NO WAY TO CROP: ON ROBUST IMAGE CROP LOCALIZATION

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ABSTRACT

Previous image forensics schemes for crop detection are only limited on predicting whether an image has been cropped. However, cropping different areas in a same image leads to different semantic changes. This paper presents a novel scheme for image crop localization using robust watermarking. We train an anti-crop processor (ACP) that embeds a watermark into a target image. The visually indistinguishable protected image is then posted on the social network instead of the original image. During data sharing, the cloud users may tamper, crop or benignly attack the image using JPEG compression, scaling, etc. At the recipient’s side, ACP extracts the watermark from the attacked image, and we conduct feature matching on the original and extracted watermark to locate the position of the crop in the original image plane. We further extend our scheme to detect tampering attack on the attacked image. We demonstrate that our scheme is the first to provide high-accuracy and robust image crop localization. Besides, the accuracy of tamper detection is comparable to many state-of-the-art methods.

Index Terms— image crop localization, image tamper detection, robustness, image forensics

1. INTRODUCTION

To fight against daily-world image forgery, researchers have developed a number of schemes which detect various kinds of digital attacks, e.g., against tampering [24] [13] [12], DeepFake [18] and cropping [22] [21] [19]. Among them, cropping is a simple yet powerful way to maliciously alter the message of an image. This kind of forgery has historically been less investigated by the forensic community than other image manipulations. The main difficulty is that much less semantic or statistical clue of cropping can be discovered. The existing crop detection algorithms [21] [19] mainly focus on predicting whether an image is cropped. They are represented by detecting the exposing evidences of asymmetrical image cropping. However, cropping different areas in a same image will definitely result in different semantic changes, and therefore we need to locate the position of the crop in the original image plane.

There is little previous arts for image crop localization. Van et al. [22] proposes to investigate the impact that cropping has on the image distribution, featured by chromatic aberration and vignetting. However, there are certain limitations. First, it requires the images to be untouched and uncompressed so that the camera pipeline artefacts and photography patterns are preserved. Otherwise the scheme cannot be applied. Second, the clues from the camera pipeline artefacts are usually not enough to ensure high-accuracy localization results. Therefore, the real-world application of [22] is rather limited. Motivated by the short-comings of the previous schemes, we propose the first image crop localization scheme using robust watermarking.

Since the original clues are weak, we propose to hide crafted clues into a targeted image to protect them in the first place. We further observe that besides cropping, there are also benign attacks, e.g., JPEG compression, scaling, etc. These usually cause a significant drop in performance of many other computer vision tasks such as data hiding [62] or tamper detection [13]. It requires the scheme to be robust against these typical attacks. We further extend our work to localize tamper on the protected image before crop localization. The proposed scheme is efficient in revealing misleading photojournalism or copyright violation. Fig. 1 shows two examples of malicious image cropping, where our scheme accurately localizes the cropped area on receiving the ambiguous cropped images.

We train a normalizing-flow-based anti-crop processor (ACP) to embed a watermark into a targeted image. The watermark is shared with the recipient. ACP produces a visually indistinguishable protected image, which is then posted on the social network instead of the unprotected version. On receiving the attacked version of the protected image, we use ACP again to extract the watermark, and conduct a feature matching algorithms (SURF [1]) between the original and extracted watermark to determine where the crop was positioned in the original image plane. We further extend our work to detect tamper on the doubted image by introducing a tamper detector to predict the tamper mask. The features within the predicted tamper mask is disabled to prevent mismatching. We test our scheme by introducing man-made hybrid attacks. The results demonstrate that our scheme can accurately localize the cropped region. We also show the effectiveness of tamper detection by comparison with some state-of-the-art schemes [12] [13].

The highlights of this paper are three-folded. 1) This paper presents the first high-accuracy robust image crop localization scheme. 2) With the embedded watermark, the proposed scheme can also conduct high-accuracy tamper detection, which is comparable with the state-of-the-art works. 3) We use normalizing flows to build an efficient invertible function for image forensic problems.

Fig. 1. Examples of crop localization. (a) Given an image to be protected, (b) we conduct imperceptible data hiding on the targeted image. (c) The social network users redistribute, crop, and even modify the image. (d) The recipient identifies the cropped-out area.
Robust Watermarking and its Application on Forensics.

and image rescaling [32], INNs are also used for various low-level computer vision tasks such as image colorization [31] and image inversion [16].

