CNN-BASED DETECTION OF GENERIC CONTRAST ADJUSTMENT WITH JPEG POST-PROCESSING

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ABSTRACT
Detection of contrast adjustments in the presence of JPEG post processing is known to be a challenging task. JPEG post processing is often applied innocently, as JPEG is the most common image format, or it may correspond to a laundering attack, when it is purposely applied to erase the traces of manipulation. In this paper, we propose a CNN-based detector for generic contrast adjustment, which is robust to JPEG compression. The proposed system relies on a patch-based Convolutional Neural Network (CNN), trained to distinguish pristine images from contrast adjusted images, for some selected adjustment operators of different nature. Robustness to JPEG compression is achieved by training the CNN with JPEG examples, compressed over a range of Quality Factors (QFs). Experimental results show that the detector works very well and scales well with respect to the adjustment type, yielding very good performance under a large variety of unseen tonal adjustments.

Index Terms— Adversarial multimedia forensics, adversarial learning, deep learning for Multimedia Forensics, contrast manipulation detection, cybersecurity.

I. INTRODUCTION
Adjustment of contrast and lighting conditions of image sub-parts is often performed during forgery creation. Therefore, the problem of detecting such manipulation has been widely studied in image forensics, and, more recently, in scenarios encompassing the presence of an adversary [1], [2]. Due to the peculiar traces left by contrast adjustment operators, most early works were based on the analysis of first order statistics [3]–[5]. Such approaches, however, are easily circumvented by the adversary, by means of both targeted [6] and also universal approaches [7]. To cope with such attacks, countermeasures were developed in turn, based on a second-order analysis [8], [9]. However, in most cases, the attack is of laundering-type, consisting in the application of a post-processing operation, e.g., a geometric transformation, filtering or compression. Laundering attacks have been shown to be very powerful against manipulation detectors in general [10]. In particular, the performance of contrast manipulation detectors proposed so far decrease significantly in the presence of even mild post-processing and, above all, they all exhibit poor robustness against JPEG compression [3], [5], [8], [10], [11], even when the compression is very weak. Since images are often stored and distributed in JPEG format, JPEG compression is also one of the most common post-processing images are subject to. Therefore, designing a JPEG-robust contrast adjustment detector is of primary importance.

In this paper, we face with the above problem by resorting to JPEG-aware data-driven classification [12], that is, by designing a data driven detector for contrast adjustment which is trained to recognise the specific class of JPEG laundering attacks. In particular, we look for a generic detector of contrast adjustment, that is, a detector which generalizes well to a wide variety of tonal adjustments. The proposed method relies on a Convolutional Neural Network (CNN) architecture. The CNN is directly fed with image pixels (with no pre-processing), hence the discriminative features for our problem are self-learned by the CNN. Specifically, the proposed detector relies on a JPEG-aware, patch-based CNN, which is used to classify image regions, i.e. image patches. A test image is then divided into patches which are tested separately by feeding them to the CNN. The soft patch scores (CNN outputs) are collected and the global decision on the image is performed on the score vector. All the compression QFs inside a range of values are considered to train the CNN. Noticeably, we could also exploit the knowledge of the QF, which can be estimated from the image header, and specialize the CNN to work for one QF only (hence training several CNNs). However, such an approach has the drawback of being easily prone to attacks: just re-saving the image in uncompressed format (e.g., PNG) or compressing again the image with a different QF would prevent the correct identification of the QF used to compress the image. Therefore, for our global manipulation detection task, we considered only one CNN model; the final detection accuracy is raised by exploiting the fact that patches coming from a same image are generated under the same hypothesis (being all pristine or contrast adjusted patches), and hence should all result in a small (or large) soft value as CNN output.

Experiments show that our system achieves good performance over a wide range of QFs. Thanks to the fact that the CNN is simultaneously trained with different contrast adjustments, our detector achieves good scalability with respect to the contrast adjustment type, yielding good performance over a large variety of contrast, brightness and tonal adjustments, i.e. under processing mismatch conditions. Good performance are maintained in the absence of JPEG, that is, when the contrast adjustment is the last step of the manipulation chain.

The rest of the paper is organized as follows: in Section II we define the detection task we focus on, describe the proposed CNN-based detector and the network architecture. In Section III-A we first detail the methodology followed for conducting our experiments, then we report and discuss the results.

