Self-Adversarial Training incorporating Forgery Attention for Image Forgery Localization

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Abstract—Image editing techniques enable people to modify the content of an image without leaving visual traces and thus may cause serious security risks. Hence the detection and localization of these forgeries become quite necessary and challenging. Furthermore, unlike other tasks with extensive data, there is usually a lack of annotated forged images for training due to annotation difficulties. In this paper, we propose a self-adversarial training strategy and a reliable coarse-to-fine network that utilizes a self-attention mechanism to localize forged regions in forgery images. The self-attention module is based on a Channel-Wise High Pass Filter block (CW-HPF). CW-HPF leverages inter-channel relationships of features and extracts noise features by high pass filters. Based on the CW-HPF, a self-attention mechanism, called forgery attention, is proposed to capture rich contextual dependencies of intrinsic inconsistency extracted from tampered regions. Specifically, we append two types of attention modules on top of CW-HPF respectively to model internal interdependencies in spatial dimension and external dependencies among channels. We exploit a coarse-to-fine network to enhance the noise inconsistency between original and tampered regions. More importantly, to address the issue of insufficient training data, we design a self-adversarial training strategy that expands training data dynamically to achieve more robust performance. Specifically, in each training iteration, we perform adversarial attacks against our network to generate adversarial examples and train our model on them. The proposed method is based on the assumption of content-changed manipulations. Extensive experimental results demonstrate that our proposed algorithm steadily outperforms state-of-the-art methods by a clear margin in different benchmark datasets.

Index Terms—Forgery localization, forgery attention, coarse-to-fine network, self-adversarial training.

I. INTRODUCTION

The prevalence of digital image forgery is negatively affecting our lives, such as Internet rumors, insurance fraud, fake news, and even academic cheating. Ghanim and Nabil revealed that image forgery might cause huge financial loss. Bik et al. estimated that there were 3.8% of 20,621 papers containing problematic figures with potential deliberate manipulation in biomedical research publications.

Therefore, real-world media forensics is desperate for a new generation of algorithms that can obtain more refined results at the pixel level, as well as the detection of general manipulations.

However, it is challenging to localize multiple image forgeries at the pixel level since well-tampered images leave few visual traces. Conventional detection methods based on manually constructed statistical features rely heavily on the domain knowledge of human experts.

Forgery localization task aims to localize the content-changed tampering techniques, including splicing, copy-move and removal, since content-changed techniques may cause serious misunderstandings while tampering with unchanged content does not change the semantics without causing misunderstandings. Please note that non-content-changed manipulations, such as Gaussian blur and JPEG compression, are excluded in the literature of image forgery localization, since those manipulations do not affect the semantic information expressed in the image scene. Therefore, all of the existing image forgery localization approaches only focus on three common semantic forgeries, i.e., image splicing, copy-move and removal.

Recent works, including Mantra-Net, RGB-N, J-
it is important to construct a novel network structure which to guide networks’ attention to tampered regions. Therefore, real scenarios, traditional object attention modules might fail image. Since quite a few tampered regions are not objects in object detection, and consequently are not well incorporated in problem of all of the mentioned attention-module based methods demonstrate that our approach has achieved state-of-the-art results on all primary benchmark datasets.

As for the experiments, the notable public datasets for forgery localization, including DEFACTO [25], NIST [26], Columbia [25], COVERAGE [27], CASIA [9] and PS-dataset [15], are established on the content-changed manipulations. Therefore, the assumption of our experiments is that the forgery localization models aim to localize the content-changed regions. Based on this assumption, extensive experiments demonstrate that our approach has achieved state-of-the-art results on all primary benchmark datasets.

To be summarized, our main contribution is to propose a novel image deep-learning based forgery localization framework that organically combines the domain knowledge of
multimedia security and image recognition. The novelty of this work can be explicitly highlighted as follows: 1) we propose **Forgery attention**, a novel attention mechanism for forgery localization, that fuses domain knowledge well-established in multimedia security into attention mechanism, and makes a combination of channel-wise and spatial dependencies. 2) A new training strategy, namely SAT, is first introduced to alleviate the problem of the lack of training data for improving the localization performance and the model robustness. 3) we move a further step for HPF layer and present CW-HPF that exploits the inter-channel relationships and generates more precise noise features.

The remainder of the paper is organized as follows. In Section II, we present our proposed approach in details. Then, we show the results of our extensive experiments in Section III. Finally, we conclude this paper in Section IV.

II. PROPOSED APPROACH

In this section, we present the general framework of our proposed network as well as self-adversarial training strategy and then formulate our approach.

A. Overview

Given an image, we aim to localize its tampered regions at the pixel level. The general framework of our proposed model is illustrated in Fig. 2. Furthermore, we propose self-adversarial training to promote the robustness of the network since forged training samples are ultra-limited, whose details will be given in Sect. II-F. Overall, we construct a coarse-to-fine network containing a coarse output mask and a refined output mask. Next, we propose a two-phase training strategy called self-adversarial training strategy to perform our training process, where our network is trained using the original input-output pairs commonly in the first phase and then trained using new input-output pairs with adversarial samples in the second phase.

Our network has a coarse-to-fine architecture. It is composed of two sub-networks, i.e., a coarse net and a refined net. The coarse net is fed with a forged image $I_F$ of size $H \times W \times 3$ and outputs a coarse prediction mask of size $H \times W$ and a feature map $I_{S_i}$ of size $H \times W \times k$, where $k$ is set to 16 because the output of the last block outputs a feature map with 16 channels. The feature map $I_{S_i}$ is fed into the refined net that predicts a refined prediction mask $I_M$ of size $H \times W$. Note that $I_{M_1}$ and $I_M$ come from two output convolution layers with a kernel size of $7 \times 7$, activated by a sigmoid function. $I_{M_1}$ aims to deliver complete feature information to the refined net, which enables the refined net to be optimized along with the features. The predicted masks mark tampered regions in white and leave the rest in black. We select the refined mask $I_M$ as the final result.

As illustrated in Fig. 2, there are three key components in the coarse net, including a CW-HPF block, multiple VGG-style blocks, and a series of dilated convolutional layers. The refined net adopts similar structure, but with a forgery attention module attached.

B. CW-HPF Block

HPF layer widely used in image steganalysis [18] has been adopted in forgery localization [4, 11]. The intuition behind the usage of high-pass filters is that tampering traces are generally manifested in the middle and high-frequency sub-bands of the tampered image. However, prior works have neglected the relationships among channels of images, which may yield many unnecessary noise features. To extract more accurate noise features, we leverage the inter-channel information to enhance the noise inconsistency between tampered and pristine regions. WISERNet [22], our prior work in the field of image steganalysis has proved in theory that noise features extracted by channel-wise high pass filters could enlarge the slight difference between the authentic images and the manipulated images with tiny stego noises. However, WISERNet only uses the channel-wise high pass filters with fixed weights and three R-G-B color channels as input in a bottom pre-processing layer.

Move a step further, in our proposed framework we have introduced CW-HPF which can be fed with arbitrary input channels and can be put in arbitrary positions/branches of our framework.

