Deep Localization of Mixed Image Tampering Techniques

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Abstract—With technological advances leading to an increase in mechanisms for image tampering, fraud detection methods must continue to be upgraded to match their sophistication. One problem with current methods is that they require prior knowledge of the method of forgery in order to determine which features to extract from the image to localize the region of interest. When a machine learning algorithm is used to learn different types of tampering from a large set of various image types, with a large enough database we can easily classify which images are tampered. However, we still are left with the question of which features to train on, and how to localize the manipulation. In this work, deep learning for object detection is adapted to tampering detection to solve these two problems, while fusing features from multiple classic techniques for improved accuracy. A Multi-stream version of the Faster RCNN network will be employed with the second stream having an input of the element-wise sum of the ELA and BAG error maps to provide even higher accuracy than a single stream alone.

Index Terms—Faster RCNN, Deep learning, Image fraud

I. INTRODUCTION

Images are often trusted as evidence or proof in fields such as journalism, forensic investigations, military intelligence, scientific research and publications, crime detection and legal proceedings, investigation of insurance claims, and medical imaging [1]. In order to protect legal and political photos while maintaining research integrity or reproducibility, image manipulation detection is a highly necessary tool [2]. As technology advances, common image tampering techniques such as retouching or resampling which involves geometric transformations on part of the image, image splicing, copy-move fraud [3], or removal, are widely available to the public. Worse yet, this often includes post-processing such as Gaussian smoothing, making it even more difficult for humans to recognize the tampered regions with the naked eye. Due to the difficulty of distinguishing fake and authentic images, research in this field has become integral to preventing hacking.

However, detection of different methods such as copy-paste fraud, added WGN (White Gaussian Noise), and color enhancements, each require different filters and algorithms which must also be applied at different sized bounding boxes depending on the size of the tampered region [4]. These details are often not provided, making it difficult to determine which technique to apply to which image. A method of detection that is generalizable to various differences between images or even new types of tampering is of great need today.

A. CNN for Tampering Detection

With the increase in image data available, and the increase in efficiency of modern GPUs to handle bigger problems, there has been interest in the application of machine learning for image fraud detection. These more sophisticated techniques have been able to train a model to estimate the probability of the images feature map (or sub-image feature blocks) being tampered [5]. Convolutional Neural Networks (CNN)s, are particularly well suited for image tampering detection due to their ability to automatically learn a combination of highly detailed or pixel-level features, unable to be detected by the human eye. They have been shown capable of detecting textures, noise, and resampling much more efficiently than classic techniques in a number of studies [6] [7] [8] [9] [10].

With the increase in use of deep-learning for more and more diverse image tasks, one study found that networks which are trained in object-detection can be adapted to manipulation detection. In this case, instead of localizing the objects in the image, the network can be used to localize tampering artifacts by re-training on the manipulated dataset so that the network learns the manipulated features. Using a network designed for extracting regions of interest solves the problem of having to apply the specified network or filter to each sub-image box. For example, Zhou et. al. [11] employed Faster RCNN to outperform the speed and accuracy of image forgery detection over all previous classic methods and most CNN-based on multiple popular image datasets. A bilinear approach was then used to simultaneously examine both the RGB image content and noise information, providing an even higher accuracy. This helped by combining some of the specific noise information extracted from the image with those picked up by the CNN.

B. The Present Work

However, comprehensive experimental results on multiple datasets have shown that our version of Error Level Analysis (ELA) and Block Artifact Grid (BAG) method work much better than various Noise Analysis (NA), DCT-based, or PCA-based methods in extracting tampering artifacts not brought
out by the CNN alone. This is because ELA simultaneously extracts the change in the compression local noise artifacts. Further, when the error level output map is combined with the Block Artifact Grid (BAG) method map (eg. summed pixel-wise) results are even more superior over other top classic methods.

These results have also verified that this algorithm will work on any image type since all images will have different levels of compression, regardless of whether they were originally store din JPEG. The BAG method was proven effective on detecting both copy-move and splicing forgery with varying levels of compression or quality level. This was shown by Wang et al. [13] and Liu et. al. [14], which tested compression rates of 5 % to 100 % including those with added noise.

II. METHODS & MATERIALS

The Multi-Stream Faster R-CNN framework presented here builds on the Faster RCNN network [15] and is a modification of the bilinear Faster RCNN [11]. The JPEG compression stream will have an input of the combined BAG and ELA maps of the image to provide additional features of manipulation as shown in [1].