Pioneering research on INN-based operations are in the same network. Yu [37] is the first to ensure robustness and large capacity at training. Fanfani et al. [21] exploits the camera principal point insensitive to image processing operations. Yershulmy et al. [19] detects whether there are vanishing points and lines on structured image content. Many tamper detection schemes [12] are developed upon the classic U-Net architecture. Ying et al. [24] not only detects tampers, but also proposes to conduct image self recovery. Besides, Mantra-Net [13] significantly improves the detection and localization performance by using self-supervised learning of the robust image manipulation traces.

Invertible Neural Networks (INN). Invertible neural network learns a stable invertible mapping from the source distribution $P_s$ to a targeted distribution $P_t$, and the forward and back propagation operations are in the same network. INNs are also used for various low-level computer vision tasks such as image colorization [31] invertible data hiding network (ISN) [36], and image rescaling [32].

Robust Watermarking and its Application on Forensics. Nowadays, several robust watermarking schemes [42] are proposed where a differentiable attacking layer is proposed for adversarial training. Yu [27] is the first to ensure robustness and large capacity at the same time. Previously, robust watermarking has been introduced to aid preventing images from being inpainted [27] or reconstructed by super-resolution [25].

2. RELATED WORKS

Detection on Image Cropping and Tampering. Fanfani et al. [21] exploits the camera principal point insensitive to image processing operations. Yershulmy et al. [19] detects whether there are vanishing points and lines on structured image content. Many tamper detection schemes [12] are developed upon the classic U-Net architecture. Ying et al. [24] not only detects tampers, but also proposes to conduct image self recovery. Besides, Mantra-Net [13] significantly improves the detection and localization performance by using self-supervised learning of the robust image manipulation traces.

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3. METHOD

3.1. Overview

Fig. 2 shows an overview of our scheme. The pipeline of our method is composed of an Anti-Cropping Processor (ACP) $P$, an attack layer $A$, a tamper detector $V$, a discriminator $D$ and a feature matcher $M$. The proposed scheme consists of five stages: watermark embedding, image redistribution, tamper detection, watermark extraction and crop localization. We regard the embedding and extraction of the watermark $W$ as the inverse problem, even if the protected image is cropped and attacked. It comes from the observation that many data hiding schemes embed the secret image into the host image according to the spatial order [62]. We formulate the inverse problem of the ACP as:

$$\hat{I}_M = \mathcal{P}^{-1}(A(I_M, R), R),$$

where $R$ and $\hat{R}$ are the pseudo-random output and input to keep the consistency of the channel number. For the invertibility, $W$ and the ground-truth cropped watermark $W_C$ should be as close as possible. $W_C$ is obtained by cropping out the same region from $W$ as on $I_M$. Besides, $I_M$ should be visually indistinguishable from $I$.

First, we embed the watermark $W$ into the targeted image $I$ using the ACP. The protected image $I_M$ is generated and we upload it onto the social cloud instead of the unprotected targeted image. We simulate the image redistribution stage and generate the attacked image $I_A$ by freely adding three kinds of attacks (benign attacks, cropping, tampering) on the protected images. On the recipient’s side, the tamper detector $V$ predicts the tamper mask $M$ on the attacked image to see which parts of the image are tampered. We inversely run the ACP and feeds the attacked image to extract the watermark $\hat{W}$. Afterwards, we rectify the extracted water by $\hat{W} = W \cdot (1 - M)$ to discard the tampered contents. Finally, with the original watermark $W$ as reference, we uses the feature matcher $M$ to locate the position of the crop in the original image plane.

In the training stage, the pipeline is slightly modified in order to properly train the networks. We let the ACP focus on the learning of robust data hiding and extraction by feeding it with non-tampered attacked images. We further add tampering attacks on the non-tampered attacked images to train the tamper detector.

3.2. Network Design

Considering the efficiency of the invertible U-Net proposed in [32], we build our ACP on top of this architecture. The network consists of six invertible blocks each of which contains a Haar wavelet transformation and a double-side affine coupling. The network ends with a conditional split layer. The number of the input and output channels are four. The sizes of $R$ and $\hat{R}$ are of the same as $W$. $R$ and $\hat{R}$ are not required to be the same.

In the attacking layer $A$, we first use a differentiable quantization layer to transfer the data type of the protected image from float to 8-bit integer. Then, we build differentiable methods to simulate the benign attacks $B$, the cropping attack $C$ and the tampering attack $T$. In $B$, we take the implementation from [42] except that we build our own JPEG simulator $J$. In $C$, we randomly crop a portion of the protected image $I_M$. In $T$, we first randomly select random areas using a binary matrix $M$ inside $I_M$, and generate the tampered image by $I_A = I_{rrr} \cdot M + I_M \cdot (1 - M)$. $I_{rrr}$ refers to the source of the tamper.

