ABSTRACT

Digital watermarking has been widely used to protect the copyright and integrity of multimedia data. Previous studies mainly focus on designing watermarking techniques that are robust to attacks of destroying the embedded watermarks. However, the emerging deep learning based image generation technology raises new open issues that whether it is possible to generate fake watermarked images for circumvention. In this paper, we make the first attempt to develop digital image watermark fakers by using generative adversarial learning. Suppose that a set of paired images of original and watermarked images generated by the targeted watermarker are available, we use them to train a watermark faker with U-Net as the backbone, whose input is an original image, and after a domain-specific preprocessing, it outputs a fake watermarked image. Our experiments show that the proposed watermark faker can effectively crack digital image watermarkers in both spatial and frequency domains, suggesting the risk of such forgery attacks.

Index Terms — Digital watermarking, generative adversarial networks (GANs), image-to-image translation, forgery

1. INTRODUCTION

The rapidly developed Internet and Web technology makes it easy to copy images and videos for unauthorised uses as well as to make fake information. As a technique for security, digital watermarking fights against those illegal acts in the fields of copyright protection and tamper detection. Recently, digital watermarking is combined with a lot of techniques to improve its ability in those fields, e.g., genetic algorithms [11], singular value decomposition [12], deep learning [3, 4, 5], etc. In terms of the domain where watermarks hide, watermarking methods can be divided into spatial domain watermarking (e.g., LSB-based) and frequency domain watermarking (e.g., discrete cosine transform based) [6]. Previous studies on digital image watermarking mainly focus on improving the robustness against the attacks of destroying the embedded watermarks, but underestimate the risk of forgery attacks by generating fake watermarked images, with which attackers could infringe the copyright in watermarks or crack the tamper detection functionality (see Fig. 1).

The process of embedding watermarks into images is essentially a kind of image-to-image translation or image generation, which has been well developed in the past few years. Thanks to the emerging deep learning techniques, particularly generative adversarial networks (GAN) [7, 8, 9, 10, 11, 12, 13, 14, 15]. In [16], Khan et al. made the first attempt to crack the least significant bit (LSB) based steganography [17] with GAN, though their method did not work well when fewer than five bits were used to embed secret messages (however, in practical usually if five or more bits are used, the changes to the original images will be visible). This motivates us to ask whether it is possible to generate fake watermarked images by using generative adversarial learning.

This paper aims to make the first attempt to generate fake watermarked images to crack digital image watermarking. To this end, we construct a watermark faker by employing U-Net as the backbone and converting the original images to bit-wise representation as the input. Given a set of paired images of original and watermarked images generated by the watermarker under attack, we use these images to train the faker via adversarial learning. In the experiments, we consider three spatial domain watermarking methods and one frequency domain method, and the quantitative and qualitative
Training Data
Genuine
Watermark
Embedding
Original Images
...
Watermarked Images
...
Fake Watermarked Images
...
Watermark Faker
Watermark
Extraction
Watermark
Fake
Genuine

Fig. 2. The basic idea of proposed forgery of a target digital image watermarking method.

results demonstrate the effectiveness of the proposed faker in forgery of digital image watermarking, which suggests the necessity of thoroughly studying such forgery attacks.

The rest of this paper is organized as follows. Section 2 introduces related work. Section 3 gives the detail of the proposed watermark faker, followed by evaluation experiments in Section 4. Finally, Section 5 concludes the paper.

2. RELATED WORK

2.1. Digital Image Watermarking

Digital image watermarking is an effective approach to address violations of information security in using multimedia data such as illegal copyright and tampering. It embeds into multimedia data with watermarks, which can be extracted or detected to make an assertion about the ownership or integrity of the data. Watermarking methods consist of two stages, embedding and extraction, i.e.,

\[ I^w = F(I, W), \quad \hat{W} = G(I^w), \] (1)

where \( I \), \( W \), \( I^w \) and \( \hat{W} \) are, respectively, the original image, the watermark, the watermarked image and the extracted watermark. \( F \) and \( G \) denote the watermark embedding and extraction functions. In this paper, the watermark faker is a forgery of the embedding component of the watermark method under attack.

