A Brief Survey on Deep Learning Based Data Hiding, Steganography and Watermarking

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Abstract

Data hiding is the art of concealing messages with limited perceptual changes. Recently, deep learning has provided enriching perspectives for it and made significant progress. In this work, we conduct a brief yet comprehensive review of existing literature and outline three meta-architectures. Based on this, we summarize specific strategies for various applications of deep hiding, including steganography, light field messaging and watermarking. Finally, further insight into deep hiding is provided through incorporating the perspective of adversarial attack.

1 Introduction

Seeing is not always believing, \textit{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, copy-right protection to content authentication. Data hiding schemes are characterized by three requirements: capacity regarding the embedded payload, security in terms of being undetectable by steganalysis, robustness against distortions in the transmission channel. There is a trade-off among the above three requirements, namely capacity, security and robustness [Kadhim \textit{et al.}, 2019; Zhang \textit{et al.}, 2020a] as depicted in Figure 1. For example, a hiding algorithm that is capacity-oriented is often subject to low security and robustness. Generally speaking, data hiding aims to hide more information given no extra constraint is applied. Secure steganography and robust watermarking, as the term suggests, prioritize security and robustness, respectively. Most traditional data hiding methods are carried out under the distortion-coding framework, which allocates different distortions to different cover elements and uses STC/SPC with approximate rate-distortion bound performance to embed messages. Recently, deep learning techniques are introduced into this framework, such as distortion learning [Yang \textit{et al.}, 2019b], secure image generation [Zhang \textit{et al.}, 2018].

Early researches [Husien and Badi, 2015; Kandi \textit{et al.}, 2017; Mun \textit{et al.}, 2017; Zhang \textit{et al.}, 2018] of applying deep learning into data hiding often adopt the DNNs to substitute only a partial stage in a larger pipeline and the trend is to train networks end-to-end for the encoding and decoding pipeline. It is an emerging and vibrant research area and has achieved significant progress that often outperforms traditional methods by a large margin [Zhu \textit{et al.}, 2018], but there are few systematic introductions on this field. Hence, we believe it is necessary and valuable to conduct a brief yet comprehensive literature review about deep learning based data hiding.

This work first presents the formulation of deep hiding, followed by discussing the multiple basic meta-architectures. With the focus of hiding a secret message in the image carrier, we conduct a complete survey on its three applications, namely secure steganography, light field messaging, and robust watermarking. We further briefly present a review on the hiding a secret message within other multimedia beyond image carriers. Finally, we discuss its link with another parallel line of work in adversarial attack.

2 Problem Formulation

The basic data hiding considers a scenario of secret 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 medium (cover, $C$) and the result is a container ($C'$) which is an encoded medium that contains secret. Bob receives $C'$ out from which the secret message can be retrieved, i.e. the revealed secret ($S'$). These operations are shown in Equation 1, where $H$ and $R$ are the hiding and reveal neural network respectively. $\theta_H$ and $\theta_R$ are their parameters.

$$C' = H(S, C; \theta_H); \quad S' = R(C'; \theta_R)$$  \hfill (1)

For secure steganography and robust watermarking, there is a new player named Eve who plays as an adversary of Alice and Bob and attempts to distinguish containers from covers by a steganalyzer $A$ in secure steganography, or perturb the containers with distortions, indicated as noise attacks $N$, to destroy secret information in watermarking.

The basic requirement of successful deep hiding is imperceptibility, i.e. minimizing the differences between $C$ and $C'$ and that between $S$ and $S'$ simultaneously:

$$\theta_H = \arg \min_{\theta_H} \text{dist}_C(C, C')$$
$$= \arg \min_{\theta_H} \text{dist}_C(C, H(S, C; \theta_H))$$  \hfill (2)

$$\theta_R = \arg \min_{\theta_R} \text{dist}_S(S, S')$$
$$= \arg \min_{\theta_R} \text{dist}_S(S, R(C'; \theta_R))$$  \hfill (3)

where $\text{dist}_C(\cdot)$ and $\text{dist}_S(\cdot)$ are the metrics of distances between two distributions. They are crucial in deep hiding as they guide the direction of neural networks’ training convergence. L2 distance is the most widely used one. One commonly used optimization loss is defined as $L = ||C' - C||_2 + \beta ||S' - S||_2$, where $\beta$ is a weight factor for balancing the parts. A higher $\beta$ often results in a higher quality of the retrieved secret at the cost of lower quality for the container. Alternatively, L1 distance, SSIM and LPIPS are also adopted commonly associated with L2 distance to evaluate perceptual quality [Zhang et al., 2020a]. For secret messages in the form of binary bits, the cross-entropy loss is widely used.