Fig. 3 shows the details of the CW-HPF block. CW-HPF takes a feature map of size $H \times W \times C$ and outputs a noise feature map of size $H \times W \times 3C$. Firstly, the input feature map is converted to a feature map set $S$ with $C$ feature maps. $S_i$ represents the $i$-th channel of the input feature map. We define $S$ as $S = \{S_1, S_2, S_3, \ldots, S_C\}$. We employ three high pass filters originated from SRM [18] to initialize a convolution layer of size $5 \times 5 \times 3$, which we call HPF-Conv. As shown in Fig. 4, the selected high pass filters involve a KB filter, a KV filter and a first order kernel, which are the same as RGB-N [11]. Unlike steganalysis, the forgery localization task needs only three high pass filters from thirty steganalysis rich model filters to achieve decent performance and save computing resources [11]. We apply HPF-Conv to perform convolution with each element of the feature map set $S$, and the results are concatenated to produce noise features of size $H \times W \times 3C$.

Our motivation is that the slight high-frequency differences between the authentic images and the manipulated images ought to be passed on through cascaded layers. As a result, CW-HPF can be used in different parts of our proposed framework to extract more precise noise features by leveraging the inter-channel relationships, and thus improves the overall performance.

CW-HPF in this work is unlearnable, and the filters are handcrafted.

C. Forgery Attention

Attention mechanism enables a neural network focus on important regions of its feature representations. Attention helps it build input-aware connections to focus more on meaningful regions by replacing fixed weights with input dependent weights. Attention mechanism has been heavily involved in different application fields of deep-learning frameworks, such
as machine translation \(^{28}\), image captioning \(^{29}\) and object detection \(^{30}\).

SPAN \(^{13}\) borrowed a single spatial attention mechanism from image recognition, with two downsides: 1) it ignores the color-channel-wise dependencies, which are important for forgery localization of true color images with multiple color channels; 2) it only focuses on salient objects on the scene while quite a few tampered regions are not with salient objects.

To overcome the downsides of normal attention mechanism in forgery localization, we have fused domain knowledge well established in multimedia security into attention mechanism, as well as made a combination of channel-wise and spatial dependencies. Here, we propose a forgery attention mechanism to focus on tampered traces instead of salient objects in order to make it adapt to forgery localization tasks. The details of our forgery attention are formulated in Algorithm \(^{1}\).

We construct two attention branches to obtain global noise attention features, as shown in Fig. \(^{5}\). We feed local features \(F \in \mathbb{R}^{H \times W \times C}\) generated by the dilated convolutional module of the refined net into two CW-HPF-based parallel attention branches, namely a spatial attention branch and a channel attention branch.

Our motivation is that with our proposed forgery attention module, the extracted attention features can provide the similarity map of noise features in both channel and spatial dimensions. It can reflect long-term contextual information in the noise domain since any two positions with similar noise features can contribute mutual improvement regardless of their distance in both spatial dimension and channel dimension.

The spatial attention branch generates a Spatial-dimension Attention Feature map (denoted as SAF\(_{H}\)). It draws the spatial relationship between pairwise positions of the noise features. We update the features of each position by aggregating noise features of all positions with a weighted sum, where the weights are calculated by the similarities of the noise features between the corresponding two positions. For any two positions with similar noise features in the spatial dimension, they can contribute to mutual improvement.

Specifically, in the spatial dimension, the input \(F\) is fed into the CW-HPF block, followed by a convolution layer, to extract noise features. Three convolution layers are applied over the noise feature map in parallel to generate three feature maps \(F_{1}, F_{2}, F_{3} \in \mathbb{R}^{H \times W \times C}\), respectively. \(F_{1}\), \(F_{2}\) and \(F_{3}\) are then reshaped to two-dimensional feature maps \(F'_{1}, F'_{2}\) and \(F'_{3}\), each of which belongs to \(\mathbb{R}^{(H \times W) \times C}\). \(F'_{1}\) is further transposed to \(F''_{1} \in \mathbb{R}^{C \times (H \times W)}\). Matrix cross product of \(F'_{2}\) and \(F''_{1}\) is performed to calculate the distances between different positions. Here, the result of the product measures the impact of \(i^{th}\) position on \(j^{th}\) position, where \((i, j)\) in \((\mathbb{R}^{H \times W} \times \mathbb{R}^{H \times W})\). The matrix cross product is further
the Forgery Attention Feature

Fig. 5. The details of forgery attention. There are two parallel branches in forgery attention. The top one is the spatial attention branch, and the bottom one is the channel attention branch. Note that the cells with different darkness in SAM_N and CAM_N indicate the amount of attention paid to the noise features of these regions.

Algorithm 1 Forgery Attention Mechanism

**Input:** the feature map $F \in \mathbb{R}^{H \times W \times C}$.

**Output:** the Forgery Attention Feature $FAF \in \mathbb{R}^{H \times W \times C}$.

1: Initialize learnable parameters $\delta$ and $\gamma$;
2: for every training iteration do
3:  Spatial attention branch:
   1) Generate noise features using CW-HPF and a followed convolution layer;
   2) Generate $F_1, F_2, F_3$ using three parallel convolution layers;
   3) Reshape $F_3$ into $\mathbb{R}^{(H \times W) \times C}$;
   4) Transpose the result of 3) to $F_1^T \in \mathbb{R}^{C \times (H \times W)}$;
   5) Reshape $F_2 \rightarrow F_2^T \in \mathbb{R}^{(H \times W) \times C}$;
   6) $\text{Sigmoid}(F_2^T \cdot F_1^T) \rightarrow \text{SAM}_N \in \mathbb{R}^{(H \times W) \times (H \times W)}$;
   7) Reshape $F_3 \rightarrow F_3^T \in \mathbb{R}^{(H \times W) \times C}$;
   8) Reshape $\delta \cdot (\text{SAM}_N \times F_3^T)$ into $\mathbb{R}^{H \times W \times C}$;
   9) Element-wise addition of the result of 8) and $F \rightarrow \text{SAF}_N \in \mathbb{R}^{H \times W \times C}$;
4:  Channel attention branch:
   1) Generate noise features $F'$ using CW-HPF and a followed convolution layer;
   2) a) Reshape $F' \rightarrow F'_R \in \mathbb{R}^{(H \times W) \times C}$;
      b) Transpose $F'_R \rightarrow F'_R^T \in \mathbb{R}^{C \times (H \times W)}$;
      c) $\text{Sigmoid}(F'_R^T \cdot F'_R) \rightarrow \text{CAF}_N \in \mathbb{R}^{C \times C}$;
      d) Reshape $\gamma \cdot (\text{CAF}_N \times F_3^T)$ into $\mathbb{R}^{H \times W \times C}$;
      e) Add the result of d) and $F \rightarrow \text{CAF}_N \in \mathbb{R}^{H \times W \times C}$;
5:  $\text{SAF}_N + \text{CAF}_N \rightarrow FAF$;
6:  Update $\delta$ and $\gamma$ with back-propagation.
7: end for
8: return $FAF$

Fused to a Sigmoid activation to get the Spatial Attention Matrix of noise features $\text{SAM}_N \in \mathbb{R}^{(H \times W) \times (H \times W)}$. $\text{SAM}_N$ describes the similarity between any two different positions in the spatial dimension of the noise feature map. According to [23], the more similarity between two positions in the noise feature map is, the greater the correlation between two points in $F$ becomes. $\text{SAM}_N$ is then multiplied with $F_3$, and the result is reshaped back to $H \times W \times C$. Finally, a learnable scaling factor $\gamma$ is multiplied with the result of the last step and then is added with the input features $F$ to generate $\text{SAF}_N \in \mathbb{R}^{H \times W \times C}$. It is formulated as follows:

$$\text{SAF}_N = \gamma(\text{SAM}_N \times F_3) + F = \gamma(\text{sigmoid}(F_1^T \times F_2^T) \times F_3^T) + F,$$

where we initialize $\gamma$ as 0 and update it with back-propagation learning.