Watermarking methods can be divided into spatial domain watermarking and frequency domain watermarking. Spatial domain watermarking methods embed watermarks directly by modifying some pixel values of original images. Frequency domain watermarking methods convert the original images to another domain (usually, frequency domain) before embedding. In this paper, we try to counterfeit three kinds of spatial domain watermarking methods, i.e., LSB \[17], LSB-M \[18] and LSB-MR \[19], and a frequency domain watermark, i.e., DCT-based watermarking \[6\], which are widely used in protecting the copyright and integrity of multimedia data.

2.2. Image-to-Image Translation

Image-to-image translation is to learn a mapping from a source image domain to a target image domain \[14, 15\]. Recently, many prominent image-to-image translation methods are inspired by conditional generative adversarial network (cGAN) \[20\]. Considering the characteristics of used training data, we can split these methods into two categories. One takes paired data \[7, 8, 9, 10\], while the other takes unpaired data \[11, 12, 13, 14, 15\]. Generally, to learn a translation model from unpaired images is much more challenging. In this paper, we assume that paired data of original and watermarked images are available for training. Therefore, we design our watermark faker following the basic idea of pix2pix \[7\], which is the first and highly influential framework for cGAN-based image-to-image translation.

3. METHOD

3.1. Overview of Proposed Watermark Faker

Figure 2 depicts the basic idea of the proposed forgery of a target digital image watermarking method. As can be seen, a set of original images and the corresponding watermarked images generated by the to-be-attacked watermarking model are available for the attacker to train the watermark faker. Note that neither the embedded watermark nor the detail of the watermark embedding and extraction processes are known to the attacker. The trained watermark faker aims to generate fake watermarked images such that the watermarks extracted by the watermark extraction process from these fake images are close to the genuine watermark as much as possible.

The specific diagram of the implemented watermark faker is shown in Fig. 3. Given an original image, it is first undergoing some preprocessing such that the image is converted to proper representation in either spatial domain or frequency domain. The image is then translated into its watermarked version by a generator whose backbone is U-Net. This generator is trained via adversarial learning along with a discrim-
3.2. Domain-Specific Preprocessing

Bit-wise representation: preprocessing for spatial domain watermarking. The range of pixel values of digital images in spatial domain is determined by the number of bits used to represent the values. Because human vision systems are not sensitive to the least significant bits, spatial domain watermarking methods usually embed watermarks into these bits. As a result, if we directly compare the pixel values between real and fake watermarked images, the difference would be too minor to drive the training process (such issue is also known as gradient vanishing). This is essentially due to the fact that the impact of different bits varies according to their significance.

To balance the contribution of different bits in the training process and better reveal the hidden pattern of watermark, we convert images to bit-wise representations by using Pixel Expansion (PE) as shown in Fig. 4. For each pixel value $X$ of an image (say a eight-bit gray-scale image), we transform it from a decimal number to its corresponding binary form (eight bits):

$$X = \sum_{i=0}^{L-1} 2^i \times x_i, \quad (2)$$

where $x_i$ denotes the $i^{th}$ bit of pixel value $X$, and $L$ is the number of bits used to represent pixel values. Then, $x_i$ of all $X$ in the image form a new channel. Finally, by translating a one-channel gray-scale image to an $L$-channel image, we get the bit-wise representation of the image. For a three-channel RGB image, we process each channel in the same way, resulting in a $(3 \times L)$-channel image. By taking bit-wise representation of images as input, the faker can better learn the pattern of spacial domain watermarks.

Preprocessing for frequency domain watermarking. To achieve forgery of frequency domain watermarking, we implement the faker in frequency domain also. Specifically, we transform the original image into the frequency domain before applying the generator, and convert the result of the generator back to the spatial domain to obtain the fake watermarked image. In practice, since we have no prior of the specific transformation used by the watermarker under attack, we simply employ a blind search strategy among the typical image transformations between spatial and frequency domains.

3.3. Adversarial Learning

To train the watermark faker (more specifically, the generator $G$ in Fig. 3), we introduce a discriminator $D$ to implement adversarial learning between $G$ and $D$. As being motivated by the pix2pix image-to-image translation model [7], we take the original image $I$ (in its preprocessed form) and a random noise vector $z$ (implemented in the form of dropout) as the input of $G$, and produce a synthetic image $G(I, z)$ as the fake watermarked image.

