A Brief Survey on Deep Learning Based Data Hiding

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Abstract

Data hiding is the art of concealing messages with limited perceptual changes. Recently, deep learning has enriched it from various perspectives with significant progress. In this work, we conduct a brief yet comprehensive review of existing literature for deep learning based data hiding (deep hiding) by first classifying it according to three essential properties (i.e., capacity, security and robustness), and outline three commonly used architectures. Based on this, we summarize specific strategies for different applications of data hiding, including basic hiding, steganography, watermarking and light field messaging. Finally, further insight into deep hiding is provided by incorporating the perspective of adversarial attack.

1 Introduction

Seeing is not always believing, *i.e.*, a natural-looking image can contain secret information that is invisible to the general public. Data hiding enables concealing a secret message within a transport medium, such as a digital image, and its essential property lies in *imperceptibility* for achieving the fundamental goal of being hidden. With easy access to the Internet and gaining popularity of the social media platform, digital media, such as image or video, has become the most commonly used host for secure data transfer in applications ranging from secret communication to copy-right protection. Data hiding schemes can be characterized by three requirements: i) *capacity*, regarding the embedded payload; ii) *security*, in terms of being undetectable by steganalysis; iii) robustness, against distortions in the transmission channel. There is a trade-off among the above three requirements [Kadhim et al., 2019; Zhang et al., 2020a], as depicted in Figure 1. For example, a large-capacity hiding algorithm is often subject to low security and weak robustness. We term the capacity-oriented task as "basic data hiding", which aims to hide more information given no extra constraint (except imperceptibility) is applied. Secure data hiding and robust data hiding, as the term suggests, prioritize security and robustness, respectively.



Figure 1: Trade-off among capacity, security and robustness for information hiding techniques.

However, their shared constraint still lies in being imperceptible for the human eyes.

Most traditional data hiding methods are carried out under a distortion-coding framework, which aims to minimize a particular distortion metric and allocate different distortions to different elements in the information carrier to embed hidden messages [Pevny et al., 2010; Holub and Fridrich, 2012; Holub et al., 2014]. With the increasing popularity of deep learning in recent years, numerous works apply deep neural networks (DNNs) to the task of data hiding. Early researches of applying deep learning into data hiding often adopt DNNs to substitute only a partial stage in the hiding-and-extraction pipeline [Husien and Badi, 2015; Kandi et al., 2017; Mun et al., 2017]. The trend is to train networks end-to-end for embedding as well as revealing information [Baluja, 2017; Zhu et al., 2018; Weng et al., 2019; Zhang et al., 2020a; Lu et al., 2021; Guan et al., 2022], as most of them are less cumbersome and outperform former methods in capacity, security and/or robustness by a large margin. In this work, we term deep learning based data hiding methods as *deep hiding*. It is an emerging and vibrant research area and has achieved significant progress, but there are relatively few systematic introductions on this field. We believe that it is necessary and valuable to conduct a brief yet comprehensive literature review about deep hiding.

In the remainder of this survey, we first present the formulation of deep hiding, followed by introducing the three basic architectures for the hiding-and-extraction pipeline. With the focus of adopting images as the carrier for information transfer, we conduct a complete survey on its applications, includ-

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ing i) large-capacity basic hiding, ii) secure steganography, iii) robust watermarking and iv) light field messaging, which place emphasis on different properties of data hiding. We further present a brief review on hiding a secret message within other multimedia beyond images. Finally, we discuss the link between deep hiding and another parallel line of research in the adversarial attack.

2 **Problem Formulation**

The *basic data hiding* considers a scenario of communication between two agents: Alice and Bob, where Alice is the sender and Bob is the recipient. Alice is responsible for concealing secret information (*secret*, S) within transport carrier (*cover*, C) and the result is a *container* (C') which is encoded to contain secret. Bob receives C' after a communication with Alice, and then the *revealed secret* (S') can be retrieved. These operations are described in Equation 1, where \mathcal{H} and \mathcal{R} are the hiding and reveal neural network in deep hiding, with $\theta_{\mathcal{H}}$ and $\theta_{\mathcal{R}}$ as their respective parameters.

$$C' = \mathcal{H}(S, C; \theta_{\mathcal{H}}); \quad S' = \mathcal{R}(C'; \theta_{\mathcal{R}}) \tag{1}$$

