Generative Steganography by Sampling

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Abstract: In this paper, a new data-driven information hiding scheme called generative steganography by sampling (GSS) is proposed. The stego is directly sampled by a powerful generator without an explicit cover. Secret key shared by both parties is used for message embedding and extraction, respectively. Jensen-Shannon Divergence is introduced as new criteria for evaluation of the security of the generative steganography. Based on these principles, a simple practical generative steganography method is proposed using semantic image inpainting. Experiments demonstrate the potential of the framework through qualitative and quantitative evaluation of the generated stego images.

1 Introduction

In 1550, Girolamo Cardano [1] (1501-1576), known in French as Jérôme Cardan, inspired by ancient Chinese wisdom, proposed a simple grid for writing hidden messages. He intended to cloak his messages inside an ordinary letter so that the whole would not appear to be a cipher at all. Such a disguised message is considered to be an example of steganography, which is a sub-branch of general cryptography. For a long time, the difficulty of constructing the ordinary letter made steganography nearly going to be cover modification. In Fridrich’s groundbreaking work of modern steganography [1], steganographic channel is divided into three categories, cover selection, modification and synthesis. KL divergence is used as a measure of security for steganography. Cover selection method does not modify the cover image, thereby avoiding the threat of the existing steganalysis technology. This method cannot be applied to practical applications because of its low payload. Cover modification is the most studied method so far. In terms of KL divergence as a security measure, it can only achieve $\varepsilon$-security or the perfect security for a certain explicit model. These methods such as [2] [3] had to struggle against steganalysis [4]. Cover synthesis seems more consistent with the earliest Cardan grille. However, about ten years ago, this method is only a theoretical concept, rather than a practical steganography, because it is difficult to obtain multiple samples.

Fortunately, a data-based sampling technique, generative adversarial networks (GANs)[5], have become a new research hot spot in artificial intelligence. The aim of GAN is to estimate the potential distribution of existing data and generate new data samples from the same distribution. In this paper, under the guidance of cover synthesis, inspired by Cardan grille, a new framework called generative steganography is proposed. Jensen-Shannon Divergence is introduced as the new measure of generative steganography security. We also discuss the differences between the cover generation and modification methods. Based on this framework, a practical cover generation method called Digital Cardan Grille is
2 Related Work

Fridrich etc. [1] first discuss the cover synthesis and selection method. With the help of texture synthesis, [6, 7] use the texture sample and a bunch of color points generated by secret messages to construct dense texture images. [8] improves the embedding capacity by proportional to the size of the stego texture image. Qian etc. [9] propose a robust steganography based on texture synthesis. Xue etc. [10] use marbling, a unique texture synthesis method that allows users to deliver personalized messages with beautiful, decorative textures for hiding message. This kind of texture-based steganography is based on the premise that the cover may not represent the content in real world which is counter-intuitive for steganography which objective is to maintain the nature of the cover. Similar to [1], Zhou etc.[11] proposed a cover selection method based on the bag-of-words model (BOW). A set of sub-images with visual words related to the text information is found. The images containing these sub-images are used as stego images for secret communication.

Recently, adversarial training has also been applied to steganography. Volkhonskiy etc.[12] first propose a new model for generating image-like containers based on Deep Convolutional Generative Adversarial Networks (DCGAN[13]). This approach allows to generate more steganalysis-secure message embedding using standard steganography algorithms. Similar to [12], Shi etc.[14] introduce a new generative adversarial networks to improve convergence speed, the training stability the image quality. Abadi [15] used adversarial training to teach two neural networks to encrypt a short message that fools a discriminator. Similar to the [15], [16] define a game between three parties, Alice, Bob and Eve, in order to simultaneously train both a steganographic algorithm and a steganalyzer. Tang etc.[17] propose an automatic steganographic distortion learning framework using a generative adversarial network, which is composed of a steganographic generative subnetwork and a steganalytic discriminative subnetwork. However, most of these GAN-based steganographic schemes are still the cover modification. These methods focus on the adversarial game while ignoring the core aim of the GAN is to build a powerful sampler.