II. PROPOSED SYSTEM
Figure 1 schematizes the problem addressed in this paper. We let hypothesis $H_0$ correspond to the case of pristine images and $H_1$ to the case of contrast adjusted images. In both cases, the image is JPEG compressed at the end, with a given QF. In this scheme, JPEG compression can also be viewed as a counter-forensic, laundering-type, attack, due to its known effectiveness in erasing the traces of contrast manipulations [1], [3], [5], [8], [10], [11].

The architecture of the proposed detection scheme is reported in Figure 2. The color image is divided into non-overlapping patches...
of size $64 \times 64$ which are fed to a JPEG-aware CNN detector. The patch scores, i.e. the CNN soft outputs for all the patches, are then collected and the final decision is based on the score vector $s = (s_1, s_2, \ldots, s_{NM})$ (where $N \times M$ is the total number of blocks). The decision is made by simply thresholding the sum of the scores, i.e. according to the statistic $\frac{\sum s_i}{(M \cdot N)}$. Since patches coming from the same image are drawn under the same hypothesis, such normalised sum is expected to be large in one case (contrast adjusted image) and small in the other (pristine image).

The JPEG-aware CNN is trained with JPEG compressed images on one hand ($H_0$) and images subject to contrast adjustment followed by JPEG compression on the other ($H_1$). The network architecture and the training strategy are detailed in the following sections. In the attempt to build a detector which generalizes to unseen adjustments, we consider contrast adjustments of different nature to train the network. Specifically, the processing we selected are: adaptive histogram equalization, gamma correction (both compression and expansion) and histogram stretching.

Regarding the compression QF, we focus on values ranging from medium-high to high values (i.e., $QF \geq 80$), which are commonly used in many practical applications.

II-A. CNN architecture

Our first attempts to train a network for our problem by using architectures similar to those adopted for other forensic tasks [13]–[15] were unsuccessful. A possible explanation is the following: while some processing operations, e.g. local filtering and double JPEG, introduce local patterns that a properly trained CNN with few layers is able to ‘easily’ learn, common contrast adjustments do not leave local visual artifacts, thus making self CNN learning harder and calling for the adoption of deeper models. We were in fact able to get higher accuracies by switching to deeper architectures, with small kernel sizes and small strides of the convolutional layers, inspired by those adopted in image classification and pattern recognition applications [16]. In particular, as suggested in [16], we adopt a kernel size of $3 \times 3$ and stride 1 for all the convolutional layers, and only 1 fully connected layer. We set the number of convolutional layers to 9, which, although lower than that adopted in [16] (16-19), is still a significant depth compared to those commonly considered for forensic tasks [13]–[15] (up to 4-5).

More specifically, the architecture of our network for patch classification (see Figure 3) is detailed as follows: it takes a color patch of size $64 \times 64$ as input and consists of

- 5 convolutional layers followed by a max-pooling layer. In the first convolutional layer 32 filters are applied. Then, the number of filters increases by 32 at each layer. For all the filters, the kernel size is $3 \times 3$ and the stride is always 1. Max-pooling is applied with kernel size $2 \times 2$ and stride 2 producing a final $27 \times 27 \times 160$ feature map.
- 3 convolutional layers followed by a max-pooling layer. As before, the number of filters of size $3 \times 3$ (applied with a stride 1) increases by 32 at each layer. The pooling is the same as before, yielding a $10 \times 10 \times 256$ feature map.
- A final convolutional layer with 128 filters of size $1 \times 1$ generating a $10 \times 10 \times 128$ feature map.
- A fully-connected layer with 250 input neurons, dropout 0.5, and 2 output neurons, followed by a softmax layer (last 3 blocks in the scheme of Figure 3).

Some comments regarding the main features of the above architecture are in order: the use of many convolutions (5) before the first pooling layer permits to consider a large receptive field for each neuron, which is good to capture relationships among pixels in large neighborhoods; the stride 1 permits to retain as much spatial information as possible. The purpose of the final convolutional layer is to reduce the number of parameters by halving the number of maps (from 256 to 128), without affecting spatial information. The adoption of only one fully connected layer also permits to reduce the number of parameters without affecting too much the performance. Finally, we observe that using small patches ($64 \times 64$) permitted us to increase the depth of the network for the same number of parameters. The use of small patches is also suitable for tampering localization (the detection accuracy is then raised by aggregating the patch scores).