Meanwhile, the channel attention branch generates a Channel-dimension Attention Feature map (denoted as $\text{CAF}_N$) to model the channel relationship between any two channels of noise features. We update each channel feature map with a weighted sum of all channel feature maps.

The calculation in the channel dimension is similar to that in the spatial dimension. Firstly, a CW-HPF and a convolution layer are used to generate the noise features $F'$ of input $F$, where $F' \in \mathbb{R}^{H \times W \times C}$. $F'$ is reshaped to $F'_R \in \mathbb{R}^{(H \times W) \times C}$. $F'_R$ is then performed matrix cross product with $F_3^T$. A Sigmoid activation is applied to calculate the Channel Attention Matrix $\text{CAM}_N \in \mathbb{R}^{C \times C}$ of noise features. Like $\text{SAM}_N$, $\text{CAM}_N$ describes the similarity between any two different positions in the channel dimension of the noise feature map. Then $F'_R$ is performed matrix cross product with $\text{CAM}_N$, whose result is reshaped to $H \times W \times C$. Finally, the matrix cross product result is multiplied by another learnable scaling factor $\delta$, and the multiplication result is added with the input $F$. 

In the bottom branch, $\text{CAF}_N$ is used as the attention feature map to generate the attention feature map $\text{FAF} \in \mathbb{R}^{H \times W \times C}$.
to obtain $\text{CAF}_N \in \mathbb{R}^{H \times W \times C}$:
\[
\text{CAF}_N = \delta(\text{CAM}_N \times F^R_i) + F,
\]
\[
\text{CAF}_N = \delta(\text{sigmoid}(F^T \times F^R_i) \times F_R + F), \quad (2)
\]
where $\delta$ starts from 0 and gradually adjusts to assign more weight during training.

The introduction of the two learnable scaling factors, namely $\gamma$ and $\delta$, during the training procedure of $\text{SAF}_N$ and $\text{CAF}_N$ is borrowed from [23], in order to enhance network representation. In addition, please note that there are only two classes (i.e., forged or not) in the forgery localization task, and usually prediction of every pixel ranges from 0 to 1. Therefore, in forgery attention, $\text{SAF}_N$ and $\text{CAF}_N$ are generated with Sigmoid activation rather than traditional Softmax function since the value of Sigmoid activation is confined in $[0,1]$.

After that, $\text{SAF}_N$ and $\text{CAF}_N$ are then fused to obtain the Forgery Attention Features (FAF). In particular, an element-wise addition is performed on $\text{SAF}_N$ and $\text{CAF}_N$, of which the result is fed into a convolution layer to generate FAF. As a result, FAF provides the similarity map of noise features in both channel and spatial dimensions. It reflects long-term contextual information in the noise domain, but any two positions with similar noise features contribute mutual improvement regardless of their distance in both spatial dimensions and channel dimension.

D. VGG Block and Dilated Convolutional Block

The architecture of VGG blocks originates from Mantra-Net [4]. Each VGG block contains three or four stacked convolution layers with kernel size $3 \times 3$. In coarse net, the VGG blocks are denoted as $\mathcal{V}_i(f)$ ($i \in \{1, 2, 3, 4, 5\}$), where $f$ denotes the input features and $\mathcal{V}_i$ denotes VGG block. $\mathcal{V}_i$ performs encoding when $i = 1, 2, 3$ while performs decoding when $i = 4, 5$. The VGG blocks are of size $32 \times 2^i$ when $i = 1, 2, 3$, and size $32 \times 2^{2-i}$ when $i = 4, 5$. Max pooling layers follow $\mathcal{V}_i(f)$ and $\mathcal{V}_i(f)$ to down-sample the features, and the output of them is skip-connected with that of $\mathcal{V}_i(f)$ and $\mathcal{V}_i(f)$, respectively. $\mathcal{V}_i(f)$ and $\mathcal{V}_i(f)$ are followed by up-sampling layers to restore the size of feature maps.

Zhong et al. [15] has pointed out that for forgery localization task the deep-learning framework needs larger receptive fields to avoid learning features from narrow local regions. Thus following their approach, four dilated convolution layers are applied to inflate the kernels by inserting zeros between kernel elements with different dilation rates for extracting features with larger receptive fields. The dilated convolution layers are then used to bridge the encoders and the corresponding decoders in both the coarse net and the refined net. Specifically, the dilation rates in the four dilated convolution layers are 2, 4, 8, and 16, respectively.

E. Self-Adversarial Training

Frankly speaking, deep-learning based models are all training data hungry. It is a huge challenge to train a deep-learning based framework in a scenario with limited training samples, such as image forgery localization. Data augmentation techniques can alleviate this issue. However, the common data augmentation techniques, such as image flipping and rotation, used in existing forgery localization methods (e.g. Mantra-Net [4] and SPAN [14]) do not utilize the feedback of the target deep-learning based framework in training samples augmentation.

Our proposed SAT strategy can realize training samples augmentation with endless supply of adversarial samples generated with the latest gradients of the target deep-learning model in every training iteration.

The motivation behind SAT is that the detection model can easily over-adapt to the texture features of the image datasets it is trained on, since the tampering noise is very subtle. SAT not only increases the robustness of the model with adversarial attack during training, but also improves its performance by providing training data dynamically. In the field of object detection, YOLO v4 [31] has used self-adversarial training to augment the training data and achieve better performance. We first attempt for applying self-adversarial training strategy and making experimental analysis of it for forgery localization.

In the first training phase, like the traditional training process, our model is trained on the forged image $I_F \in \mathbb{R}^{H \times W \times C}$ and its corresponding ground-truth mask $y_{gt}$.