Since GAN's biggest advantage is to generate samples, it seems that it is a very intuitive idea to use GANs to generate a semantic stego carrier from a message directly. However, the extraction of message is an important constraint to steganography by GANs. Some researchers have made a preliminary attempt on this intuitive idea. Ke [18] first proposed generative steganography method called GSK in which 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. In [18], we first introduce the term ‘generative steganography’. Liu etc.[19] propose a method that using ACGAN [20] to classify the generated samples, and they make the class output information as the secret message. In our previous work [21], the secret message is written to the corrupted area of image that needs to be filled by a Cardan grille, then the corrupted stego image is fed into a Generative Adversarial Network (GAN) for stego generation.

In this article, a new practical method called Digital Cardan Grille (DCG), based on generative steganography framework, is proposed. A mask called digital Cardan grille for determining the hidden location is introduced to hide the message. The message is written to the uncorrupted region that needs to be kept in the corrupted image in advance. Then the corrupted image with secret message is fed into a Generative Adversarial Network (GAN) for semantic completion. The adversarial game not only
reconstruct the corrupted image, but also generate a stego image which contains the logic rationality of image content.

This paper has the following contributions:

1. We propose a data-driven framework for steganography by learning a generator with large data, which simplifies the design of steganography schemes. Steganographic process to a large extent be automated. We can obtain a large number of stego images by sampling from the generator. It can also be extended to other media, such as text, audio, video etc.

2. A new criterion for steganography security is defined, generative steganography algorithms based on our framework can be theoretically compared with the same data set. This scheme is also a key-dependent steganographic schemes adhere to Kerckhoff's principle.

3. Compared with texture-based methods, semantic image completion technology is used to ensure the logical rationality of cover contents. Compared with our previous work, the new digital Cardan grille in this paper not only has faster convergence speed, but also has lower visual distortion.

### 3 Framework

The Generative Steganography framework of this paper is shown in Fig.1 as follows:

![Fig 1. Generative steganography framework.](image)

In this scenario, the sender create a stego carrier from a generator with message directly. The embedding algorithm actually turns into a stego sampling (generation) process. The secret key shared by both parties ensures the security of the message, the natural real degree of stego determines the security of the communication channel.

#### 3.1 Representation Formula

Ideally, the Generative steganography scheme should satisfy the following three conditions. We call this Generative Steganography Conditions, or GSC:

\[
\begin{align*}
  s &= G(m, k) \\
  m &= C(s, k) \\
  p_{\text{stego}} &= p_{\text{real}}
\end{align*}
\]

where \( s \) denotes the fake stego carrier, \( m \) denotes message, \( k \) is the secret information shared by two parties. \( G(.) \) in Equation (1) is a generator, it indicates that the scheme is a Generative steganography, stego \( s \) is sampled from a generator without an explicit cover. \( C(.) \) is the message extraction operation. Equation (2) guarantees the accuracy of message extraction. \( p_{\text{stego}} \) and \( p_{\text{real}} \) denote the distribution of fake stego carrier and real data. GSC (3) guarantees the security of communication channel, which is a key issue for the generator to be used for generative steganography. Therefore, our goal is to find a generator that will enable \( p_{\text{stego}} \) equal to \( p_{\text{real}} \). Interestingly, suppose all these conditions are satisfied, if every fake stego sample from generator is exactly as same as a real data sample. The generator can be seen as a way to select real samples from the world. This also means that the generator will be able to construct an infinite real sample database, in which every sample contain a secret message.
3.2 A Measure of Security