The discriminator $D$, working as a classifier, takes either a pair of synthetic image $G(I, z)$ and original image $I$ or a pair of target image $y$ and original image $I$ as input, and judges whether the image patches of $G(I, z)$ or $y$ are real. Here, we discriminate the image realness in local scale rather than in global scale, which enables the faker to better learn the detailed patterns of watermarks. Besides, we include the original image in the input, because the original image is an import
tant reference to reveal the embedded watermark, especially when the watermark is related to the content of the original image (this is common in tamper-proof watermarking).

In adversarial learning, while $D$ is trying to distinguish the synthetic watermarked image $G(I, z)$ from the target real watermarked image $y$, $G$ is trained to do as well as possible in improving the quality of $G(I, z)$ to fool $D$. With the competition between $G$ and $D$, the generator learns a mapping from original images to the corresponding watermarked images. To fulfill the above learning process, we employ the following loss function, which is a conditional form of the least squares loss function inspired by CycleGAN [11] and LSGAN [21].

$$
\begin{align*}
\min_D L(D) &= \mathbb{E}_y [(D(I, y) - 1)^2] + \mathbb{E}_{I,z} [D(I, G(I, z))^2], \\
\min_G L(G) &= \mathbb{E}_{I,z} [(D(I, G(I, z)) - 1)^2] + \mathbb{E}_{I,y,z} [||y - G(I, z)||^2].
\end{align*}
$$

(3)

4. EXPERIMENTS

4.1. Data, Baselines and Metrics

To evaluate the effectiveness of the proposed watermark faker, we randomly pick up 12,288 images from Caltech256 [22] for training, and 2,048 images from Caltech256 for testing. Three LSB-based watermarking methods (LSB [17], LSB-M [18], and LSB-MR [19]) and one DCT-based watermarking method ($8 \times 8$ block DCT-based watermarking [6]) are chosen as target watermarkers to attack. Since this work is the first for forgery of digital image watermarking, we cannot find any existing watermark fakers for direct comparison. Hence, we choose pix2pix, which is a widely-used image-to-image translation model and contributes part of the backbone of our network, as the baseline. For quantitative comparison, we take PSNR [23] and SSIM [24] as metrics to compute the similarity between the fake watermarked images as well as the extracted fake watermarks (i.e., $\hat{I}_w$ and $\hat{W}_F$) and the corresponding real ones (i.e., $I_w$ and $W_G$). The higher the metric values are, the more effective the watermark fakers are.

4.2. Forgery Results of Spatial Domain Watermarking

Fig. 5 shows some fake watermarked images generated by the baseline pix2pix and the proposed methods in contrast to the corresponding real watermarked images. As can be seen, visually, the watermarked images generated by the two methods both appear quite similar to the real ones; however, in terms of the extracted watermarks, the baseline pix2pix method results in pure noise, whereas the proposed method successfully counterfeits the watermark.

Quantitative results in terms of PSNR and SSIM are presented in Table 1. Although the baseline method achieves a little bit higher similarity between fake and real watermarked images when attacking LSB, the proposed method performs substantially better in generating fake watermarks when attacking all the three watermarkers. These results prove that the proposed method is much more effective in forgery of spatial domain image watermarks while keeping the fake watermarked images visually plausible.

4.3. Forgery Results of Frequency Domain Watermarking

For frequency domain watermarking, because the extracted real watermarks are usually not exactly same as the watermarks embedded into the original images (see Fig. 6), we compute the PSNR and SSIM metrics between the extracted watermarks and the embedded ones, and then compare the metric values obtained by the proposed watermark faker with those obtained by the to-be-attacked target watermarker. The goal of the watermark faker is to make its metric values as close to the metric values of the target watermarker as pos-
Table 1. The average PSNR and SSIM values of different forgery methods for spatial domain watermarking.

|           | Image | Watermark |          | Image | Watermark |          | Image | Watermark |
|-----------|-------|-----------|----------|-------|-----------|----------|-------|-----------|
| Baseline  | 34.204| 0.953     | 8.789    | 0.009 | 35.096    | 0.965    | 3.013 | 0.001     |
| Ours      | 30.963| 0.941     | 36.805   | 0.986 | 34.555    | 0.987    | 42.112| 0.999     |