In the second training phase, an adversarial image $I_{adv}$ from $I_F$ is firstly generated with the Fast Gradient Sign Method (FGSM) [23], a fast and famous adversarial attack method. Due to the fast attack speed of FGSM, we apply it instead of other adversarial attacks as our attack method. Other well-known adversarial attack algorithms, such as BIM [32] and MI-FGSM [33], spend more time on attacking an image. Specifically, BIM takes 0.94 second, MI-FGSM takes 1.13 second, while FGSM only take 0.2 second to perform adversarial attack on an image. FGSM attacks the latest gradients of our model to generate an adversarial example $I_{adv} \in \mathbb{R}^{H \times W \times C}$, which can be formulated as follows:
\[
I_{adv} = I_F + \epsilon \cdot \text{sign} \left( \nabla_{I_F} L(\theta, I_F, y_{gt}) \right), \quad (3)
\]
where $\theta$ denotes the current parameters of our model, $\nabla_{I_F}$ is the gradient of $L(\theta, I_F, y_{gt})$ with respect to $I_F$, and $\epsilon$ is the attack strength.

Algorithm 2: Self-Adversarial Training Strategy

**Input:** The tempered image $I_F$ and $y_{gt}$, the corresponding binary mask of ground truth;

**Output:** The parameters $\theta$ of our network;

1: Initialize the parameters $\theta$, including weights and biases, of our network as illustrated in Fig. 3;
2: for every training iteration do
3: \quad (Begin Phase 1)
4: \quad Predict the coarse prediction mask $I_{M_1}$ and the refined prediction mask $I_{M_2}$ for the forged image $I_F$;
5: \quad $[I_F, (I_{M_1}, I_{M_2}, (y_{gt}, y_{gt}))] \rightarrow \text{FirstTrainSet}$
6: \quad Update parameters $\theta$ of our network with FirstTrainSet;
7: \quad \quad (End Phase 1)
8: \quad (Begin Phase 2)
9: \quad Random(0, 0.01) $\rightarrow \epsilon$;
10: \quad Initialize FGSM algorithm (Equation 3) with $\epsilon$ and the updated $\theta$;
11: \quad $\text{FGSM}(I_F, y_{gt}) \rightarrow I_{adv}$;
12: \quad Predict the coarse prediction mask $I_{M_1}$ and the refined prediction mask $I_{M_2}$ for the adversarial image $I_{adv}$;
13: \quad $[I_{adv}, (I_{M_1}, I_{M_2}, (y_{gt}, y_{gt}))] \rightarrow \text{SecondTrainSet}$
14: \quad Update parameters $\theta$ of our network with SecondTrainSet;
15: \quad \quad (End Phase 2)
16: end for
denotes obtaining the gradients of our model when input $I_F$ and $L$ denotes the loss function. $\epsilon$ is taken a random number in the range $(0, 0.01)$ in every iteration to increase randomness, which generates more training data during SAT and would make the network more robust. The model is then trained on the obtained adversarial example $I_{adv}$ and $y[gt]$, the corresponding ground-truth mask also used in the first training phase. We update the parameters $\theta$ of our network in Step 6 and Step 14 by back-propagation to minimize the loss function of Eq. 4.

We draw a flowchart to explain the training phase in Fig. 7. The first phase is the traditional training process. In a single training iteration, we add a second phase to perform SAT. Specifically, after the normal back-propagation using the input-ground-truth pairs and updating the network’s parameters, the same inputs are used to generate adversarial samples $Input_{adv}$ by adversarial attack method, FGSM, according to the updated model. Although $Input_{adv}$ has the same content as $Input$, which can be localized the tampered regions by the updated model, $Input_{adv}$ is with adversarial samples and can mislead the detection result, shown in Fig. 6(b). In other words, $Input_{adv}$ is new data for the model. This phase increases the training data dynamically since the adversarial samples are generated according to the updated model’s parameters in every training iteration. Note that we optimize the same network in both the first and the second training phase.

With two-phase self-adversarial training, SAT can provide new training data dynamically from limited original samples. Those training data generated via adversarial attacks, e.g. FGSM, can make our model more robust.

To illustrate the impacts of SAT, we draw the residual map between $I_F$ and $I_{adv}$ and then enlarge it by 20 times, as shown in Fig. 6(a). The residual map will change in the following epoch because $I_{adv}$ is constantly changing. Meanwhile, to differ the forged image $I_F$ and its corresponding adversarial example $I_{adv}$, we illustrate the inference results of them before training $I_{adv}$ in Fig. 6(b). As shown in Fig. 6(b), before the second training phase, the model predicts an approximately precise mask using $I_F$ but predicts a wrong mask using $I_{adv}$.

F. Visualization Analysis

To explore the internal mechanism of our proposed CW-HPF and forgery attention, visualization analysis was conducted in this section. As illustrated in Fig. 8, a forged image was taken as examples. We visualized the activation maps of different noise features extracted from a normal high pass filter layer [11] and our proposed CW-HPF. CW-HPF uses the inter-channel information while HPF does not. Then in Figs. 9 and 10 we visualized the activation maps of different attention feature maps predicted by a normal attention module [23] and our proposed forgery attention. The activation maps with heatmaps were super-imposed on the forged image, where the red regions were with high activation values while the blue ones were with low values.

1) CW-HPF: As we can see in Fig. 8, the flower (fake), the rock (pristine) and the birds (pristine) all naturally contain high-frequency information, which both normal HPF layer and our proposed CW-HPF can extract. However, we can see HPF extracts all high-frequency information while our proposed CW-HPF can just focus on the more precise noise features in the manipulated area by leveraging the inter-channel relationships. As a result, the flower is much more prominent in the heatmap corresponding to our proposed CW-HPF.
The variance of each noise feature map was also calculated. As shown in Fig. 8, the variance $\sigma^2$ of our CW-HPF noise features is only one-ninth of that of HPF noise features, which also reveals that CW-HPF noise features have a smaller internal gap. The small variance enables CW-HPF to extract more consistent noise features in the tampered regions.

One possible reason of this phenomenon is that our CW-HPF takes advantage of inter-channel relationships to enhance the correlation between all channels. These relationships amplify the slight perturbations of noise inconsistency. Therefore CW-HPF focuses more on the tampered regions.

2) Forgery Attention: Figs. 9 and 10 visualize different regional attention of normal attention features and our proposed forgery attention features. Especially in Fig. 10, the redder regions in the heatmap of normal attention features fell in two persons while forgery attention had higher responses to the background. It indicates that the forgery attention focuses more on the tampered regions instead of the salient objects. That’s because architectures of normal attention modules are designed to detect the texture of objects. On the contrary, our forgery attention aims to pay more attention to the tampered traces.

The possible reason why forgery attention aims to pay more attention to the tampered traces is that it explores global contextual noise information by building associations among noise features with the attention mechanism. In addition, it can also be attributed to CW-HPF which extracts the noise features first. Our method can adaptively aggregate long-term contextual information of noise features, thus improves feature representation for forgery localization.

Specifically, two attention branches contribute to focusing on noise interdependencies. It can be inferred from Equation 1 that the resulting feature $S_{AF_N}$ at each position is a weighted sum of the noise features across all pixels and the original feature, which gives it a global contextual view and selectively aggregative contexts. Similar noise features achieve mutual gains, thus improving the noise consistency between the tampered and original regions. Furthermore, Equation 2 shows that the final feature of each channel is a weighted sum of the noise features of all channels and original features, which further models long-term noise dependencies among feature maps to boost noise feature discriminability. Each high-level channel can be regarded as a class-specific response, and different noise responses are associated with each other. Exploiting the interdependencies between channel maps emphasizes interdependent feature maps and improves the feature representation of tampered traces. Therefore, forgery attention achieves better performance in forgery localization tasks.