A key requirement of successful data hiding is *imperceptibility* for hiding and *precision* for revealing, *i.e.*, simultaneously minimizing the differences between C and C' and that between S and S':

$$\theta_{\mathcal{H}}^{*} = \arg\min_{\theta_{\mathcal{H}}} dist_{c}(C, C')$$

= $\arg\min_{\theta_{\mathcal{H}}} dist_{c}(C, \mathcal{H}(S, C; \theta_{\mathcal{H}})),$ (2)

$$\theta_{\mathcal{R}}^{*} = \arg\min_{\theta_{\mathcal{R}}} dist_{s}(S, S')$$

= $\arg\min_{\theta_{\mathcal{R}}} dist_{s}(S, \mathcal{R}(C'; \theta_{\mathcal{R}})),$ (3)

where $dist_c(\cdot)$ and $dist_s(\cdot)$ are the metrics of distances between two distributions. L2 distance is the most widely used one and cross-entropy loss is widely used as $dist_s(\cdot)$ when Sis in the form of binary bits. One commonly used loss for optimization is defined as $\mathcal{L} = ||C' - C|| + \beta ||S' - S||$ [Baluja, 2017], where β is a weight factor for balancing imperceptibility and precision. A higher β often results in a higher quality of the retrieved secret at the cost of lower quality for the container. Alternatively, L1 distance, PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index Measure) [Hore and Ziou, 2010] and LPIPS (Learned Perceptual Image Patch Similarity) [Zhang *et al.*, 2018] are also adopted commonly associated with L2 distance to evaluate perceptual quality [Zhang *et al.*, 2020a].

In secure data hiding, there is a new participant who plays as an adversary of Alice and Bob by distinguishing containers from covers by a steganalyzer \mathcal{A} . An effective algorithm with high security is expected to confuse \mathcal{A} such that it cannot perform better than a random guess, *i.e.*, the confidence score of an image being C or C' is approximately equal to each other:

$$|\mathcal{A}(\mathcal{H}(S,C;\theta_{\mathcal{H}})) - \mathcal{A}(C)| < \epsilon, \tag{4}$$

where ϵ is a sufficiently small positive number.

In *robust data hiding*, the adversary perturbs containers with distortions to destroy secret information within them. A robust scheme should maintain secret information even after container C' is attacked by a noise attacker (denoted as \mathcal{N}):

$$\min_{\theta_{\mathcal{H}},\theta_{\mathcal{R}}} dist_s(S, \mathcal{R}(\mathcal{N}(C'); \theta_{\mathcal{R}})).$$
(5)

3 Deep Hiding Architectures

Deep steganography [Baluja, 2017; Baluja, 2019] defines a new task of hiding a full image in another. This task is different from traditional steganography that requires perfect decoding of secret messages. Instead, the goal is to improve the image quality for the retrieved secret image by minimizing $dist_s(S, S')$. Moreover, the hiding capacity of traditional steganography is often very low, *e.g.*, HUGO [Pevnỳ *et al.*, 2010] hides < 0.5 bpp (bits per pixel), while that for deep steganography [Baluja, 2017] is 24bpp. Due to the trade-off between capacity and secrecy, most deep steganography can be relatively easily detected by some steganalysis algorithms. Thus, to make a distinction, this kind of capacity-oriented task is termed "basic data hiding" in this survey, instead of "steganography".

In terms of how C and S are processed as the input of hiding network \mathcal{H} , we summarize three basic architectures which can be directly applied for the task of *basic* data hiding. Meanwhile, these architectures can be extended to other applications including steganography, watermarking and light field messaging by adding some targeted strategies.

Cover-Dependent Deep Hiding with Preparation. The first deep learning based framework for hiding data in large capacity is proposed by Baluja [2017; 2019], which places a full-size color image within another image of the same size. Specifically, it has three networks: preparation, hiding and reveal network in Figure 2(a). The preparation network (\mathcal{P}) is adopted to transform secret images S into features that are commonly useful for compressing images, such as edges and orthogonal components. The hiding network takes the concatenated cover image C and *prepared* secret image $\mathcal{P}(S)$ as the input. With the reveal network, recipients can retrieve the secret image S' from the container image C'. In Figure 2(a), how a secret image is encoded is dependent on the cover image. Thus, following the terminology in [Zhang et al., 2020a], we call it cover-dependent deep hiding, or DDH in short, architecture. Specifically, it also has an additional network \mathcal{P} , thus this kind of architecture is termed DDH with P in this survey.