Table 2. The average PSNR and SSIM values of different forgery methods for frequency domain watermarking.

| Image | Watermark |          | Real→GT | Fake→GT |
|-------|-----------|----------|---------|---------|
|       | PSNR      | SSIM     | PSNR    | SSIM    |
| Baseline | 26.809029 | 0.848049 | 17.271548 | 0.750439 |
| Ours   | 32.668204 | 0.920432 | 17.271548 | 0.750439 |

Table 3. Ablation study results of forgery of spatial domain watermarking.

| Image | Watermark |          |          |
|-------|-----------|----------|----------|
| Baseline | PSNR      | SSIM     | PE       |
| Ours without PE | 34.204748 | 0.953002 | 8.789933 | 0.009935 |
| Ours with PE | 29.209504 | 0.911588 | 4.693388 | 0.117471 |

Fig. 6. Example forgery results of the proposed method for DCT-based frequency domain watermarking.

Table 2 gives average PSNR and SSIM values of the proposed watermark faker and the target watermarker. From these results, we can see that frequency domain watermarks are more difficult to counterfeit than spatial domain watermarks; nevertheless, as shown in Fig. 6, the proposed method can still to some extent learn the pattern of embedded watermarks.

4.4. Ablation Study

In this section, we compare some different implementations of the proposed watermark faker to assess (i) how much the pixel expansion (PE) operation contributes to the forgery of spatial domain watermarking, and (ii) what if directly generating fake watermarked images in the spatial domain when attacking frequency domain watermarking. The results are summarized in Tables 3 and 2 from which we can observe that (i) for the spatial domain watermarker (i.e., LSB), applying PE during preprocessing can significantly improve the effectiveness of counterfeiting watermarks, though the visual quality of the generated fake watermarked images becomes somehow worse (but still acceptable); (ii) for the frequency domain watermarker (i.e., DCT-based), the similarity between extracted fake watermark and the embedded watermark (taken as the ground truth) is obviously closer to that between extracted real watermark and the ground truth, which suggesting that it is more effective to crack DCT-based watermarking in frequency domain than in spatial domain.

5. CONCLUSIONS

This paper for the first time shed light on the new open issue of forgery of digital image watermarking using latest deep learning based image generation technology. With U-Net as the backbone, we construct a watermark faker, and via adversarial learning, we get the faker trained with respect to a specific target watermarker. Our quantitative and qualitative evaluation results demonstrate that the proposed watermark faker can effectively counterfeit digital watermarks in both spatial and frequency domains. Although existing forgery results we obtain for frequency domain watermarking are not yet as good as the results for spatial domain watermarking, our study in this paper reveals the potential risk caused by forgery of digital watermarking with deep learning technology, which is however seriously under-estimated by contemporary researchers and practitioner in the field of digital watermarking. In the future, we are going to investigate the possibility of cracking more advanced watermarking methods and to study how to detect forgery of digital watermarks.
6. REFERENCES

[1] Behrouz Bolourian Haghighi, Amir Hossein Taherinia, and Amir Hossein Mohajerzadeh, “Trlg: Fragile blind quad watermarking for image tamper detection and recovery by providing compact digests with optimized quality using lwt and ga,” Information Sciences, vol. 486, pp. 204–230, 2019.

[2] Zurinahni Zainol, Je Sen Teh, Moatsum Alawida, et al., “A new chaotic image watermarking scheme based on svd and iwt,” IEEE Access, vol. 8, pp. 43391–43406, 2020.

[3] Jiren Zhu, Russell Kaplan, Justin Johnson, and Li Fei-Fei, “Hidden: Hiding data with deep networks,” in Proceedings of the European conference on computer vision (ECCV), 2018, pp. 657–672.

[4] Chaoning Zhang, Philipp Benz, Adil Karjauv, Geng Sun, and In-So Kweon, “Udh: Universal deep hiding for steganography, watermarking, and light field messaging,” in 34th Conference on Neural Information Processing Systems (NeurIPS), 2020, pp. 10223–10234.

