in the security of the steganography system. The security (undetectability of secret messages and the hidden channel, specifically) always relies on the secrecy of the design or implementation, *i.e.*, "security through obscurity". However, "security through obscurity" may have theoretical or actual security vulnerabilities [4]. In general, specific methods of steganalysis often show more advantages in feasibility than universal methods by taking advantage of the insecure aspects of a steganography algorithm [5]. In contrast to "security through obscurity", Kerckhoffs' principle [6], a fundamental principle of cryptosystem, is more appropriate for modern security systems. Because the fewer and simpler the secrets that one must keep to ensure system security, the easier it is to ensure system security.

In this letter, we attempt to treat the above drawbacks through a distinctive method. We propose Generative Steganography with Kerckhoffs' principle (GSK) in this letter. In GSK, the secret messages are sent out by using the cover to generate them rather than recoding the cover to carry them. There is no modification on the cover resulting in no distortion for steganalysis. The generator can be trained based on an emerging technology, generative adversarial networks (GAN) [7]. To ensure the security, Kerckhoffs' principle is introduced in this letter. Furon et al., has translated Kerckhoffs' principle from cryptography to data hiding and classified the setups of watermarking attacks into four categories in [8][9]. Levels of security have been defined in these setups. The highest level called stego-security is defined in Watermarked Only Attack setup based on Kerckhoffs' principle [10]. Our scheme is also designed to meet Kerckhoffs' principle, i.e., the secret messages should be secure even if everything about GSK (including the trained generators), except the extraction key, are public knowledge. Specifically, the generator is required to output the desired results if and only if the extraction key and the cover image are both inputted.

The remainder of this letter is organized as follows: We detail the framework of GSK in the following section. Section III elaborates the training architecture of the generator. Section

IV describes the working processes of GSK. Experiment results are demonstrated in Section V. Section VI concludes this research and details our future work.

II. FRAMEWORK OF GSK

The exchange of the secret messages in GSK is achieved by the cover images' generating rather than their modification. To meet Kerckhoffs' principle, the generator should be trained with following three objectives:

- 1) Any image can be the cover, and the secret message can be generated with the cover image.
- 2) The secret message can be obtained if and only if both the extraction key and the cover image are inputted.
- 3) The extraction key itself or the cover image cannot reveal any knowledge of the secret message.

The framework of GSK is shown in Fig. 1: The trained generators would be public knowledge. The sender first chooses an innocent image I as the cover. Then he obtains the extraction key k using the secret message s and the cover image I (Fig.1a). Second, I is sent out through the public channel and k through the key channel. We consider there is a channel to share the extraction key, and we pay no attention to the key channel anymore [8][9] (Fig.1b).

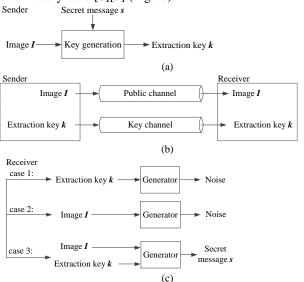


Fig. 1. Framework of GSK: (a) Extraction key generation; (b) Data delivery; (c) The three cases of the receivers.

As for the receivers (Fig.1c): Case I, only k is received corresponding to a failed message delivery, there is only noise output. Case I, only I is received corresponding to an intercept from attackers (we assume a worst case here that attackers would intercept the key channel due to its random-like form and I should be undetectable during its lossless delivery), there is only noise output. Case I, I and I are both received, the message I could be obtained.

III. TRAINING ARCHITECTURE OF THE GENERATOR

The generator is the crucial piece of GSK. In this letter, we design to obtain such generators based on GAN. GAN aims to generate artificial samples indiscernible from the real counterparts via competition between a generator (G) and a

discriminator (D), *i.e.*, alternating the maximization and minimization steps in (1).

$$\min_{G} \max_{D} V(D,G) = E_{s-P_s} \left[\log D(s) \right] + E_{x-P_{\text{noise}}} \left[\log \left(1 - D(G(x)) \right) \right]$$
 (1)

where D(s) is the probability that s is a real image rather than synthetic, and G(x) is a synthetic image for input x. In fact, it is easy to obtain a generator outputting desired results using GAN. However, GAN usually works under the unsupervised learning. All it needs to input is only noise to output a desired result. If so, we cannot control the output with a key. Our training goal is more complex than a general GAN. We attempt to establish two associations between the message s and the key s, and between the message s and the cover s. Therefore, training of the generator includes two stages: Message-GAN and Cover-GAN.