III. EXPERIMENTS

In this section, we carry out comprehensive experiments to demonstrate our proposed approach on several benchmark datasets and compare the results with state-of-the-art methods. Besides, we evaluate the robustness of our method in the scenarios of resizing, JPEG compression, and adversarial attacks. All of our experimental results are obtained on real-world datasets under the actual hardware experiments. There are no numerical simulations in our experiments. The source codes and auxiliary materials are available for download from GitHub.

A. Setup

1) Datasets: The following datasets are used in our experiments:

- **DEFACTO** [25] is a synthesized dataset generated from MSCOCO [34]. Three typical types of forgeries (i.e.,
### TABLE I

| Model                          | AUC   | $F_1$   |
|-------------------------------|-------|---------|
| Baseline                      | 0.978 | 0.855   |
| CW-HPF Model                  | 0.986 | 0.878   |
| Forgery Attention Model        | 0.990 | 0.890   |
| Coarse-to-fine Forgery Attention Model | 0.992 | 0.904   |
| Coarse-to-fine Forgery Attention Model+SAT | 0.996 | 0.920   |
| Coarse-to-fine Forgery Attention Model+SAT+Flipping+Rotation | **0.998** | **0.929** |

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**splicing, copy-move, and removal** are involved in DEFACTO. 98,779 tampered images are selected from DEFACTO as our base dataset for ablation study and pre-training. We have to emphasize that our base dataset contains fewer images than other studies’, such as MantraNet [4] (102,028 samples) and SPAN [14] (102,028 samples). The training-testing ratio is set to 9:1.

- **Columbia** [35] provides 180 splicing images with edge masks. The ground-truth masks are generated by ourselves from the corresponding edge masks
- **CASIA** [27] contains splicing and copy-move images in which forged regions are carefully selected. Some forged images have been further post-processed with filtering and blurring. It can be split into CASIA 2.0 (5,123 samples) for training and CASIA 1.0 (921 samples) for testing. Both of them are provided with ground-truth masks.
- **COVERAGE** [9] contains 100 forged images manipulated by copy-moving. All the images are post-processed to remove visual traces. It is provided with ground-truth masks.
- **NIST** [26] is composed of 564 samples manipulated with splicing, copy-move, or removal. The visible traces of manipulations are concealed by post-processing. The dataset has ground-truth masks for evaluation.

**PS-dataset** is a large-resolution dataset introduced in the latest work [15]. It involves three sub-datasets, namely PS-boundary dataset, PS-arbitrary dataset and PS-script dataset. Among these sub-datasets, the PS-boundary dataset and PS-arbitrary dataset are created manually with Photoshop®, while the PS-script dataset is tampered with the automatic script.

Please note that for the sake of fair comparison, our experiments follow the training-testing ratio configuration in RGB-N [11] on NIST, COVERAGE, and CASIA.

2) **Implementation Details:** Our approach has been implemented based on TensorFlow. Our framework was trained with input images resized to $512 \times 512$ on a single Tesla P100 GPU. An ADAM solver was used to optimize the model with a learning rate of 0.002.

3) **Evaluation Metrics:** Pixel-level $F_1$ score and Area Under the receiver operating Curve (AUC) were employed as our evaluation metrics. $F_1$ score and AUC measured the performance of binary classification for every pixel, where higher scores indicate better performance. Both pixel-level AUC and $F_1$ score values range in [0,1]. Kindly note according to observations based on our experimental results, $F_1$ score is more accurate than AUC. This is due to the fact that $F_1$ score drops significantly when the predicted masks contain quite a few false-positive predictions (the pristine pixels are marked as tampered). On the contrary, AUC still remains at a high score on account of some factors such as threshold settings in this case.

4) **Loss Function:** During training, binary cross-entropy loss was used as our training loss function. It was minimized by optimizing the model parameters. The loss function is formulated as follows:

$$\text{Loss} = L_{\text{BCE}}(y_{gt}, y_{M_1}) + L_{\text{BCE}}(y_{gt}, y_{M}),$$

where $L_{\text{BCE}}$ denotes Binary Cross-Entropy loss, $y_{gt}$ denotes ground-truth masks, $y_{M_1}$ denotes coarse masks, and $y_{M}$ denotes refined masks.

OpenCV package was used to resize the images. We set interpolation=INTER_AREA when resizing the forged images and interpolation=INTER_NEAREST for resizing the masks.
5) Compared Methods: We have selected several advanced methods compared with our approach. The advanced methods can be categorized into two types, namely unsupervised methods and deep-learning based methods. The unsupervised methods [39, 37, 17] leverage feature extraction techniques to seek unnatural traces. Recently, the deep-learning based methods [13, 11, 4, 14] have demonstrated superior performance by using convolutional neural networks. In our work, we have compared our approach with these two types of methods.

B. Ablation Study

We have conducted extensive ablative experiments to validate each component of our framework. In particular, we have first generally conducted the progressive ablation study and then carefully conducted detailed experiments for each of the proposed components. All of the ablative experiments were conducted on the DEFACTO dataset.

1) Progressive Ablation Study: The progressive ablative experiments were conducted to validate our proposed components and SAT. The setup models were as follows:

- **Baseline**: The baseline model contained an HPF filter layer, a dilated convolutional module, and VGG blocks. It did not have a coarse-to-fine architecture.
- **CW-HPF Model**: The HPF filter layer was replaced in the baseline model with a CW-HPF filter block. Others remained the same.
- **Forgery Attention Model**: It was constructed based on the CW-HPF model, composed of CW-HPF, VGG blocks, a dilated convolutional module, and a forgery attention module.
- **Coarse-to-fine Forgery Attention Model**: A coarse-to-fine net was constructed using the CW-HPF model as the coarse net and forgery attention model as the refined net. This is actual our proposed model.

All models were trained using the same setting, and the results are reported in Table I. From Table I, it can be seen that our proposed components are all effective and improve the AUC and $F_1$ scores significantly. The CW-HPF block improves the performance by 0.008 in AUC and 0.023 in $F_1$. The forgery attention module further improves by 0.004 in AUC and 0.012 in $F_1$ over the CW-HPF model. The coarse-to-fine architecture further improves by 0.002 in AUC and 0.014 in $F_1$ over the forgery attention model.

To evaluate our proposed self-adversarial training strategy, data augmentation techniques were applied for the well-trained coarse-to-fine forgery attention model, namely our proposed SAT plus flipping and rotation. As also shown in Table II, our proposed SAT further boosts the performance by 0.004 in AUC and 0.016 in $F_1$. SAT provides dynamic training data for more robust performance. For optimal performance, flipping and rotation were employed to further augment the training dataset and achieve 0.998 in AUC and 0.929 in $F_1$.