Cover-Dependent Deep Hiding without Preparation. Despite being conducive to embedding analysis, preparation network \mathcal{P} complicates the entire pipeline and requires much more GPU memory [Wu *et al.*, 2018]. Later works [Weng *et al.*, 2019; Mishra *et al.*, 2019; Zhang *et al.*, 2020a] show that \mathcal{P} is not necessary and can be combined with hiding network into a single network [Baluja, 2019]. Excluding \mathcal{P} network results in a simpler DDH, *i.e.*, **DDH without P**, in Figure 2(b). As it is the most commonly adopted architecture for deep hiding, the methods mentioned later belong to **DDH without P** without special explanation.

Universal Deep Hiding. Further, [Zhang *et al.*, 2020a] proposes a new architecture termed Universal Deep Hiding



Figure 2: Schematic diagram for three basic architectures in the form of hiding images within images, where P, H and R represent preparation, hiding and reveal network respectively.

(UDH). The key difference between UDH and DDH is that UDH disentangles the encoding of secret from cover, *i.e.*, how the secret image is encoded is independent of the cover image. This disentangling facilitates the visualization of the encoding operation of secret images and their results show that secret images are encoded into repetitive high-frequency components. The encoded secret image in UDH can be directly added to any random cover image to form a container, which enhances the flexibility of information hiding. Based on this UDH architecture, [Zhang *et al.*, 2020a] shows the success of hiding M (6 for instance) image in N (3 for instance) images. The universal property of UDH also makes it efficient for watermarking, because it only requires a single summation, which is a noticeable advantage when a large number of images need to be watermarked.

4 Applications of Deep Hiding

4.1 Large-Capacity Basic Hiding

Increasing the capacity of data hiding easily leads to contour artifacts and color distortion [Guan *et al.*, 2022], which makes the goal of remaining imperceptible a non-trivial challenge. The high payload of a certain method is often demonstrated by simultaneously hiding multiple images into one image of the same size. Alternatively, independent pixelwise sources for supplementary information, such as depth and motion, are also proper choices to take full advantage of extra capacity [Baluja, 2019]. A simple and widely used implementation to hide multiple images is to concatenate them along the RGB channel, and treat the concatenated tensor as an integrated secret S for the network input [Baluja, 2019; Zhang *et al.*, 2020a; Lu *et al.*, 2021].

The primal motivation to hide multiple images in [Baluja, 2019] is to obfuscate the remnants of the hidden image in the container. However, significant color distortion occurs when hiding 2 images. Thanks to the cover-independent property for secret embedding, UDH in [Zhang *et al.*, 2020a] can hide M secret images into N cover images, where embedding space is not limited to the RGB channels in one image.

By training multiple pairs of \mathcal{H} and \mathcal{R} , UDH can also hide multiple secret images within one image, but the specific secret can only be revealed by the corresponding \mathcal{R} , *i.e.*, different recipients get different secret messages from the same cover. [Lu *et al.*, 2021] and [Jing *et al.*, 2021] adopt invertible neural network to archive high capacity, where \mathcal{H} and \mathcal{R} share the same parameters. However, considering the simple concatenation neglects the correlation between secret images, follow-up DeepMIH [Guan *et al.*, 2022] hides multiple secret images in series, *i.e.*, the concealing result of the previous image can assist the current concealing to improve the overall hiding performance for hiding multiple images.

4.2 Secure Steganography

Steganography deals with hiding information imperceptibly and *undetectably*, while steganalysis plays as its adversary by detecting the potentially hidden information from observed data with little or no knowledge about the hiding algorithm. Steganography and steganalysis defeat but also enhance each other.