In mathematical statistics, the Kullback–Leibler divergence is a measure of how one probability distribution diverges from a second, expected probability distribution. Fridrich [1] introduces a formal information theoretic definition of security in steganography based on the Kullback–Leibler divergence between the distributions of cover and stego objects:

$$D_{KL}(P_{\text{stego}} \parallel P_{\text{cover}}) = E_{x \sim p_{\text{cover}}}[\log \frac{P_{\text{stego}}}{P_{\text{cover}}}]=E_{x \sim p_{\text{cover}}} [\log P_{\text{stego}} - \log P_{\text{cover}}]$$  \hspace{1cm} (4)$$

where $P_{\text{cover}}$ and $P_{\text{stego}}$ are the distributions of cover and stego, respectively. However, KL divergence doesn't satisfy the symmetric and triangle inequality conditions, it cannot be strictly considered as a metric. The security of different steganography cannot be evaluated with this divergence. In this paper, a new measure of security is defined by the Jensen–Shannon divergence, which is based on the Kullback–Leibler divergence, with some notable (and useful) differences, including that it is symmetric and it is always a finite value. It is defined by

$$D_{JS}(P_{\text{stego}} \parallel P_{\text{cover}}) = \frac{1}{2} D_{KL}(P_{\text{stego}} \parallel M) + \frac{1}{2} D_{KL}(P_{\text{cover}} \parallel M)$$  \hspace{1cm} (5)$$

$$M = \frac{1}{2} (P_{\text{stego}} + P_{\text{cover}})$$  \hspace{1cm} (6)$$

The Jensen–Shannon divergence is bounded by 1 for two probability distributions, given that one uses the base 2 logarithm

$$0 \leq D_{JS}(P_{\text{stego}} \parallel P_{\text{cover}}) \leq 1$$  \hspace{1cm} (7)$$

when $P_s = P_c$, Jensen–Shannon divergence is zero.

In generative steganography, we can use this metric to evaluate which generator is closer to the real data distribution. It means that we can sample a security stego from the best generator. In fact, the generator in generative adversarial network [5] is trained based on the Jensen–Shannon divergence, the adversarial game make the divergence between generator distribution $p_s$ and data distribution $p_{data}$ is gradually reduced with the increasing of adversarial iteration. In generative steganography, $P_s, P_{\text{stego}}$ and $P_{\text{fake}}$ have the similar meaning, $P_{\text{cover}}$ is $p_{data}$. Since in our scheme, there is no explicit cover, we use $p_{data}$ instead of $p_{\text{cover}}$.

In [5], Goodfellow etc. train discriminative model $D$ to maximize the probability of assigning the correct label to both training examples and samples from $G$. They simultaneously train $G$ to minimize $\log(1 - D(G(z)))$. In other words, $D$ and $G$ play the following two-player minimax game with value function $V(G; D)$:

$$\min_G \max_D V(D, G) = E_{x \sim p_{data}}[\log D(x)] + E_{x \sim p_s}(x) [\log(1 - D(G(z)))]$$  \hspace{1cm} (8)$$

They also prove that this minimax game has a global optimum for $p_s = p_{data}$. For $G$ fixed, the optimal discriminator $D$ is

$$D^*_G(x) = \frac{p_s (x)}{p_s (x) + p_s (x)}$$  \hspace{1cm} (9)$$

The training criterion for the discriminator $D$, given any generator $G$, is to maximize the quantity $V(G; D)$

$$\min_G \max_D V(D, G) = \int p_{data}(x) \log(D(x))dx + \int p_s (x) \log(1 - D(G(z)))dx$$

$$= \int p_{data}(x) \log(D(x)) + p_s (x) \log(1 - D(x))dx$$  \hspace{1cm} (10)$$
The minimax game can be reformulated as:
\[
C(G) = \max_D V(G, D) \\
= E_{x \sim p_{data}} \left[ \frac{p_{data}(x)}{p_{data}(x) + p_g(x)} \right] + E_{x \sim p_g} \left[ \frac{p_g(x)}{p_{data}(x) + p_g(x)} \right]
\] (11)