For JPEG simulation $J$, there are already many scheme which include a carefully-designed JPEG simulator, e.g., JPEG-SS [62], JPEG-Mask [43], MBRS [63]. However, the real-world JPEG robustness of these schemes is still limited. We believe it mainly attribute to that the networks are over-fitted to a fixed compression mode. For example, [62][42] uses a fixed quantization table to mimic JPEG compression while in the real world the quantization table greatly varies. Luo [69] proposes a trainable attack network that competes with the baseline network during training, but previous works have reported that it usually makes the training very hard and unstable. In this paper, we propose to apply the Mix-Up strategy [70] to conduct an instance-agnostic interpolation by:

$$I_{jpg} = \theta \cdot I_M + (1 - \theta) \cdot \sum_{J_k \in J} \sum_{QF \in [100]} \epsilon \cdot J_k(I_M, QF),$$

where $\theta$ and $\epsilon$ are the mixing fractions and the parameter of the Mix-Up strategy, respectively.
where $\theta \in (0, 1)$, $\sum_{b \in B} \epsilon = 1$ and $\mathcal{F} \in \{\text{JPEG-SS, JPEG-Mask, MBRS}\}$. $QF$ stands for the quality factor. The first part of $QF$ is to prevent the image recovery from being too hard under simulated JPEG compression at the beginning of the training stage. Thus, we slowly decline $\theta$ to zero.

We accept the implementation of the edge generator and the PatchGAN-based discriminator proposed in [54] as our tamper detector $\mathcal{V}$ and discriminator $\mathcal{D}$. We use the SURF algorithm [1] to implement the feature matcher $\mathcal{M}$. SURF is an efficient local feature detector and descriptor widely used to extract points of interest. The crop localization is realized by applying linear weighted fusion algorithms on the SURF descriptors of the two images.

3.3. Objective Loss Function

For the ACP, we encourage the protected image $I_M$ and the extracted watermark $I$ to respectively resemble the targeted image $I$ and the ground-truth cropped watermark $W_C$. $L_{\text{rec}} = \mathcal{F}(I, I_M) + \mathcal{F}(W_C, W)$, where $\mathcal{F}$ is the $L_2$ distance. Owing to the invertibility of the ACP, we do not use the perceptual loss. We also need to randomize the extra output by $L_{\text{ran}} = \mathcal{F}(R, \hat{R})$. The adversarial loss is to further control the introduced distortion by fooling the discriminator. We accept the least squared adversarial loss (LS-GAN) [57]. The total loss for ACP is $L_{\text{ACP}} = L_{\text{rec}} + \alpha \cdot L_{\text{ran}} + \beta \cdot L_{\text{ran}}$, where $\alpha$ and $\beta$ are hyper-parameters. For the tamper detector, we minimize the binary cross entropy (BCE) loss between the estimated tamper mask $M$ and the ground-truth mask $\hat{M}$. $L_{\mathcal{V}} = BCE(M, \hat{M})$.

4. EXPERIMENTAL RESULTS

4.1. Experiment Setup

We train the scheme on the COCO training/test set [38] with automatically generated attacks. The scheme is tested with human-participated attacks. We resize the images to the size of $256 \times 256$. The hyper-parameters are set as $\alpha = 1, \beta = 8$. The batch size is set as 16. We use Adam optimizer [35] with the default parameters. The learning rate is $1 \times 10^{-4}$. We provide the volunteers with some generated protected image, which are then cropped and processed by benign attacks such as lossy compression, scaling, etc. The volunteers may add, modify or delete some important image contents at their free will using typical image processing tools like Adobe Photoshop. The crop rate is roughly $\delta \in [0.25, 1]$. During training, we arbitrarily and evenly perform one kind of benign attacks. Sometimes the benign attack is skipped to simulate lossless communication. Also, to avoid over-fitting, we sometimes skip the tampering attack, in which case we force the tamper detector to predict a zero matrix. We adaptively convert the predicted tamper mask $\hat{M}$ into a binary matrix.

4.2. Real-World Performance of Crop Localization

Quality of the protected images. In Fig. 3, we randomly sample different pairs of images as the targeted and watermark. In the first two groups, we use a shared watermark. From the figures, we can observe that the difference $D$ is imperceptible. Little detail of the watermark can be found. We have conducted more embedding experiments over 1000 images from the test set, and the average PSNR between the protected images and the targeted images is 36.23dB, and the average SSIM [51] is 0.983.