Generally speaking, to archive being undetectable for steganalysis, targeted designs are required. Some methods that are not specifically designed for steganography also conduct steganalysis evaluation in their works. Most of them can not be detected by classic steganalysis tools (e.g., StegExpose [Boehm, 2014], which combines several traditional steganalysis techniques), but fail when facing deep learning based steganalyzer. To be specific, when facing one of the state-of-the-art steganalyzer SRNet [Boroumand et al., 2018], the detection accuracy for [Baluja, 2017], [Weng et al., 2019], [Lu et al., 2021] and [Guan et al., 2022] is 99.58%, 77.43%, 75.69% and 75.54%, respectively [Guan et al., 2022]. The accuracy closer to 50% (random guess) indicates a higher security level. It is worth noting that the SRNet steganalysis accuracy for HiNet [Jing et al., 2021] is reported as 55.86%, which indicates that C' of HiNet is nearly indistinguishable from nature cover images. This is mainly attributed to their proposed low-frequency wavelet loss which makes the lowfrequency sub-bands of C' and C similar to each other.

Adversarial Architecture

On account of the undetectability of secure steganography, the above three architectures cannot be directly applied. Hence, *adversarial architecture* is widely adopted to enhance security and visual quality [Hayes and Danezis, 2017]. The core of an adversarial architecture lies in an adversarial model where containers and covers are fed in, and form a 3-player game. The adversarial model can be either fine-tuned from an off-the-shelf steganalysis network [Xu *et al.*, 2016; Ye *et al.*, 2017], or assumed to be a regular convolutional neural network (CNN) [Zhang *et al.*, 2019a; Weng *et al.*, 2019] or similar structure to reveal network [Zhu *et al.*, 2018; Hayes and Danezis, 2017]. The work of Hayes and Danezis [2017] has shown that supervised training of the adversarial model can produce a robust steganalyzer.

As mentioned above, an adversarial architecture can be obtained simply by incorporating an additional steganalysis classifier in the basic architecture, *e.g.*, [Weng *et al.*, 2019; Zhang *et al.*, 2019c; Yedroudj *et al.*, 2020], which increases the resistance to steganalysis by adding an adversarial discriminator. However, this does not indicate that these methods can counter independently trained steganalyzers because the adversarial training strategy limits the effectiveness of the discriminator [Shang *et al.*, 2020].

Note that the adversarial network is *not* exclusively applied for security. It also helps improve the container image visual quality as well as robustness for watermarking or light field messaging [Zhu *et al.*, 2018; Liu *et al.*, 2019; Tancik *et al.*, 2020; Jia *et al.*, 2020; Plata and Syga, 2020]. Based on the adversarial architecture, the attention idea has been investigated in [Zhang *et al.*, 2019b; Yu, 2020] for biasing the mode towards hiding secrets in textures and objects that are less affected by transformations or areas that are inconspicuous to the human observer, resulting in higher robustness as well imperceptibility.

Synthesis Technology

Another interesting research direction of deep hiding for secure steganography is synthesis technology. Different from the embedding-based schemes mentioned above, there is no modification operated in synthesis technology, because containers are generated directly based on secret messages [Hu et al., 2018]. First, it derives a generator in deep convolutional generative adversarial nets (GANs) to synthesize images with random noise vectors. Second, an extractor network learns to reveal the corresponding vector fed into the generator. Finally, with the fixed generator and extractor from previous steps, Alice and Bob can have an undetectable secret communication by mapping secret messages into vectors prior to synthesis. The steganographic embedding operation becomes an image sampling problem in [Zhang et al., 2019d] and containers are sampled by a well-trained generator. While Zhang et al. [2020b] establish a mapping relationship between secret message and semantic category for a generation. In contrast to [Hu et al., 2018; Zhang et al., 2019d] that divide the training process into several steps and the extractor is trained outside the adversarial training, [Wang et al., 2018; Li et al., 2020] synchronize the training of extractor and generator, leading to superior performance and training efficiency. SSteGAN proposed in [Wang *et al.*, 2018] can also be defined as adversarial architecture since there is a steganalyzer in its system.

4.3 Robust Watermarking

Compared with capacity and security, digital watermarking prioritizes robustness. Thus, it often contains a well-designed module or adopts special techniques to enhance robustness.