2) Ablation Study for Forgery Attention: We have applied four models that utilize different attention structures on top of basic CW-HPF model:

- **CAM only**: Only CAM was used as attention module;
- **PAM only**: Only PAM was used as attention module;
- **Dual Attention (Softmax)**: CAM and PAM were combined in parallel but with Softmax layer instead of Sigmoid layer.
- **Dual Attention (w/o CW-HPF)**: An alternative dual attention model [23] module was used without CW-HPF block.
- **Forgery Attention Model**: Our proposed forgery attention module.

As shown in Table II, a single CAM or a single PAM slightly decreases the performance of the basic model. Combining CAM and PAM makes good use of spatial and channel dependencies to generate more precise results. Adopting Softmax instead of Sigmoid, results in decreased AUC and $F_1$ as well. Meanwhile, applying the common dual attention module [23] without CW-HPF cannot improve the performance. This ablative study clearly shows that our proposed attention architecture with dual attention module, Sigmoid layer and CW-HPF is more adaptive to forgery localization task. Three intuitive reasons can be concluded for the effectiveness of our proposed dual attention module. Firstly, spatial and channel-wise contextual dependencies both are important to distinguish the intrinsic inconsistency; Secondly, Softmax, which is often used as the last activation function of a neural network, is not suitable to replace Sigmoid in the intermediate layers of a deep-learning framework; Thirdly, CW-HPF can further provide richer noise features for attention modules, which contributes to focusing on the high-pass inconsistency between the pristine regions and tampered regions.

3) Ablation Study for SAT: SAT is proposed to alleviate the problem of limited training data. SAT exploits adversarial attacks in every training iteration and generates new training data dynamically, which guides our model to defend from adversarial attacks and achieve more robust performance. Unlike traditional data augmentation, our SAT can provide unlimited new adversarial training data according to model updating. The main difference between SAT and regular data augmentation, such as flipping, is that SAT is based on the model’s parameters while others focus on the given data. We propose SAT to explore the possibility of augmenting data through model parameters instead of through data. Traditional data augmentation techniques do not conflict with our SAT but can further improve the performance with SAT. However, the common augmentation would not benefit for defense against the attacks. A simple augmentation flipping has been used in training our network on the DEFACTO dataset. As seen in

| Model | AUC | $F_1$ |
|-------|-----|-------|
| CW-HPF Model | 0.986 | 0.878 |
| CAM only | 0.962 | 0.840 |
| PAM only | 0.984 | 0.856 |
| Dual Attention (Softmax) | 0.986 | 0.879 |
| Dual Attention (w/o CW-HPF) | 0.985 | 0.879 |
| Forgery Attention Model | 0.990 | 0.890 |
Table III both SAT and Flipping + Rotation improved the performance of the baseline model. Based on the model with flipping and rotation, SAT can further increase the detection scores by 0.004 in AUC and 0.004 in $F_1$. However, SAT enables the network to decrease slightly while flipping and rotation do not when the forged images are imposed with Gaussian Noise attack. Specifically, the network trained with Flipping + Rotation degrades by 17% in AUC and 18% in $F_1$ after attack while the network trained with SAT only decreases by 8% in AUC and 10% in $F_1$. Since the adversarial attack used in SAT is a powerful attack technique, the network can be more robust when meeting other attacks.

4) Ablation Study for CW-HPF: The ablative experiments have been conducted to demonstrate the effectiveness of CW-HPF with parallel spatial and channel attention modules. Specifically, seven different feature extraction strategies have been evaluated in our proposed coarse-to-fine forgery attention model as follows:

- **RGB + RGB**: there was no HPF layer in neither the coarse net nor the refined net;
- **HPF + RGB**: there was only a normal HPF layer [II] at the bottom of the coarse net;
- **RGB + HPF**: there was only a normal HPF layer at the bottom of the refined net;
- **HPF + HPF**: the normal HPF layers were adopted at the bottom of both the coarse net and the refined net;
- **CW-HPF + HPF**: it contained a CW-HPF block at the bottom of the coarse net and a normal HPF layer at the bottom of the refined net;
- **HPF + CW-HPF**: it contained a normal HPF layer at the bottom of the coarse net and a CW-HPF block at the bottom of the refined net;
- **CW-HPF + CW-HPF**: the CW-HPF blocks were adopted at the bottom of both the coarse net and the refined net.

As we can see in Table IV, the proposed method with two CW-HPF modules outperforms other methods. Specifically, the method without a high-pass filters layer performs poorly in final results, with only 0.804 in AUC and 0.721 in $F_1$. Applying one HPF module in either the coarse net or the refined net improves the performance by 0.160-0.166 in AUC and 0.123-0.129 in $F_1$. Introducing HPF in both the coarse net and the refined net improves the performance in a clear margin by 0.174 in AUC and 0.135 in $F_1$ compared to the model with RGB + RGB. One possible reason is that the tempering traces are hidden in the high-frequency domain, and the high-pass filters can detect them. Then, the model with a CW-HPF block in either the coarse net or the refined net boosts the performance of two HPF blocks by 0.004-0.006 in AUC and 0.011-0.013 in $F_1$. Furthermore, our proposed model with two CW-HPF further increases the detection scores by 0.008 in AUC and 0.035 in $F_1$ compared to the model with a CW-HPF in the refined net and achieves the best performance. It indicates that our proposed CW-HPF module enhances noise features and boosts performance in both the coarse net and the refined net.

5) Ablation Study for Dilated Convolutional Module: DFCN has used a series of dilated convolution layers to enlarge receptive fields to avoid learning features from narrow local regions. Thus following their approach, four dilated convolution layers are applied to inflate the kernels by inserting zeros between kernel elements with different dilation rates for extracting features with larger receptive fields. We follow DFCN’s settings, and the dilation rates in the four dilated convolution layers are 2, 4, 8, and 16, respectively. The dilated convolution layers bridge the encoder and the corresponding decoder. There are two sub-nets in a coarse-to-fine manner. Here, we have conducted ablative experiments to validate the effectiveness of the dilated convolutional module.

To compare with our final model, the coarse-to-fine forgery attention model of the revision, with two dilated convolutional modules in both the coarse net and the refined net, we have modified the bridge of the encoders and the decoders of two sub-nets as follows:

- **Dilated + Dilated**: it contained two dilated convolutional modules in the coarse net and the refined net.
- **w/o Dilated + w/o Dilated**: it directly connected the encoders and decoders without any dilated convolutional module.
- **Dilated + w/o Dilated**: it included a dilated convolutional module in the coarse net and no dilated convolutional module in the refined net.
- **w/o Dilated + Dilated**: it consisted of a dilated convolutional module in the refined net and no dilated convolutional module in the coarse net.