A. Message-GAN

The objective of Message-GAN is to use feature codes to control the output. Feature codes are a set of discrete random variables to represent the attributes of the samples from some dataset, which are independent and salient in generating meaningful samples (*e.g.*, "face contours", "colors of skin", or "fat or thin", *etc.*, are features of the faces from CelebA. "number values", "font weight", *etc.*, are features of the digits from MNIST). As shown in Fig.2, we use noise x together with feature codes f as input. G_M aims not only to generate artificial samples indiscernible from the real samples, but to ensure the features of artificial samples conform with f. Feature codes equal to predefined constraint conditions on the output of G_M . Ideally, there should be only meaningless outputs without f.

$$G_M$$
 Generated samples D_M Real samples

Fig. 2. Structure of Message-GAN

We use an existing technique, InfoGAN [11], as Message-GAN. There is high mutual information between f and $G_M(x, f)$ in InfoGAN. Mutual information I(X; Y) between X and Y is the reduction of uncertainty in X when Y is observed:

$$I(X;Y) = H(X) - H(X/Y) = H(Y) - H(Y/X)$$
 (3)

If *X* and *Y* are determinately related, their mutual information gets a maximum. Then, we have the following minimax game:

$$\min_{G_{M}} \max_{D_{M}} V_{M} (D_{M}, G_{M}) = E_{s-P_{s}} \left[\log D_{M} (s) \right] + E_{x-P_{\text{noise}}} \left[\log \left(1 - D_{M} \left(G_{M} (x, f) \right) \right) \right] - \alpha I (f, G_{M} (x, f))$$
(4)

where α is an extra hyperparameter [11]. There are other types of GANs that could act as Message-GAN, such as Auxiliary Classifier GAN [12], Conditional GAN [13]. The performances of the GANs might vary with different training datasets, which deserves our further research.

B. Cover-GAN

The objective of Cover-GAN is to make the cover image I be a necessary conditional input that can determine the generation of the message s. The function of Cover-GAN can be abstracted as a model shown in Fig. 3: G_C , R_C , and A_C are all neural networks. The parameter-settings are denoted as θ_G , θ_R , and θ_A , respectively. The output of G_C (θ_G , P, z) is c. The output of R_C (θ_R , c, z) is e. The output of e0 are the legal message exchangers sharing the input e1. e2 acts as the

attackers. G_C generates a random-like output c to protect the communication with R_C . R_C and A_C can both receive c. R_C can recover P while A_C attempts to recover P from c without c.

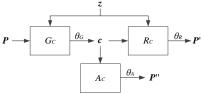


Fig. 3. Structure of Cover-GAN.

The two adversarial sides are (G_C, R_C) and A_C [14]: A_C aims at recovering P; G_C and R_C are trained jointly to ensure that R_C could recover P accurately and A_C would obtain nothing useful about P. According to the different goals of (G_C, R_C) and A_C , we give the distortion functions of the two adversarial sides.

L1 distance d on the input (X, X') is introduced to show the distortion between X and X':

$$d(X, X') = \sum_{i=1}^{N} |x_i - x_i'|$$
 (5)

where N is the length of X and X'. The loss functions of R_C and A_C are:

$$L_{R}(\theta_{R}) = L_{R}(\boldsymbol{P}, R(\theta_{R}, z, \boldsymbol{c})) = E[d(\boldsymbol{P}, \boldsymbol{P}')]$$
(6)

$$L_{A}(\theta_{A}) = L_{A}(\mathbf{P}, A(\theta_{A}, \mathbf{c})) = E \left[d(\mathbf{P}, \mathbf{P}'') \right]$$
 (7)

The goal of A_C is to reconstruct P accurately, so the optimal $A_C(O_A)$ is obtained:

$$O_A = O_A(\theta_A, \mathbf{c}) = \arg\min_{\theta_A} (L_A(\theta_A))$$
 (8)

As the adversarial side against A_C , networks G_C , R_C aim to communicate successfully and defeat the best possible version of A_C . The loss function of (G_C, R_C) is obtained:

$$L_{GR}(\theta_G, \theta_R) = L_{GR}(L_R(\theta_R), O_A(\theta_A, \mathbf{c})) = E[L_R(\theta_R) - O_A(\theta_A, \mathbf{c})]$$
(9)

where O_A is updated after each training of A_C . The optimal G_C and R_C (O_G , O_R) are obtain by minimizing $L_{GR}(\theta_G, \theta_R)$.