Data Augmentation Approach

It is widely known that a well trained deep classifier can have a non-trivial performance drop under the perturbation of noise. One straightforward approach to improve robustness against a specific type of noise is to perform data augmentation with such noise during the training. Inspired by this, one intuitive and commonly used strategy to resist noise attack for robust watermarking is to simulate such distortions in the training process, *i.e.*, distorting containers with the respective attacks before feeding them to the reveal network [Zhu et al., 2018]. In practice, the attack might occur in different forms, thus it is of high practical relevance to make the hiding pipeline robust against various types of image distortions. To this end, HiDDeN [Zhu et al., 2018] applies a single type of noise in a mini-batch and swaps it in each iteration. ReDMark [Ahmadi et al., 2020] adopts a similar approach by choosing one type of attack with a given probability in every iteration. This simple approach has been shown effective to achieve a reasonable robustness performance. Zhang et al.[2020a] introduces one simple change to this approach by dividing the mini-batch equally into multiple groups, each group applying one type of image distortion. This dividing strategy facilitates simultaneously applying all the investigated image distortions in every iteration, resulting in faster convergence as well as a significant performance boost. Compared with the swapping strategy adopted in [Zhu et al., 2018; Ahmadi et al., 2020], the dividing strategy does not cause any additional computation overhead and thus can be seen as a "free" technique to improve the performance.

Advances on Handling Non-Differentiable Compression

For reducing the bandwidth or traffic to facilitate the storage and transmission, most images/videos are often preprocessed with lossy compressions, such as JPEG or MPEG. Especially, JPEG, the most popular lossy compression for images, is often considered the most common attack against watermarking. However, it is a non-trivial task to improve the robustness against JPEG compression, because it is a non-differentiable operation, which hinders training \mathcal{H} and \mathcal{R} jointly. HiDDeN [Zhu *et al.*, 2018] has attempted to simulate the JPEG compression with JPEG-Mast and JPEG-Drop. Inspired by the fact that JPEG mainly discards the highfrequency component, JPEG-Mask keeps only low-frequency DCT coefficients with fixed masking and JPEG-Drop adopts a progressive dropout on the coefficients, *i.e.*, having a higher probability to drop high-frequency coefficients. Due to the mismatch between the simulated JPEG and real JPEG, there is a significant performance drop under real JPEG. ReD-Mark [Ahmadi et al., 2020] attempts to address this challenge by carefully designing a series of differentiable functions for mimicking every step of real JPEG compression. Similar approach has been adopted in [Luo *et al.*, 2020]. Such an approach has two limitations: i) it requires full knowledge of the attack, which is the case for JPEG attack but might not be true for other types of attacks; ii) it requires a careful engineering design of various differentiable functions to mimic the real attack, which might still fail for a real attack.

To address this challenge, [Liu *et al.*, 2019] proposes a two-stage separable deep learning framework. In the first stage, the encoder \mathcal{H} and decoder \mathcal{R} are trained simultaneously without noise, resulting in a powerful redundant-coding encoder. In the second stage, the pre-trained encoder obtained from the first stage is fixed and the loss back-propagates only through the decoder. This alleviates the non-differentiability concern because the loss does not need to back-propagate through the encoder A limitation of this two-stage approach is that the encoder is trained without JPEG compression, thus it is a sub-optimal solution compared with jointly training the \mathcal{H} and \mathcal{R} with JPEG compression.

Due to the non-differentiability of JPEG compression, jointly training the encoder and decoder seems to be a non-trivial task. A recent work [Zhang *et al.*, 2021b] proposes one elegant pseudo-differentiable approach that treats the JPEG compression as a special noise. A unique property of their approach is that the forward path and backward path are not the same. Specifically, the backward propagation does not go through the JPEG compression part. In essence, this approach is similar to the above noise augmentation approach but mitigates the non-differentiability issue by a plus and minus operation. This approach achieves the SOTA performance for robustness against JPEG attack and has also been shown to provide satisfactory performance for video compression.

Adversarial Training Inspired Approaches

To improve the robustness against unknown distortions, [Luo et al., 2020] proposes to combine the known distortions with adversarial perturbation which constitutes the worst perturbation. Such a min-max approach is inspired by another line of research on adversarial training for improving the deep classifier robustness against adversarial attack. The effect of adversarial training on the robustness against common corruptions has been investigated in [Luo et al., 2020], which shows that it improves the robustness against noise-type perturbation at the cost of performance drop for some known distortions. For example, the known Crop and Gaussian Blur distortion have a non-trivial performance drop [Luo et al., 2020]. A similar approach has also been explored in [Wen and Aydore, 2019], which selects the predefined distortion type and strength adaptively through maximizing the loss for the decoder. Both [Luo et al., 2020] and [Wen and Aydore, 2019] formulate the watermarking robustness as a min-max optimization problem and their key difference is that [Luo et al., 2020] generates an adversarial perturbation through a DNN, while [Wen and Aydore, 2019] selects it from a fixed pool of common distortions.