As we can see in Table IV, without any dilated convolutional
modules, the model decreases the performance by 0.003 in AUC and 0.010 in $F_1$. Interestingly, if a dilated convolutional module is used in the coarse net, the model’s performance declines slightly compared to that without a convolutional module. Meanwhile, the model with a dilated convolutional module in the refined net increases by 0.001 in AUC and 0.003 in $F_1$ compared to the model w/o Dilated + w/o Dilated, but decreases by 0.002 in AUC and 0.007 in $F_1$. It indicates that the coarse-to-fine network is required to generate the richer features in the refined net than in the coarse net, and applying the dilated convolutional modules in both the coarse net and the refined net improves the performance.

6) Ablation Study for Coarse-to-Fine Connection: Generally, referring to the coarse-to-fine manner, the connection from the coarse net to the refined net is to directly transmit the results of the coarse net as the inputs of the refined net. However, the result of the coarse net is a binary mask, which does not contain any semantics for refinement in forgery localization. Therefore, rather than using the final results of the coarse net as the inputs of the refined net, we deliver complete feature information generated by the last deconvolutional layer of the coarse net to the refined net, which enables the refined net to be optimized along with the features. We validate this design through an ablative experiment. We adopt the CW-HPF model as the coarse net and forgery attention model as the refined net and set two types of bridges between the coarse net and the refined net. The first type of connection uses the results of the coarse net, defined as Direct Connection, while the second one applies the output features of the last deconvolutional layer of the coarse net, defined as Feature Connection.

The results are shown in Table VI. The coarse-to-fine manner with Direct Connection shows a poor performance compared to the Feature Connection significantly. Specifically, the AUC of Feature Connection is 40% higher and the $F_1$ is 185% than Direct Connection. The possible reason is that Feature Connection provides integral features for the refined net while Direct Connection does not.

### Table V

| Model               | AUC  | $F_1$ |
|---------------------|------|-------|
| Dilated + Dilated   | 0.996| 0.920 |
| w/o Dilated + w/o Dilated | 0.993| 0.910 |
| Dilated + w/o Dilated | 0.990| 0.907 |
| w/o Dilated + Dilated | 0.994| 0.913 |

### Table VI

| Model            | AUC  | $F_1$ |
|------------------|------|-------|
| Direct Connection| 0.709| 0.322 |
| Feature Connection| 0.996| 0.920 |

7) Trade-off Experiments: We have conducted the trade-off experiments based on the Coarse-to-fine forgery attention model to achieve a better trade-off. We employ different numbers of basic filters (8, 16, 32, 48, 64) to conduct the trade-off experiments on the DEFACTO dataset. The different number of basic filters (nbf) represents the last deconvolutional layer’s filter numbers while other filters of convolution layers in the network have multiples. The more filters indicate the larger parameters and cost, whereas the double nbf indicates the double network parameters and four calculation resources. Therefore, we gain our trade-off by this experiment.

The results are shown in Fig. 11. As we can see, there is a significant rise of $F_1$ score from 8 to 32 nbf while the raising speed slows down dramatically after 32 nbf. We can conclude that we achieve a better trade-off when applying 32 as the number of basic filters.

We have also added this experiment into the main text of the revised version in Section III B. For details, please refer to the corresponding context.

C. Quantitative Results Compared against State-of-the-art Methods

We compare the performance of our framework against several related methods on four benchmarks, namely NIST, COVERAGE, Columbia, and CASIA. The related methods include classic unsupervised methods, such as ELA [36], NOI1 [37], and CFA1 [17], and the latest deep networks, including H-LSTM [13], RGB-N [11], Mantra-Net [4], and SPAN [14]. We evaluated our framework under different setups: (1) benchmark training only; (2) fine-tuning. Under the benchmark training only setup, our model was trained on each benchmark separately. Under the fine-tuning setup, to achieve optimal performance, our pre-trained model was fine-tuned using several benchmarks, including NIST, COVERAGE, and CASIA, and tested on the corresponding testing split. Note that a training-testing ratio was set to 7:3 during benchmark training on the Columbia dataset. The actual reason has been given in accompanying discussions of Table VII.

The results are reported in Table VII. When adopting the benchmark training setup that uses only a small amount of
training data, e.g., 75 forged images from COVERAGE, our model shows superior performance compared to state-of-the-art approaches, especially on the Columbia dataset where our $F_1$ score outperforms all other methods. It indicates that our approach does not rely on large-scale training data to achieve decent performance, which shows the effectiveness of our approach. In the fine-tuning setup, our approach takes good advantage of large-scale training data. It can be concluded that our approach is further boosted by large-scale training data. In particular, our approach outperforms SPAN by 0.296 in $F_1$ score on NIST dataset and 0.048 in AUC on COVERAGE dataset. Note that because all of the forged regions in Columbia dataset are large while the forged regions in DEFACTO are small ones. Thus, there is a domain gap between Columbia and DEFACTO. So different from the settings of SPAN and Mantra-Net, our results on Columbia dataset are based on 30% testing data and the other 70% data is used for finetuning. It is clear from Table VII that our model that is trained on DEFACTO dataset and finetuned on each benchmark datasets achieves state-of-the-art performance. The possible reason is that the proposed components and SAT training strategy work jointly and achieve optimal performance.

Furthermore, we compare the effectiveness of our model with the most recent algorithm, i.e., dense fully convolutional network (DFCN) [15]. We followed this setting [15] and used 512×512 image patches for training while full images for testing. Our model was trained using PS-script dataset and finetuned using only 10% forged images of several datasets, respectively, i.e., 100 samples in PS-arbitrary dataset, 100 samples in PS-boundary dataset and 56 samples in NIST dataset. Note that in the setting of [15], which is different from our experiments on NIST dataset in Table VII, NIST dataset is split into 512×512 patches. Note that DFCN aims to localize the tampered region with high-resolution while other advanced methods do not. Therefore, for a fair comparison, we make two settings on NIST dataset. When we compare our method with other advanced methods, we apply the typical pre-processing process that resizes the tampered images into 512×512 resolutions. When we compare our method with DFCN, we follow DFCN’s setting and crop the tampered images in NIST dataset into 512×512 patches. It can be seen from Table VIII that the performance of our model outperforms DFCN on three datasets. Before fine-tuning in each benchmark dataset, our results are slightly lower than DFCN in AUC on PS-arbitrary and NIST datasets. However, our model has been over DFCN by 0.01 in AUC on PS-boundary dataset. About $F_1$ score, our results are about 25% higher on PS-boundary dataset and 15% higher on NIST than DFCN’s. After fine-tuning on each dataset, our method has made a good improvement and outperforms DFCN on three datasets. In particular, our results achieve about 10% in $F_1$ score higher on PS-boundary dataset, slightly higher in AUC and $F_1$ score on PS-arbitrary dataset, and about 6% in AUC on NIST dataset than DFCN.