The global minimum of the virtual training criterion \(C(G)\) is achieved if and only if \(p_g = p_{data}\). At that point, \(C(G)\) achieves the value - \(\log 4\).
\[
C(G) = -\log(4) + KL \left( \frac{p_{data} + p_g}{2} \right) + KL \left( p_g \ || \ p_{data} + p_g \right)
\] (12)

where \(KL\) is the Kullback–Leibler divergence. We recognize in the previous expression the Jensen–Shannon divergence between the model’s distribution and the data generating process:
\[
C(G) = \log 4 + D_{js}(p_{data}, p_g)
\] (13)

Since the Jensen–Shannon divergence between two distributions is always non-negative, and zero if they are equal, we have shown that \(C_* = -\log(4)\) is the global minimum of \(C(G)\) and that the only solution is \(p_g = p_{data}\), i.e., the generative model perfectly replicating the data distribution. If \(G\) and \(D\) have enough capacity, and at each step of adversarial game, the discriminator is allowed to reach its optimum given \(G\), and \(p_g\) is updated so as to improve the criterion then \(p_g\) converges to \(p_{data}\). In practice, adversarial nets represent a limited family of \(p_g\) distributions via the function \(G(z, \theta_g)\) and we optimize \(\theta_g\) rather than \(p_g\) itself.

Similar to Fridrich’s \(\varepsilon\)-security steganography, we define a \(\varepsilon\)-security for generative steganography system based on Jensen–Shannon divergence:
\[
D_\text{js}(p_{stego}, p_{data}) \leq \varepsilon
\] (14)

Ideally, when the generator is optimal, i.e., \(\varepsilon = 0\), the system could be regards as absolutely safe for statistical analysis in steganalysis. In generative steganography, we not only require the JSD between \(p_g\) and \(p_{data}\) is 0, but we also require the generator to satisfy the request for message extraction as shown in equation (2). Therefore, we consider generative steganography as a constrained image generation problem and take advantage of the recent advances in generative modeling.

### 3.3 Constrained Modification and Constrained Generation

Currently, the state-of-the-art methods of cover modification can be viewed as a constrained coding problem, which minimizing the distortion between cover and stego with Syndrome Trellis Coding (STC). The embedding and extraction mappings are realized using a binary linear code \(C\) of length \(n\) and dimension \(n - m\):
\[
\text{Ext}(\text{Emb}(x, m)) = m \ \forall x \in \{0,1\}^n, \ m \in \{0,1\}^m
\] (15)

\[
\text{Emb}(x, m) = \arg \min_{y \in C(m)} \text{D}(x, y)
\] (16)

\[
\text{Ext}(y) = H y
\] (17)

where \(x\) is cover, \(m\) denotes message, \(y\) is stego. \(\text{D}(x, y)\) is the distortion function. \(\text{Emb(.)}\) and \(\text{Ext(.)}\) denotes embedding and extraction operation. Embedding processing is an optimum problem to find a stego \(y\) that satisfying the message extraction condition and minimizing the distortion, simultaneously. The embedding problem can be optimally solved by the Viterbi algorithm. This implementations of steganography that lack a shared secret are forms of security through obscurity which is the reliance on
the secrecy of the design or implementation as the main method of providing security for a system or component of a system.

Similarly, we can give a representation of optimum problem for generative steganography.

\[
\text{Ext}(\text{Gen}(m, k), k) = m \quad \forall m \in \{0, 1\}^n
\]

(18)

\[
\text{Gen}(m, k) = \arg \min_{y \in \mathbb{Y}} D_{\text{js}}(p_{\text{stego}}, p_{\text{data}})
\]

(19)

\[
\text{Ext}(y, k) = C_k y
\]

(20)

where \( \text{Gen}(\cdot) \) is a generator. \( C_k \) is an extract matrix based on the secret key \( k \). Note that our generative steganography is a key-dependent steganographic scheme adhere to Kerckhoffs's principle. We will give the details of the \( C_k \) with a practical algorithm in the next section. This representation can be considered as a constrained image generation problem. It is important to note that an explicit cover \( x \) is unnecessary. Stego \( y \) does not depend on any specific cover, it is regarded as sampling from generator distribution \( p_p \). The emergence of the generative adversarial network makes the generative steganographic scheme will be more and more attention to how to ensure the accuracy of information extraction.