1) Block Artifact Grid (BAG): The Block Artifact Grid (BAG) method uses the difference in the JPEG Quality (Q levels) found throughout image blocks to estimate the locations with high amounts of artifacts indicated by different compression rates [16]. The steps of the BAG method (which are similar to reverse JPEG compression) are summarized below:

- Divide the image into 8×8 blocks. Take the DCT of the blocks (using an 8×8 DCT matrix and matrix multiply).
- Make a histogram of the color-quantized DCT values for each of the 64 locations of the blocks (where the number of blocks and the number of values in each histogram is equal to the number that can fit into the image).
- Take the Fast-Fourier Transform (FFT) of the histogram of each of the 64 frequencies to get the periodicity and then power spectrum to get peaks.
- Calculate the number of local minimums of the extrema. This is the estimated Q value.
- Get a Q estimate for at least 32 Q values, and use it to calculate the block artifact (error in the Q value) for each image block. Output an error map of the image.

2) Error Level Analysis (ELA): The Error Level Analysis (ELA) outputs is an image that is created as follows: One saves the image at a slightly lower JPEG Q level, reads it back in, and computes the pixel-by-pixel difference within 8×8 blocks from the original image. Since image regions with lower Quality in the original image will degrade at a higher rate when compressed, subtracting the decompressed image from the original image gives the difference in Q levels in each block. Image blocks that originally had lower Quality levels will have the highest error and brightest color in the output.

B. Bilinear Pooling

Since the RGB stream alone has been shown to be highly accurate in detection of manipulated regions, only this stream provides the region proposals of the RPN layer [11]. Bilinear pooling is used to combine both streams while maintaining the spatial information. The output is \( x = f_{RGB} f_{JPGC} \), where \( f_{RGB} \) is the RoI of the RGB stream and \( f_{JPGC} \) is the RoI of the JPEG compression analysis stream. The total loss function is the sum of all of the RPN, fused classification, and regression losses, as shown in Equation 1.

\[
L_{total} = L_{RPN} + L_{tamper}(f_{RGB}, f_{JPGC}) + L_{bbox}(f_{RGB})
\]

where

- \( L_{RPN} \) denotes the RPN loss
- \( L_{tamper} \) denotes the final cross entropy classification loss (based on the output of multi-stream pooling)
- \( L_{bbox} \) denotes the final bounding box regression loss
- \( f_{RGB} \) represents the RoI from the RGB stream

\[\text{Equation 1}\]
•  $f_{JPGC}$ represents the RoI from the JPEG compression stream

C. Experimental Setup

1) Hardware: The model was implemented in Python with a modified version of the official Faster RCNN library [17] on a Quadro 6000 cloud GPU.

2) Datasets: The network was first trained and tested on a self-made spliced image database constructed from the PASCAL VOC data [18]. It was created by digitally selecting the random objects by their pixel maps provided in each dataset, pasting them into another image, and moving the new object annotation with it. Second, it was fine-tuned and tested on a few classic image manipulation datasets, which have been highly re-used in literature. These are below.

- CASIA 1 & 2 (2013) [19]: sizes $374 \times 256$, $320 \times 240$ to $800 \times 600$; Includes splicing with pre/post-processing, in TIFF/JPEG/BMP image formats.
- CoMoFoD (2013) [20]: sizes $512 \times 512$; Includes copy-move, in JPEG/PNG format.
- COVER (2016) [21]: sizes $400 \times 486$; Includes copy-move forged images.

All non-JPEG images were first converted to JPEG. Also, only images in the CASIA datasets with clear bounding boxes were used for testing so that it would be easy to make a fair judgement of the overall prediction accuracy on this dataset. Table I provides the Test/Train distributions and number of Training steps used respectively, for each dataset.

Table II shows the performance comparison to the single stream version (RGB Net) and the bilinear version with the second stream as the noise features (RGB-N) [11], as well as the BusterNet [23], which is the past top performing model on these datasets. Kumar and Bhavasar obtained slightly higher scores on CASIA and CoMoFoD dataset to 80.3% and 78.8%, but only tested the copy-paste forged images.

III. Results

A. Synthetic Dataset Tests

The accuracy was over 90% on the synthetic dataset. Top methods such as, Yan et. al. [22] also created a synthetic dataset using PASCAL VOC 2012 and obtained 87%. They used a CNN-based deep architecture, which consists of three feature extraction blocks and a feature fusion module.

B. Official Image Manipulation Dataset Tests

Figure 2 shows the output of BAG and ELA in the top left and right, respectively. The bottom row shows the sum of the outputs and the output of the MS-Faster RCNN, respectively. The predicted bounding box (in red) is around the tampered region (the cat).

Table II shows the performance comparison to other models.

IV. Conclusion

The multi-stream version localized tampered regions better than other methods. Fusing more classic features including the JPEG or compression artifacts helps extract more tampering types than other features such as noise. Older methods normally use a sliding window of feature maps to test for manipulated regions, while a deep network uses bounding box regression on various anchor box sizes to estimate the probability of a region being tampered allowing us to automatically capture more information. As future work, fusing more classically used features, obtained from DCT or PCA-based methods may help to even further increase the score.
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