### TABLE VII

| Method     | Training Method | NIST   | COVERAGE | Columbia | CASIA |
|------------|----------------|--------|----------|----------|-------|
|            |                | AUC    | $F_1$    | AUC      | $F_1$ | AUC    | $F_1$ |
| ELA        | unsupervised   | 0.429  | 0.236    | 0.583    | 0.222 | 0.581  | 0.470 |
| NOI1       | unsupervised   | 0.487  | 0.285    | 0.587    | 0.269 | 0.546  | 0.574 |
| CFA1       | unsupervised   | 0.501  | 0.174    | 0.485    | 0.190 | 0.720  | 0.467 |
| H-LSTM     | fine-tuning    | 0.794  | —        | 0.712    | —     | —     | —     |
| RGB-N      | fine-tuning    | 0.937  | 0.722    | 0.817    | 0.437 | 0.858  | 0.697 |
| Mantra-Net | pre-training   | 0.795  | —        | 0.819    | —     | 0.824  | —     |
| SPAN       | fine-tuning    | 0.961  | 0.582    | 0.937    | 0.558 | 0.936  | 0.815 |
| Ours       | benchmark training | 0.943  | 0.622    | 0.856    | 0.526 | 0.917  | 0.891 |
| Ours       | finetuning     | **0.990** | **0.878** | **0.985** | **0.843** | **0.999** | **0.983** |

### TABLE VIII

| Method           | PS-boundary | PS-arbitrary | NIST |
|------------------|-------------|--------------|------|
|                  | AUC | $F_1$ | AUC | $F_1$ | AUC | $F_1$ |
| DFCN (w/o fine-tuning) | 0.90 | 0.61 | 0.91 | 0.57 | 0.63 | 0.20 |
| Ours (w/o fine-tuning) | **0.91** | **0.76** | 0.90 | **0.58** | 0.61 | **0.23** |
| DFCN (fine-tuning) | 0.99 | 0.82 | 0.97 | 0.67 | 0.80 | 0.38 |
| Ours (fine-tuning) | **0.99** | **0.90** | **0.98** | **0.69** | **0.85** | **0.40** |

**D. Computational Complexity Analyses**

The computational complexities have been calculated and compared to the existing benchmarks with 512×512 NIST forged images as input in a single NVIDIA® Tesla® P100 GPU card. As for the benchmarks, we adopt two popular methods, namely Mantra-Net [4] and SPAN [14], for comparison.
TABLE IX

| Method       | Params(M) | FLOPs(M) | Inference time(ms) | Training time (mins)* |
|--------------|-----------|----------|--------------------|-----------------------|
| Mantra-Net   | 3.80      | 7.58     | 392                | 16                    |
| SPAN         | 4.06      | 8.11     | 527                | 18                    |
| Our          | 12.31     | 31.26    | 126                | 8                     |

The analytic report can be found in Table IX, in which the inference time is the average over randomly selected 1,000 samples, and the training time if the average over 20 epochs on NIST dataset.

Please note that for deep-learning image forgery localization models, average training time as well as inference time with every input images are the better metrics rather than model parameters and FLOPs, since quite a few existing approaches have adopted complex training/inference tricks which cannot be measured with only model parameters and FLOPs.

From Table IX we can see that compared with Mantra-Net and SPAN, our proposed framework consumes much less training time as well as inference time, though our framework is with more model parameters and FLOPs. Our framework takes only roughly 126ms per image on a single Tesla P100 GPU. This is due to the fact that our proposed framework is trained and validated in a fully end-to-end manner, while Mantra-Net and SPAN are with quite a few extra off-model time-consuming operations/calculations, such as the nested-and-sliding window based feature extractor, a large number of matrix operations.

E. Qualitative Results

In Fig. 12 we show the prediction masks of our proposed framework for some selected images. From a standalone testing set, we select six tampered images which are generated with three popular tampering techniques, including splicing, copy-move and removal, from the mentioned datasets. As shown in Fig. 12 in the tampered images the original semantics has been changed and consequently, a considerable understanding gap is caused. For example, the left splicing image added a stop sign on the road, damaging the auto-driving system. However, our algorithm can localize their forged regions credibly. From Fig. 12 it can be seen that our approach produces accurate results against different tampering techniques. No matter whether they are tampered objects or background without recognizable objects such as snow, our method detects them with high precision. In summary, our method makes good use of spatial and channel-wise attention to noise features and can precisely spot tampering areas that are obvious or even indistinguishable to human beings.

F. Robustness Experiments

Robustness experiments of our framework have been conducted in this section. OpenCV built-in functions (including AREAResize, GaussianBlur, GaussianNoise, and JPEG-Compress) and adversarial attacks (FGSM) were employed to generate content-preserving manipulations on NIST. Note that epsilons of FGSM used in our SAT strategy were valued from 0 to 0.01 while the epsilon was 0.02 in the testing stage, which is a fair comparison. As shown in Table IX, our framework is quite immune to several types of attacks. All results except FGSM of SPAN are reported in SPAN [14].

IV. Conclusion

In this paper, we propose a novel deep neural network solution and a self-adversarial training strategy to effectively localize tampered regions in an image. The major contributions of our work areas follows:

- We have proposed a novel attention mechanism adapting to forgery localization task, named forgery attention which can be used to effectively capture noise feature dependencies in both spatial and channel dimensions.
- We have presented a novel self-adversarial training strategy for forgery localization, which augments training data dynamically to enable our model to achieve more robust performance, and alleviates the problem of limited labeled training data in this scenario.
- We have proposed a novel forgery localization framework in a coarse-to-fine manner, equipped with the Channel-Wise High Pass Filter (CW-HPF) block. Extensive experiments conducted on de-facto benchmarking datasets demonstrate that our approach outperforms other state-of-the-art solutions in the literature by a clear margin.

Our future work will mainly focus on two aspects: (1) introduction of few-shot learning and even unsupervised learning based strategies to further tackle the issue of limited training data; (2) further exploration of the feasibility of our proposed approach in the wider multimedia forensics applications, e.g., video forgery localization and deepfake detection.

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TABLE X
ROBUSTNESS ANALYSIS OF OUR FRAMEWORK ON THE NIST DATASET. THE RESULTS ARE REPORTED IN PIXEL-LEVEL AUC.

| Manipulations                          | Mantra-Net | SPAN       | Ours     |
|----------------------------------------|------------|------------|----------|
| None                                   | 0.795      | 0.8395     | 0.990    |
| Resize (0.78x)                         | 0.7743     | 0.8324     | 0.984    |
| Resize (0.25x)                         | 0.7552     | 0.8032     | 0.979    |
| GaussianBlur (kernel size=3)           | 0.7746     | 0.8310     | 0.983    |
| GaussianBlur (kernel size=5)           | 0.7455     | 0.7915     | 0.951    |
| GaussianNoise (sigma=3)                | 0.6741     | 0.7517     | 0.937    |
| GaussianNoise (sigma=15)               | 0.5855     | 0.6728     | 0.866    |
| JPEGCompress (quality=100)             | 0.7791     | 0.8359     | 0.978    |
| JPEGCompress (quality=50)              | 0.7438     | 0.8068     | 0.938    |
| FGSM (eps=0.02)                        | 0.5058     | 0.5401     | 0.986    |

Fig. 12. Sample results of our framework in three popular manipulations, namely splicing, copy-move, and removal. The samples are from NIST, Columbia, COVERAGE, CASIA, and DEFACTO.

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