More specifically, we also formulate the process of finding stego \( y \) as an optimization problem. Let \( m \) be the message and \( k \) be the secret key shared by two parties. Using this notation we define the “closest” encoding \( \hat{y} \) via:

\[
\hat{y} = \arg \min_z \{ L_m(y | m, k) + \lambda L_p(y) \}
\]

(21)

where \( L_m \) denotes the message loss, which constrains the generated image given the message \( m \) and the extract key \( k \), \( L_p \) denotes the prior loss, which penalizes unrealistic images. The details of the proposed loss function will be discussed in the following sections.

Security analysis
In our design, to reach the global minimum of the loss \( \hat{y} \), we first train a DCGAN to eliminate the prior loss, i.e., to make sure \( L_p = 0 \). So far, we do not consider the message loss. As section 3.1 discussed, the training target of DCGAN is to reach the optimum state of \( C(G) \):

\[
C(G) = -\log(4) + D_{\text{js}}(p_{\text{data}}, p_{\text{cover}})
\]

(22)

In which \( C_* = -\log(4) \) is the global minimum of \( C(G) \) in the proposed scheme. It indicates \( p_{\text{stego}} = p_{\text{data}} \), i.e., \( L_p = 0 \).

Next, we keep DCGAN fixed to eliminate the message loss, i.e., to make sure \( L_m = 0 \). Back-propagation to the input data is introduced to optimize the coding of the input data \( z \) on DCGAN. The back-propagation based methods require specifically designed loss function. In this task, we use \( L1 \) distance as \( L_m \).

\[
z \leftarrow z - \gamma_z \nabla_z \left( L_m + \lambda L_p \right)
\]

(23)

\[
\nabla_z L = -\frac{\partial (L_m + \lambda L_p)}{\partial z}
\]

(24)

We iteratively update \( z \) using back-propagation by Eq. (23)-(24). After enough training iterations, the input data on DCGAN would get optimized to make the loss the minimum “0”.
4. Digital Cardan Grille

Before constructing the practical generative steganography algorithm, we can assume that a generator has already met $D_{JS}(p_{stego}, p_{data})=0$, and then we can focus on how to design a scheme to ensure that messages extracted correctly. In our previous work [21], a balance cannot be achieved between the visual distortion and the message extraction accuracy. In this paper, the message is written to the uncorrupted region that needs to be keep in the corrupted image, the stability of the message was guaranteed by the generator, the generator stop updating until the stego is natural enough.

![Diagram of the proposed method with Cardan grille.](image)

**Fig.2.** The proposed method with Cardan grille.

In our framework, as illustrated in Fig.2, the process of information hiding is in line with the basic idea of traditional Cardan grille. The sender defines a mask, called Digital Cardan grille, to determine where the message is hidden, and the secret messages go directly to these uncorrupted locations of the input image. Then, an image inpainting method based on GANs is used to finish the image completion. A well-filled image is transmitted to the recipient through the public channel. The receiver extracts a secret message using the Cardan grille shared by the two parties in the reconstructed image. The core of this method is to define generator that not only ensure the consistency of the secret messages but also the natural reality of the stego.