A steganography algorithm with high security is expected to confuse $A$ such that it cannot perform better than random guess, i.e. the confidence score of an image being $C$ or $C'$ is approximately equal to each other:

$$|A(H(S, C; \theta_H)) - A(C)| < \epsilon$$  \hfill (4)

where $\epsilon$ is a sufficiently small positive number. A robust scheme applied for robust watermarking should maintain secret information even after container $C'$ is attacked by $N$:

$$\min_{\theta_H, \theta_R} \text{dist}_s(S, R(N(H(S, C; \theta_H)); \theta_R))$$  \hfill (5)

### 3 Deep Hiding Meta-Architectures

Deep steganography introduced in [Baluja, 2017] 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. In other words, the secret image does not require perfect decoding, but the gap between the retrieved and original secret image needs to be minimized. Moreover, the hiding capacity of traditional steganography is often low, e.g. HUGO hides $< 0.5$ bpc (bits per pixel), while that for deep steganography is 24bpc. Due to the trade-off between capacity and secrecy, deep steganography can be easily detected by some steganalysis algorithms. Thus, this kind of task is called “data hiding” roughly, instead of “steganography”, to make a distinction.

We can generalize three plain meta-architectures from the existing researches, which can directly applied for the task of data hiding. Meanwhile, these meta-architectures can be extended to other applications including steganography, light field messaging and watermarking by some targeted strategies.

The first framework for hiding an image in another is proposed by Baluja [2017; 2019]. Specifically, it has three networks: preparation, hiding and reveal network in Figure 2 (a). The preparation network ($P$) is adopted to transform the secret image $S$ 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 images as the input. With the reveal network, the recipient can retrieve the secret image, i.e., \( S' \) from the container image \( C' \). In Figure 2 (a), how secret image is encoded in container image 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, meta-architecture. Specifically, it also has an additional \( P \) network, this kind of architecture is called DDH with \( P \) in this survey. Later works [Weng et al., 2019; Mishra et al., 2019; Zhang et al., 2020a] show that \( P \) is not absolutely necessary. Excluding \( P \) network results in a more simple DDH, i.e., DDH without \( P \) in Figure 2 (b). Further, [Zhang et al., 2020a] proposes a new meta-architecture termed Universal Deep Hiding (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 eases 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 meta-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 merit when watermarking a large number of images.