4.4 Light Field Messaging

As a practical application for data hiding, light field messaging (LFM) [Wengrowski and Dana, 2019] describes the process of embedding, transmitting and receiving hidden information in an image displayed on a display screen and captured by a camera. The LFM process is also often termed screen-camera communication [Cui et al., 2019] or photographic steganography but has no concern of being detected by steganalysis. Instead, the challenge of this task lies in the robustness against image transformations induced by the light effect which can be seen as a mixed influence of electronic display characteristics, camera exposure and camera-display angle. In essence, it is very similar to robust watermarking, but the goal is to transmit useful information instead of proving the ownership. [Wengrowski and Dana, 2019] found that directly applying the DDH architecture without taking the light effect leads to total failure of extracting the hidden barcode information. To this end, they collect a huge (1.9TB) dataset of camera-captured images from 25 cameradisplay pairs and then trains a camera-display transfer function (CDTF) to mimic the distortion caused by light field transfer. However, it requires lots of resources for training on such a huge dataset, and its performance is not satisfactory, especially for the unknown camera-display pairs.

To address the above disadvantages, StegaStamp [Tancik et al., 2020], extending the application also to printed images, proposes to augment the container images with a mixture of image transformations, such as perspective warp, motion/defocus blur, color manipulation, noise as well as JPEG compression. Moreover, their approach requires a relatively complex weighted loss that has L2 residual regularization, perceptual loss, critic loss and cross-entropy loss for the message. Such a complex loss requires a careful choice of the hyper-parameters. Zhang et al. [2020a] provides a much simpler solution based on the proposed UDH. Specifically, they adopt only the perspective warp as the image transformation and the same simple loss for basic data hiding in [Baluja, 2017] can be directly used. This simple approach yields competitive performance and the reason has been attributed to the fact that UDH is more robust against perturbation on the container images, especially for the constant pixel value shift, like color change. Moreover, UDH is more versatile in the sense that it can also hide a secret image, while [Wengrowski and Dana, 2019] and [Tancik et al., 2020] can only hide limited binary information. Concealing information in vector drawings such as SVG files has also been explored in Deep-Morph [Rasmussen et al., 2020] with the artistic freedom to convey information via their own designed drawings, but it's not as versatile as UDH that can hide all kinds of images, including natural images. RIHOOP [Jia et al., 2020] incorporates a distortion network based on differentiable 3D rendering to better simulate realistic distortions introduced by camera imaging. It would be an interesting direction to combine the techniques in RIHOOP [Jia et al., 2020] and UDH [Zhang et al., 2020a] for future research to achieve the purpose of being both robust and versatile.

5 Hiding Data within Other Multimedia

The master branch of research on data hiding adopts images as information carrier to hide either binary messages [Hayes and Danezis, 2017; Zhu *et al.*, 2018; Liu *et al.*, 2019; Tancik *et al.*, 2020] or natural images [Baluja, 2017; Wengrowski and Dana, 2019; Zhang *et al.*, 2020a; Yu, 2020]. Nonetheless, there are also a variety of other multimedia that can be adopted, such as video, audio and text. The basic architectures and strategies for improving security and robustness mentioned before are suitable for other forms of carriers. However, some adaptive approaches might be necessary according to the characteristics of these multimedia.

In essence, video can be seen as a sequence of images, thus the framework of hiding an image in another can be easily extended to the new task of hiding videos in videos by encoding each frame of the secret video within that of the cover video in a sequential manner. However, this naive approach does not exploit the temporal redundancy within the consecutive frames, since the residual between two consecutive frames is highly-sparse. To this end, Weng *et al.* [2019] propose a straightforward solution that contains two branches: one for the benchmark secret frame reference and the other for the frame residuals. By dividing the video into frame groups each containing 8 frames, [Mishra *et al.*, 2019] exploits 3D-CNN to hide 8 frames within 8 frames via exploiting the motion relationship between consecutive frames.