### 4.1 Message Preprocessing

In this paper, the process of generating stego is decomposed into two steps to simplify the designing. First of all, we define a expanding operation $E(.)$:

$$m' = E(m)$$  \hspace{1cm} (25)

The secret message $m$ by Cardan grille which is shared by both parties to a new expanded message $m'$ subject to follow constrain:

$$m = C(m', k)$$  \hspace{1cm} (26)

Then, we can get the stego carrier by:

$$s = G(m', k)$$  \hspace{1cm} (27)

We will show that this simple separation trick make it easier to build a generator.
Firstly, we select the secret input corrupted image $y$, message $m$, and Cardan grille $C_k$. It’s important to note the structure and location of this Cardan grille in the corrupted image are shared by both parties. Assume that the size of the corrupt region is $m \times n$, where $m = n = 64$ in Fig 3. Then a Cardan grille with same size is defined as:

$$C_k = \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mn} \end{bmatrix}$$ \hspace{1cm} (28)

Where $c_{ij} \in \{0, 1\}, C_k$ is the key that shared by both parties. A value of 1 represents the parts of the region we want to hide message and a value of 0 represents the parts of the image we cannot write message. Ideally, the Cardan grill is designed to have a $m \times n$ bit key, key length would coincide with the lower-bound on an algorithm’s security. Then the message can be written into the uncorrupted regions of the input image. We get a corrupted image contains secret message shown as $m'$. Note that $m = m' \odot C_k$, $\odot$ denotes the element-wise product operation. The preprocessing is so important that it will transform the image completion into steganography. In the next subsection, we will give the details for the image completion based on the GANs, which complete the generative steganography procedure.

### 4.2 Semantic Inpainting

As mentioned above, the image completion used for steganography should satisfy two objectives, one is the rationality of the complete image content, the other is the stability of the message. In this paper we use the a image inpainting method which proposed by Yeh [22] based on a Deep Convolutional Generative Adversarial Network (DCGAN)[14].

A binary mask $M$ is used for completion that has values 0 or 1. A value of 1 represents the parts of the image we want to keep and a value of 0 represents the parts of the image we want to complete. Suppose we’ve found an image from the generator for some that gives a reasonable reconstruction of the missing portions. The completed pixels can be added to the original pixels to create the reconstructed image $x$:

$$x_{\text{reconstructed}} = M \odot y + (1 - M) \odot G(z)$$ \hspace{1cm} (29)

The contextual and perceptual information in [22] are used for defining loss functions.

**Contextual Loss:** To keep the same context as the input image, make sure the known pixel locations in the input image $y$ are similar to the pixels in $G(z)$. We need to penalize $G(z)$ for not creating a similar image for the pixels that we know about. Formally, we do this by element-wise subtracting the pixels in
y from $G(z)$ and looking at how much they differ:

$$L_{contextual}(z) = \|M \odot G(z) - M \odot y\|_1$$  \hspace{1cm} (30)

where $\|\cdot\|_1$ is the $L_1$-norm. In the ideal case, all of the pixels at known locations are the same between $y$ and $G(z)$. Then $G(z)_i - y_i = 0$ for the known pixels $i$ and thus $L_{contextual}(z) = 0$.

**Perceptual Loss:** To recover an image that looks real, let’s make sure the discriminator is properly convinced that the image looks real. We’ll do this with the same criterion used in training the DCGAN:

$$L_{perceptual}(z) = \log(1 - D(G(z)))$$  \hspace{1cm} (31)

Contextual Loss and Perceptual Loss successfully predict semantic information in the missing region and achieve pixel-level photorealism.

**Message Loss:** The key of using image completion for information hiding is that the messages extracted by the Cardan mask $C_k$ should be as stable as possible. The pixel value of the corresponding position of the generated image is equal to the value of the secret message.

$$L_{message}(z) = \|C_k \odot G(z) - C_k \odot m\|_1$$  \hspace{1cm} (32)

In the ideal case, all of the pixels at hiding locations are the same between $m'$ and $G(z)$. Then $G(z)_i - m'_i = 0$ for the known pixels $i$ and thus $L_{message}(z) = 0$. In our particular case, $y = m'$, $C_k = M$. $L_{message}$ is the same as $L_{perceptual}$. In practice, for each 8 bits pixel point on each layer, we cannot guarantee that the generator will converge to the model that can successfully satisfying $L_{message}(z) = 0$. Intuitively, we believe that the lower bits are affected by the pixel generation, while the higher bits have a higher stability. We define a bit plane index (BPI = 1, ..., 8.) to indicate the layer where the message is located. Where, BPI=1 represents the lowest significant bit (LSB), and BPI=8 represents the most significant bit (MSB). The element-wise product $\odot$ is operated on the bit plane level.