$$(O_G, O_R) = \arg\min_{(\theta_G, \theta_R)} \left(L_{GR} (\theta_R, \theta_G) \right)$$
 (10)

During the training of Cover-GAN, we start with (G_C, R_C) . G_C may initially produce c that neither R_C nor A_C could understand. After a few steps, R_C could understand c better and better with (θ_G, θ_R) while c is not understood by the present A_C . Then we keep the G_C , R_C fixed and train A_C given the obtained value of (θ_G, θ_R) to obtain another O_A . Next, we update O_A and continue with (G_C, R_C) to obtain (O_G, O_R) .

We alternate the training on (G_C, R_C) and A_C to reach the equilibrium state of them. It is typical of the continuous game and their outputs converge to equilibrium in which R_C can accurately recover P while A_C has a 50% chance to output the correct bits of P. It is noted that the reconstruction error of A_C is not maximized [14]. If it were, all the outputs of A were completely wrong, and A could output P accurately in the next step by flipping all the present bits. Therefore, it is the mutual information between P and P that gets minimized and A_C produces answers indistinguishable from random guesses.

IV. GENERATIVE STEGANOGRAPHY WITH KERCKHOFFS' PRINCIPLE

All the generators trained on different datasets are public in GSK. The scenario of GSK is that a sender intends to send out

the secret message s to a receiver by using a cover image I and appropriate generators chosen according to the content type of s. The workflow is shown in Fig. 4. The sender's manipulation (Fig. 4a) is to obtain the extraction key k: First, the sender chooses feature codes to predefine s and ensure that G_M could output s with the feature codes f. Then he chooses random codes f' of the same length as f and calculates f'':

$$f'' = f \oplus f' \tag{11}$$

The input of G_C in Fig. 3 is (P, z), in which P = f'' and z is the identification code filtered from the cover image I through an advance appointed method. For simplicity, z is the LSB of I in this letter. The output of G_C is c. The extraction key k is given by (c, f'). For security reasons, random codes f' instead of feature codes f is used to make up the extraction key k in case that k is intercepted and k itself should not divulge any useful information about f.

The receiver's manipulation (Fig. 4b) is to obtain the secret message s with k(c, f') and z of I: First, z and c are inputted into R_C to obtain f''. Then f is calculated:

$$f = f'' \oplus f' \tag{12}$$

The secret message s can be outputted by G_M with input f. Above knowable, k and z are both necessary for the generation of s. The security of GSK depends solely on the secrecy of k and the randomizer of f'.

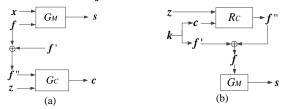


Fig. 4. Workflow: (a) sender's manipulation; (b) receiver's manipulation.

V. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental results on the training processes including Message-GAN and Cover-GAN are demonstrated first. Then an example is provided to show the working processes of GSK.

A. Training processes of GSK

The training of Message-GAN is to obtain the feature codes f of a target message. The experiments are based on two datasets, MNIST and CelebA. Secret messages are contained in the output images of generators. The content types of the messages include decimal handwritten digits on MNIST or faces on CelebA. The training of Cover-GAN is to ensure R_C could recover f'' losslessly while A_C only outputs random bits.

Message-GAN: We first test on MNIST by applying the setup in [11] mechanically. We use 1 ten-dimensional feature code, 2 latent codes and 62 noise variables as the input with a dimension of 74. Feature codes f of 4-bit indicates the number of one decimal digit. The outputs are a 28×28 8-bit gray image. The generated digit is recognizable from the output image, *e.g.*, digit "5" in Fig. 5a. The results in Fig.5b-5e demonstrate that we can control the number of the generate digit using f and digits are randomly generated without f (Fig.5e). According to [11], more characteristics of the written digits, such as the

rotate direction or font weight of the digit, can already be controlled by feature codes. That could enhance the amount of the meaningful information contained in an output image.



Fig. 5. Sample results on MNIST: (a) digit "5" in the output image; (b) f: digits 0,1,2,3; (c) f: digits 4,5,6,7; (d) f: digits 6,7,8,9; (e) Outputs without f.