Hiding audio in audio has been demonstrated in [Kreuk et al., 2019]. It has been found that the framework for hiding images in images is suitable for the audio domain but requires including a short-time Fourier transform and inversetime transform as differentiable layers during the training. Deep learning has also been applied in cross-modal hiding applications, such as hiding images or video in audio, with favourable performance. Taking advantage of the serialization feature of audio, Cui et al. [2020] present a method for hiding image content within audio carriers by multi-stage hiding and reveal networks. They progressively embed multilevel residual errors of the secret image into cover audio in a multi-stage hiding network. Subsequently, the decreasing residual errors from the modified carrier are decoded with corresponding stage sub-networks and added together to produce the final revealed result. Yang et al. [Yang et al., 2019a] provide a different approach for this cross-modal task of hiding video in audio, which is practically challenging because of the high bitrate of video files. One of its potential drawbacks is that the reveal stage also needs access to the original clean audio.

Data hiding in text is also a broad research direction. Different from those generative methods [Yang *et al.*, 2018; Yang *et al.*, 2019b], Abdelnabi *et al.* [2020] introduce the Adversarial Watermarking Transformer (AWT) with a jointly trained encoder-decoder and adversarial training. With an input text and a binary message, the watermarking system can generate an output text that is unobtrusively modified with the given message. It is worth mentioning that text data hiding is highly related to the field of natural language processing.

6 Link with Adversarial Attack

A Small Change Makes a Big Difference. In essence, the container image is just a cover image with an imperceptible change. The reveal network is very sensitive to such small invisible changes. In other words, there is a misalignment be-

tween human vision and DNNs. Such misalignment has also been observed in another line of research on the adversarial attack, where an imperceptible perturbation can fool the deep classifier with high confidence.

Recently, Zhang et al. [2021a] has performed a joint investigation of such misalignment phenomenon in both tasks, providing a unified Fourier perspective on why such small perturbation can dominate the images in the context of universal attack and hiding. The reason for the misalignment has been attributed to the fact that DNNs are sensitive to highfrequency content [Zhang et al., 2021a] with the observation that frequency is a key factor that influences the performance for both tasks. The joint investigation of deep learning based watermarking and adversarial attack has also been previously explored in [Ouiring et al., 2018], with a unified notion of black-box attacks against both tasks, the efficacy of which is demonstrated by applying the concepts from adversarial attack to watermarking and vice versa. For example, countermeasures in watermarking can be utilized to defend against some model-extraction adversarial attacks and the techniques for improving the model adversarial robustness can also help mitigate the attacks against the watermarking [Quiring *et al.*, 2018]. Moreover, the lesson in multimedia forensics has also been found useful for facilitating the detection of adversarial examples [Schöttle et al., 2018]. On the other hand, adversarial machine learning against watermarking has also been explored in [Quiring and Rieck, 2018], adopting a neural network to detect and remove the watermark. It is worth mentioning that adversarial training techniques for improving adversarial robustness have also been investigated in [Luo et al., 2020] for improving the deep learning based watermarking robustness against unknown distortion, as discussed in Sec. 4.3.

Overall, there exists a unified Fourier perspective [Zhang *et al.*, 2021a] on the success of deep hiding and attack. Meanwhile, techniques from watermarking are often found effective in adversarial attack, vice versa [Quiring *et al.*, 2018]. A single universal secret adversarial perturbation has also been demonstrated in [Zhang *et al.*, 2021a] to perform an attack while containing a secret message simultaneously. However, the joint investigation of them is still in its infancy and we believe it is an interesting direction to perform deep analysis of them together for both theoretical and practical relevance.

7 Conclusion

Deep hiding has become an emerging field to attract significant attention. Our work conducts a brief yet comprehensive survey on this topic by first classifying data hiding by its essential properties and outlining three basic architectures. Moreover, we discuss the challenges of deep hiding in various applications, including large-capacity basic hiding, secure steganography, robust watermarking and light field messaging. For completeness, we also summarize hiding data within other multimedia content. Finally, we discuss its impact on the field of adversarial attack and vice versa. A joint investigation of data hiding and adversarial attack will be an interesting direction with potential new insights.

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