We’re finally ready to find $\hat{z}$ with a combination of the all these losses:

$$L(z) \equiv L_{contextual&message}(z) + \lambda L_{perceptual}(z)$$  \hspace{1cm} (33)

$$\hat{z} = a r g\ min L(z)$$  \hspace{1cm} (34)

where $\lambda$ is a hyper-parameter that controls how important the perceptual loss are relative to the message loss.

### 4.3 Message Extraction

Message extraction for the receiver is simple, the basic process is as shown in the Fig.4 below:
The receiver will cover the grille directly on the image after reconstruction, and the secret message of the corresponding position can be obtained. The operation of extraction is as follows:

\[ m = x_{\text{reconstructed}} \odot C_k \]  

(35)

5 Experiments

In the following section we evaluate results qualitatively and quantitatively.

5.1 Datasets and Settings

We implemented our adversarial training scheme on the LFW datasets [23]: a database of face photographs designed for studying the problem of unconstrained face recognition. The data set contains more than 13,000 images of faces collected from the web. We use alignment tool to pre-process the images to be 64x64, as shown in Fig. 5. We used the DCGAN model architecture from Yeh et al. [22] in this work. I emphasize that we modify Brandon Amos’s implementation [24] for information hiding. 12000 samples are used for training DCGAN. Our setting of training parameters for image completion is same as the Brandon Amos’s. The size of grille is fixed as 64*64 which is same as the size of corrupted image. We intentionally randomize the secret message on all uncorrupted regions so that the stability of embedded messages can be given in a quantitative manner.

![Fig. 5. Aligned samples form b LFW database](image)

We test four random pattern masks different shapes of masks: 1) random pattern masks approximately 20% missing; 2) 50% missing masks (randomly horizontal or vertical); 3) 90% missing complete random masks.

5.2. Visual Comparisons

Our results are shown in Fig. 6, which demonstrate that our method can successfully predict the missing content with different random mask. It's important to emphasize that, in our experiment, Cardan grille was randomly generated, and, in all the places that we could hide, we wrote the message which is also randomly generated. It is important to note that stego generation (semantic inpainting in this case) is not trying to reconstruct the ground-truth image. The goal is to fill the hole with realistic content while hiding information. Even the ground-truth image is one of many possibilities.
Fig. 6. For each example, Column 1: Ground-truth image from the LFW dataset. Column 2: Images with random region missing (row 1: 20%, row2:50%, row3: 90% ). Column 3: Cardan grille mask . Column 4: Secret message .Column 5: Corrupted stego image with BPI = 1 . Column 6: Inpainting of column 5 by our method.

We also show the completion image generation process in Fig.7, and the number of iterations is from 20 to 2000. We sample 8 generative stego images form the generator. Note that we chose some ground-truth images in Fig.7 fall out of LFW database. As can be seen from the Fig.7, the meaningless serious corrupted image (90% missing) will be transformed into a sample from $p_x$. In the first few rounds of steps, the visual quality of generator output is low. It can be seen that the complemented image becomes more real as the number of iterations increases.

Fig. 7. For each example, Column 1: Ground-truth image from the dataset. Column 2: Stego corrupted images with random region missing 90% . Column 3-10 : Samples from the generator as the number of iterations increases.

Figure 8a and Figure 8b shows the message loss and perceptual loss of one image. All stego images are sampled at 500 iterations from corrupted images with 90% region missing. In Fig.8a, in the first few rounds of sampling, the visual quality of output is low, perceptual loss is high. After approximately 250 steps, perceptual loss makes the generated sample more realistic and natural. In Fig.8 b, message loss is relatively smooth and stable after 150 steps. This is mainly due to the fact that we keep message loss have more influence on the total loss.
We also present the results of the completion of the same image with different $\lambda$ values. It can be seen that, although the gap between the generative stego images are large at the beginning, the completion stego images tend to be the same as the number of iterations increases.