4 Applications

4.1 Secure Steganography

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

Deep Learning Based Steganalysis

Before introducing deep learning based secure steganography, it’s necessary to have a review on deep learning based steganalysis techniques. The schemes of steganalysis based on deep learning have drawn lots of attention in recent years. Tan and Li [2014] propose the first shallow CNN structure for image steganalysis, but it is inferior to SRM [Fridrich and Kodovsky, 2012], a powerful traditional detector. Later, Qian et al. [2015] design a customized CNN named GNCNN (Gaussian Neural CNN) based on a pre-processing with KV kernel and a Gaussian activation function. Their model achieves comparable performance compared to SRM on BOSSbase and ImageNet datasets and demonstrates transfer learning is beneficial for steganography detection with a low embedding rate. Following the study of [Qian et al., 2015], Pibré et al. [2016] achieve better detection accuracy when reusing the same embedding key for different images but worse performance when considering an unlike key for each embedding. Meanwhile, they verify the generalization ability of CNN on different datasets, i.e., a deep learning based steganalysis model can have good performance even though the test dataset comes from a different distribution of the training dataset. XuNet proposed in [Xu et al., 2016] is the first deep learning framework whose detection accuracy outperforms SRM by adopting a deeper neural network and using batch normalization and pooling layers in the structure. As a milestone for steganalysis in 2017, YeNet [Ye et al., 2017] achieves superior performance than classic SRM on re-sample and cropped image dataset. Rather than a random strategy, the weights in the first layer of YeNet are initialized with the basic high-pass filter set used in the calculation of residual maps in a SRM, which acts as a regularizer to suppress the image content effectively. Moreover, a new activation function is adopted to better capture the structure of embedding signals. To better capture embedding artifacts, [Li et al., 2018] propose to process information diversely with a module called diverse activation module and build a wide structure with parallel subnets using several filter groups for preprocessing. Compared to the methods mentioned above that are all designed for gray-scale images, Li et al. [2019] propose a wide-and-shallow, separate-then-reunion network structure named WISERNet for color images steganalysis. Recently, You et al. [2020] focus on addressing the issue of applying steganalysis to images of arbitrary size by exploring the possibility of exploiting a network for steganalyzing images of varying sizes without retraining its parameters. SRNet [Boroumand et al., 2018] has been designed to minimize the use of heuristics and externally enforced elements that is universal in the sense that it provides favorable detection accuracy for both spatial-domain and JPEG steganography.

Adversarial Architecture

On account of the detectability of the schemes applying three plain meta-architectures by some steganalysis methods, they can’t be applied for secure steganography. Hence, adversarial architecture is widely adopted due to superior security and visual quality [Hayes and Danezis, 2017]. The core of the adversarial architecture is an adversarial network (orange dotted box in Figure 3) where containers and covers are fed in and forming a 3-player game. It can be fine-tuned from an off-the-shelf steganalysis network [Xu et al., 2016; Ye et al., 2017], or assumed to be a regular CNN [Zhang et al., 2019a; Weng et al., 2019] or similar structure to reveal network [Zhu et al., 2018; Hayes and Danezis, 2017] without loss of generality. The work of Hayes [2017] has shown that supervised training of the adversarial model can produce a robust steganalyzer.

An adversarial framework can be obtained simply by incor-
porating a classifier based on meta-architectures, e.g., [Weng et al., 2019; Zhang et al., 2019c; Yedroudj et al., 2020], which use basic models in a plain meta-architecture and increase their resistance to steganalysis by adding an adversarial discriminator directly. 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 [Zhu et al., 2018; Liu et al., 2019; Tancik et al., 2020; Jia et al., 2020; Plata and Syga, 2020], where adversarial training helps improve the container image visual quality as well as robustness for watermarking or light field messaging. Based on the adversarial architecture, attention idea has been investigated [Zhang et al., 2019b; Yu, 2020] for biasing towards hiding secrets in textures and objects that are less affected by transformations or the 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 by secret. In [Hu et al., 2018], the first phase derives a generator in deep convolutional GANs to synthesize images with random noise vectors. Next, 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 message 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. [2020c] 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 divides 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 as there is a steganalyzer in its system.

### 4.2 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. Directly applying the DDH meta-architecture without taking the light effect leads to total failure of extracting the hidden barcode information [Wengrowski and Dana, 2019]. To this end, [Wengrowski and Dana, 2019] collects a huge (1.9TB) dataset of camera-captured images from 25 camera-display pairs and then trains a camera-display transfer function (CDTF) to mimic the distortion caused by light field transfer. This approach has three advantages: (a) it requires lots of hardware resources (display and camera) as well as a large space to store the collected dataset; (b) training additional independent CDTF module on such a large dataset; (c) the performance is not satisfactory, especially for the unknown camera-display pairs due to the CDTF module being over-fitting to the hardware used for collecting the training datasets. Another less noticeable for the unsatisfactory performance is that the collected images are cover images instead of container images.

To address the above challenges, 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 the 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 more simple solution based on the proposed UDH. Specifically, [Zhang et al., 2020a] adopts 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 results in 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, the 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 DeepMorph [Rasmussen et al., 2020] with the artistic freedom to convey information via their own designed drawings but 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 3-D 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.