We continue our test on CelebA to output faces using 10 ten-dimensional feature codes and 128 noise variables as the input with a dimension of 228. f here is used to control some highly semantic variations that a generated face carries (e.g., with glasses or not in Fig. 6a, with smile or not in Fig. 6b). The specific semantic information in the faces is the message we can generate. Without f, we use deep convolutional-GAN (DC-GAN) [15] to act as the attacker who could have access to our training dataset but know nothing about f. The outputs of DC-GAN with 3×10^4 training steps on CelebA are randomlygenerated faces that cannot carry any artificially added semantic information as shown in Fig.6c.



Fig. 6. Sample results on CelebA: (a) f: with glasses or without glasses; (b) f: with smile or without smile; (c) Outputs of DC-GAN without f.

Experimental results on MNIST or CelebA demonstrate that f can act as the preconditions for generating the desired messages. However, f on CelebA cannot be set long yet, and depicting on human faces is not rich or precise enough. Therefore, we use G_M on MNIST in the following sections.

Cover-GAN: The architectures of G_C , R_C , and A_C are based on adversarial neural symmetric cryptography in [14]. We choose an image randomly as the cover image I. The identification code z is obtained from the LSB of I. During training, error rates of R_C and A_C for recovering f'' are recoded once per 1000 steps in Fig. 7. After about 1.6×10^4 steps, R_C is able to recovery each bit of f'' accurately with z while error rates of A_C approach 50% and then remain stabilized without z. It demonstrates that f'' cannot be obtained without I, thus ensuring the secrecy of feature codes f and the message s.

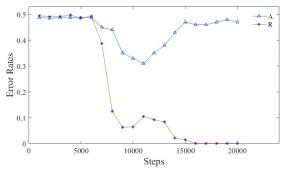


Fig. 7. Error rates of R and A.

B. Working processes of GSK

We intend to send decimal digits as an example of GSK in this section. To send one decimal digit of 4 bits, we need the trained generators on MNIST and a 4-bit identification code z

from the cover image I. Then we obtain the extraction key k of 8 bits (f'', z and c all have the same length as f). We test the performances of GSK in the 3 cases described in GSK framework (Fig.1c) on 10 sample data. Each sample has 300 decimal digits as secret messages. In case1 or case2, only random digits are generated due to the absence of k or I. In case3, the message s can be obtained accurately. Bit-error rates between s and the output bits in the 3 cases are calculated. The five best-performance samples are shown in Table. I.

TABLE. I ERROR RATES BETWEEN THE MESSAGE BITS AND THE OUTPUT BITS

	Sample1	Sample2	Sample3	Sample4	Sample5
Case 1	0.5058	0.4833	0.4908	0.4917	0.4933
Case 2	0.4817	0.5125	0.4842	0.4775	0.5050
Case 3	0.0042	0.0067	0.0008	0.0017	0.0025

Capacity of GSK is determined by the complexity of the training datasets and the control effect of feature codes. In this letter, one output of the generator on MNIST is a 28×28 8-bit gray image. The theoretical maximum of the capacity is 6272 bit when the output image is fully utilized. In our example, only one digit is carried by an output image. The available information has only 4 bits. The availability factor (AF) of the output image is 0.0638%.

Key size factor (KSF) is the length ratio of k and s, which indicates the cost of the key k for generating the message s:

$$KSF = length(k) / length(s)$$
 (11)

The KSF of GSK on MNIST is 2 in our example. In this letter, the extraction key consists of f' and c. Different from the key in cryptography, c must be transmitted through key channel, which might limit the applications of GSK. But the amount of c is small compared with the total amount of the output image. Therefore, further researches should focus on increasing AF and reducing KSF to improve the practicality.

VI. CONCLUSION

The main contribution of this letter is that we first propose a framework of generative steganography with Kerckhoffs' principle. To ensuring the security, the *generator* is required to output the secret message if and only if the cover image and the extraction key are both inputted. We give the experimental results to demonstrate the feasibility of GSK and discuss some evaluation criteria of GSK. Future work would mainly focus on 1) enhancing the capacity by applying GSK to the complicated datasets and intensifying the control effect of the feature codes, 2) optimizing the architecture of Cover-GAN to reduce the KSF of GSK, and 3) integrating Message-GAN and Cover-GAN into one to simplify the training processes.

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