![Fig. 8. The message loss and perceptual loss.](image)

5.3. Quantitative Analysis

Due to the non-convexity of the models in the training scheme, we cannot guarantee that the generator will converge to the model that can successfully recover the secret message from the steganographic image perfectly. Fig. 10a shows the relationship between the error rate of the message extraction and the number of iterations with different BPI (1-8). As shown in Fig.8. We do the message embedding and extraction at different BPI for 1000 images which not belonging to the training set. All stego images are sampled at 3000 iterations from corrupted images with 90% region missing. As expected, the accuracy of message extraction increased with the increase of BPI. The receiver was able to recover more than 95% of messages sent by sender when BPI > 3. Our scheme can perfectly decode the secret encrypted message from the steganographic image at BPI = 8. In the Fig 10b, the relationship between the average error rate and BPI is given, compare with our work in [21], the stability of the message extraction is greatly improved.

![Fig. 9. Stego Generation for the same image. For each row, Column 1: Ground-truth image. Column 2: Stego corrupted images with random missing 90%. Column 3-10 : Samples as the number of iterations increases.](image)
We steganalyse our digital Cardan grille method using blind steganalyzer for spatial domain and the ensemble classifier. 686-dimensional SPAM features [25] and 5404-dimensional SCRMQ1 features [26] with ensemble classifiers [27] implemented as random forests are used for this experiment. Different from the traditional steganalyzer for cover modification method, all 1000 stego images and
1000 normal images are generated at 1000 iterations from corrupted images by the image inpainting. The database was divided randomly into two halves, one used for training and the other for testing. The performance is averaged over ten random splits. In Figure 11, we plot the progress of the testing error PE as a function of the payloads from 0.1bpp to 0.5bpp (bits per pixel) with BPI = 1.

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From the above experiments, it can be seen that the steganography based on sampling can resist the statistical analysis of the steganography, this is mainly due to the fact that, completed stego and normal images can be regarded as samples from the same distribution \( p_g \). The normal cover and stego does not have a pairwise relationship between the extracted features. As can be seen from the figure, our method has competitive performance with HUGO [28] and HILL [29] in the case of low embedding rate.

Figure 12 shows the average classification error PE achieved with five different BPI at 0.1bpp with 1000 iterations. As the bit plane index increases, the security of our method decreases on SCRMQ1 feature. SPAM feature does not work. This is mainly because SCRMQ1 is designed for color images, and SPAM is designed for grayscale images.

We also give the error rate for different iterations. This is shown in the Figure 13 below. After dozens of iterations, SPAM and SCRMQ1 features maintain consistent performance. Experiments show that the resistance to statistical analysis, does not mean that the image generation quality is good enough, in
fact, with the increase of the number of iterations, image visual distortion reduces gradually, as shown in Figure 9.

![Image](image.png)

**Fig. 13.** Steganalyzer error PE for an ensemble classifier with different iterations at 0.1bpp with BPI=3.

### 6 Conclusion and Future Work

In this paper, a generative steganography method is proposed, and stego images are sampled from a well-trained generator to resist the statistical analysis in steganalysis. Inspired by the idea of Cardan grille, a practical method of generative steganography is proposed by image completion technology. The results of the experiment and the experimental results verify the promising of such simple method. It reduces the sophistication of the steganography design, which allows researchers in other fields to quickly build a steganographic system under this framework.

However, the generator in adversarial network is actually in its infancy. In this paper, we use a simple DCGAN for image synthesis. We will focus on more powerful generator which automatic synthesis of realistic images from image or text, to generate more realistic images. It is necessary to continually refine the performance of the generator to ensure that the security of generative steganography.

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