### 4.3 Robust Watermarking

Generally speaking, network architecture used in steganography is also suitable for watermarking as they both aim to hide information. However, deep learning based watermarking approaches have more considerations in terms of robustness, so they usually contain a well-designed module or adopt special techniques to facilitate 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 with 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 naive approach has been shown effective to achieve a reasonable robustness performance. One recent work [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 makes all the investigated image distortions are applied in every iteration simultaneously, 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 and videos are often pre-processed with lossy compressions, such as JPEG or MPEG. Especially, JPEG, as the most popular lossy compression for images, is often considered as the most common attack against watermarking. However, it is a non-trivial task to improve the robustness against JPEG compression because JPEG compression is a non-differentiable operation, which hinders training the hiding network and reveal network 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 high-frequency component, JPEG-Mask keeps only low-frequency DCT coefficients with a 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 when testing with the real JPEG. ReDMark [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: (a) it requires full knowledge of the attack, which is the case for JPEG attack but might not be true for other types of attacks; (b) 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 and decoder 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 propagates back only through the decoder. This alleviates the non-differentiability concern because the loss does not need to propagate through the encoder. However, one fundamental limitation of this two-stage approach is that the encoder is trained without JPEG compression, thus it is a sub-optimal solution approach compared with jointly training the encoder and decoder simultaneously with the JPEG compression. Due to the non-differentiability of JPEG compression, jointly training the encoder and decoder seems to be a non-trivial task. One recent work [Zhang et al., 2020b] proposes one elegant pseudo-differentiable approach that treats the JPEG compression as a special noise as shown in Figure xx, where the forward path and backward path are not exactly 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 avoids 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, such as MPEG, XVID.

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 have been investigated in xx, 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 in an adaptive manner 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 lies in [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.

5 Hiding Data within Other Multimedia

The master branch of research on data hiding adopts images as the host, i.e., 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]. Meanwhile, there also exist a variety of other multimedia that can be adopted as the information carrier, such as video, audio
and text. In general, the basic meta-architectures and strategies for improving security and robustness with the image as the information carrier are also suitable for those hiding schemes with other forms of information carrier, 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, i.e. 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 for hiding 8 frames within 8 frames for 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 to include a short-time Fourier transform and inverse-time transform as differentiable layers during the training. Deep learning has also been applied in cross-modal hiding applications, such as hiding image 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. In the hiding stage, they hide binary codes generated by the image compression network (ICN) into an audio signal. Then, a binary encoder embeds all the bits into a latent variable, which is used to generate embedded audio associated with the mel-spectrogram of the cover signal by a pretrained WaveGlow. In the reveal stage, the latent variable is reconstructed from the carrier and the mel-spectrogram of cover by WaveGlow and then each video frame can be recovered by a binary decoder and ICN. One potential drawback of [Yang et al., 2019a] is that the decoder side also needs access to the original clean audio.

Data hiding in the text is also a broad research direction. Different from those generative methods [Yang et al., 2018; Yang et al., 2019c], 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 research results in 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 change. In other words, there is a misalignment between human vision and deep model. 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., 2021] has performed a joint investigation of such misalignment phenomenon in both tasks, and 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 the DNNs being sensitive to high-frequency content [Zhang et al., 2021] with the observation that frequency is a key factor that influences the performance for both tasks. The joint investigation of deep watermarking and adversarial attack has also been previously explored in [Quiring 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, counter-measures 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 be found useful for facilitating the detection of adversarial examples [Schottl et al., 2018]. On the other hand, adversarial machine learning against watermarking has also been explored in [Quiring and Rieck, 2018] thorough adopting a neural network to detect and remove the watermark. Additionally, 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 watermarking robustness against unknown distortion, as discussed in Sec. 4.3.

Overall, there exists a unified Fourier perspective [Zhang et al., 2021] on the success of deep hiding and attack and techniques from watermarking is 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., 2021] 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 learning based data hiding has become an emerging field and is drawing increasing attention. Our work conducts a brief survey on this topic by first outlining three basic meta-architectures. We further discuss the challenges of deep hiding in various applications, such as steganography, light field messaging and watermarking. 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 possible new insights.
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