Accuracy of the Crop Localization. Fig. 4 shows the results of watermark extraction, feature matching and crop localization on the protected images in Fig. 3. In the first row, we only crop the protected image. We see that the crop mask is accurately predicted. As a result, even without the prior knowledge of the original image, we know the relative position of the attacked image in the original image plane. We suggest the readers not using images with too much repetitive patterns as watermark where SURF may find multiple matching patterns as watermark where SURF may find multiple matching

![Fig. 3. Illustration of watermark embedding. Row 1-4: targeted images $I$, watermark $W$, protected images $I_M$, Augmented difference $D = 5 \times \text{abs}(I - I_M)$](image)

![Fig. 4. Results of watermark extraction and crop localization of the protected images in Fig. 3. The attacks are respectively (a) crop, (b) crop & scaling, (c) crop & JPEG and (d) crop & JPEG & tamper.](image)
### Table 1. Average performance of cropping localization measured by IoU and SSIM between the extracted and ground-truth watermark.

| Rate | Method | IoU | SSIM | Scaling | Blur |
|------|--------|-----|------|---------|------|
| 90%  | NoAttack   | 0.919| 0.949| 0.895  | 0.903| 0.957| 0.953|
| 70%  | JPEG      | 0.858| 0.892| 0.813  | 0.927| 0.878| 0.915|
| 50%  | JPEG      | 0.821| 0.914| 0.706  | 0.603| 0.7223| 0.540|

The scheme is proven to be agnostic to the crop size in that the performance does not degrade significantly with larger crop rate.

### Robustness in the Real-World Application.

In the second and third row of Fig. 4, we test the robustness of our scheme by conducting different benign attack on the cropped protected image. In the fourth row, tampering attack is further introduced. We subtract the extracted contents within the predicted tamperea areas (Fig. 5) and prohibit the feature matcher $M$ from using the features inside. In Table 1, we can observe that our scheme provides high-accuracy crop localization despite the presence of the attacks other than cropping. The results promote the practical application of the proposed scheme. Thanks to the robustness of feature matching of SURF, the experiments show that in most cases our scheme do not require a precise watermark extraction.

### Comparison with Crop Dissection.

In Fig. 7 of [22], Van et al. discusses their application on crop localization. However, it requires that the targeted image should not have been cropped and must maintain a constant fixed aspect ratio and resolution. Otherwise, the scheme cannot be applied. In contrast, the proposed scheme does not have any restriction on the targeted image. Therefore, we only compare our scheme with [22] on crop classification. The crop classification accuracy is 86% on high-quality untouched images, while the accuracy of our scheme is 91% on normal images, as long as the users avoid using inappropriate images as watermark.

#### Table 2. F1 score comparison for tamper detection among our scheme and the state-of-the-art methods.

| Method    | NoAttack | JPEG | Blur | Scaling |
|-----------|----------|------|------|---------|
| Proposed  | 0.773    | 0.736| 0.695| 0.745   |
| Mantra-Net [13] | 0.566 | 0.480| 0.557| 0.540   |
| RRU-Net [12]  | 0.435    | 0.273| 0.244| 0.417   |

The performance of Mantra-Net on JPEG images is much worse than that on plain-text images. We believe the reason is that less statistical clue is preserved in the compressed version. In contrast, the embedded watermark signal serves as the alternative clue for tamper detection, which is designed to resist benign attacks. The performance on JPEG images does not drop too much.

#### 4.4. Ablation Study

We study the effectiveness of the network design. In Test 1, we train two individual hiding network and revealing network to replace the normalizing-flow-based ACP. In Test 2, we implement the JPEG attack with that proposed in [68, 42, 67]. The JPEG QF and the crop ratio are kept the same for fair comparison. We train the implementations together with the baseline under the same losses and batch size. Fig. 6 shows the detailed comparison results. First, the baseline results outperform the encoder-decoder network design. Second, while MBRS [68] can provide decent robustness, the extraction performance is even better using our JPEG simulator. Specifically, the average SSIM between $W$ and $W_c$ using MBRS [68] is 0.797 compared to 0.878 reported in Table 1. The Mix-Up strategy prevents the networks from being over-fitted to any single JPEG simulator, which helps the scheme significantly improve its real-world robustness. In Test 3, we do not use the discriminator $D$. The results show that it leads to visible artifacts in the protected image. The extraction result is also worse than the baseline.

### 5. Conclusion

This paper presents a novel scheme of image crop localization using robust watermarking. We produces a visually indistinguishable protected image for a targeted image using the ACP. We simulate typical attacks in the pipeline where we propose an improved JPEG simulator. On receiving the attacked image, we extracts the watermark. We then conduct tamper detection on the image and use the SURF algorithm to locate the position of the crop. The results proves that our method provides high-accuracy and robust image crop localization. Besides, the accuracy of tamper detection is also promising.
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