[5] Chaoning Zhang, Chengu Lin, Philipp Benz, Kejiang Chen, Weiming Zhang, and In So Kweon, “A brief survey on deep learning based data hiding, steganography and watermarking,” arXiv preprint arXiv:2103.01607, 2021.

[6] Vidyasagar M Potdar, Song Han, and Elizabeth Chang, “A survey of image watermarking techniques,” in 3rd IEEE International Conference on Industrial Informatics, 2005. IEEE, 2005, pp. 709–716.

[7] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros, “Image-to-image translation with conditional adversarial networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), 2017, pp. 1125–1134.

[8] Jing-Chun Wang, Ming-Yu Liu, Jun-Yan Zhu, Andrew Tao, Jan Kautz, and Bryan Catanzaro, “High-resolution image synthesis and semantic manipulation with conditional gans,” in Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), 2018, pp. 8798–8807.

[9] Taesung Park, Ming-Yu Liu, Jing-Chun Wang, and Jun-Yan Zhu, “Semantic image synthesis with spatially-adaptive normalization,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 2337–2346.

[10] Jun-Yan Zhu, Richard Zhang, Deepak Pathak, Trevor Darrell, Alexei A Efros, Oliver Wang, and Eli Shechtman, “Toward multimodal image-to-image translation,” in Proceedings of the 31st International Conference on Neural Information Processing Systems (NeurIPS), 2017, pp. 465–476.

[11] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros, “Unpaired image-to-image translation using cycle-consistent adversarial networks,” in Proceedings of the IEEE international conference on computer vision (ICCV), 2017, pp. 2223–2232.

[12] Yunjey Choi, Minje Choi, Munyoung Kim, Jung-Woo Ha, Sunghun Kim, and Jaegul Choo, “Stargan: Unified generative adversarial networks for multi-domain image-to-image translation,” in Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), 2018, pp. 8789–8797.

[13] Yunjey Choi, Youngjiung Uh, Jaejun Yoo, and Jung-Woo Ha, “Stargan v2: Diverse image synthesis for multiple domains,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 8188–8197.

[14] Pan Zhang, Bo Zhang, Dong Chen, Lu Yuan, and Fang Wen, “Cross-domain correspondence learning for exemplar-based image translation,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 5143–5153.

[15] Hsin-Ying Lee, Hung-Yu Tseng, Iia-Bin Huang, Ma-neesh Singh, and Ming-Hsuan Yang, “Diverse image-to-image translation via disentangled representations,” in Proceedings of the European conference on computer vision (ECCV), 2018, pp. 35–51.

[16] Nibraas Khan, Ruj Haan, George Boktor, Michael McComas, and Ramin Daneshi, “Steganography gan: Cracking steganography with cycle generative adversarial networks,” arXiv preprint arXiv:2006.04008, 2020.

[17] Ron G Van Schyndel, Andrew Z Tirkel, and Charles F Osborne, “A digital watermark,” in Proceedings of 1st international conference on image processing. IEEE, 1994, vol. 2, pp. 86–90.

[18] Toby Sharp, “An implementation of key-based digital signal steganography,” in International Workshop on Information Hiding. Springer, 2001, pp. 13–26.

[19] Jarno Mielikainen, “Lsb matching revisited,” IEEE signal processing letters, vol. 13, no. 5, pp. 285–287, 2006.

[20] Mehdi Mirza and Simon Osindero, “Conditional generative adversarial nets,” arXiv preprint arXiv:1411.1784, 2014.

[21] Xudong Mao, Qing Li, Haoran Xie, Raymond YK Lau, Zhen Wang, and Stephen Paul Smolley, “Least squares generative adversarial networks,” in Proceedings of the IEEE international conference on computer vision (ICCV), 2017, pp. 2794–2802.

[22] Gregory Griffin, Alex Holub, and Pietro Perona, “Caltech-256 object category dataset,” 2007.

[23] Alain Hore and Djemel Ziou, “Image quality metrics: Psnr vs. ssim,” in 20th international conference on pattern recognition. IEEE, 2010, pp. 2366–2369.

[24] Zhou Wang, Alan C Bovik, Hamid R Sheikh, and Eero P Simoncelli, “Image quality assessment: from error visibility to structural similarity,” IEEE transactions on image processing, vol. 13, no. 4, pp. 600–612, 2004.