II-B. CNN training strategy

We obtained the JPEG-aware CNN model by training the network in two steps. First, the network is trained to recognize between patches coming from pristine and contrast-adjusted images for the uncompressed case, getting an (unaware) pre-trained model. Then, the aware model is obtained by fine-tuning the unaware network, by feeding the CNN with JPEG compressed examples of the above classes. Since the network is pretty deep and then the number of images used for training is very large, we performed compression on-the-fly by augmenting the data inside the network, hence, the compression is performed directly on the $64 \times 64$ patches (that is, after image splitting). Such a strategy is viable because the JPEG compression is a local operator which can be applied separately on multiples of $8 \times 8$ image patches producing the same result as if it were applied on the entire image.

III. EXPERIMENTS

III-A. Methodology

We built the training and testing sets by starting from color images in uncompressed format. The images for the $H_0$ and $H_1$
classes were produced as detailed in Figure 1. The adjustment of the contrast under $H_1$ is obtained by considering several algorithms. As we said, to generate the images used for training, we considered the following operators: Adaptive Histogram Equalization (in particular, its refined, Contrast Limited, implementation, CLAHE [17]), Gamma Correction ($\gamma$ Corr), and Histogram Stretching (HS). Such operators are designed for one-channel images; to make them work on color images, we applied them as follows: for the images processed with CLAHE, we first converted the images from RGB to HSV, we applied the enhancement to the luminance channel only, namely the V channel, and converted them back to the RGB domain. The same strategy is adopted to generate the images processed with HS. Finally, for the $\gamma$ Corr, the contrast is modified by applying the operator to each channel (R, G and B) separately. The above operators are applied in equal percentage to generate the class of contrast adjusted images ($H_1$). Regarding the parameters, the clip-limit parameter for CLAHE is set to 0.005, the $\gamma$ value to 1.5 and 0.7 (randomly chosen with probability 0.5), and the saturation percentage of the HS to 5% for both black and white values. The above choices do not introduce visually unpleasant artifacts. For generating the test images, we also considered different values of the parameters for the same operators (to assess the performance under parameter mismatch), and different operators, by processing the images with adjustment tools provided by Photo- shop. In particular, we considered the following tonal adjustments:

- **AutoContrast, AutoColor and AutoTone**: algorithms which operate differently with respect to the color channels. The clipping is set to 7% for AutoContrast and AutoColor and to 5% for AutoTone; the snap neutral midtones option is selected for the AutoColor;
- **Curves_S**: a (hand-made) smooth S-curve is applied to enhance the contrast in the midtones;
- **Brightness and Contrast**: generic tools for enhancing and reducing brightness and contrast; for the enhancement, we set Brightness to 50 (Brightness+) and Contrast to 70 (Contrast+); for the reduction, we set Brightness to -70 (Brightness−) and Contrast to -50 (Contrast−);
- **Histogram Equalization (HistEq)**.

The HistEq manipulation is considered for completeness: although its visual impact is much stronger with respect to that of the other manipulations, and hence is rarely adopted in practice, the HistEq manipulation is often considered in multimedia forensic literature.

Regarding JPEG compression, we randomly selected the QFs (uniformly) in the range $[90, 100]$ to compress the images used for training. For testing, we also considered images compressed with QF = {85, 80}.

### III-B. Results

Uncompressed, camera-native, images (.tiff) are taken from the RAISE8K dataset [18] (of size 4288 × 2848), splitted into training and test set, and then contrast-adjusted to produce the images for $H_1$ in the unaware case (i.e., without the final JPEG). The images are then divided into 64 × 64 patches for CNN training and testing: $2 \times 10^5$ patches per class (coming from more than 1000 training images) were selected to train the CNN, whereas $2 \times 10^5$ patches were used for testing. In the aware case, the patches are JPEG compressed with QF \in $[90, 100]$. The overall performance of the detector is tested on 300 images from the test set, both uncompressed and compressed with QF = {100, 98, 95, 90, 85, 80}.

The images used for training were all processed with the OpenCV library for Python. For the tests, the Photoshop software was also adopted. We used the TensorFlow framework, via the Keras API [19], to implement our CNN. We ran our experiments using 2x Asus GeForce GTX1080TI - 11GB DDR5 gpu. The Adam solver is used with learning rate $1e^{-4}$ and momentum 0.99. We set the

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2 The straightforward application of CLAHE (and HS) to each channel separately unnaturally changes the color balance and produces visually unpleasant images.
When training and testing are performed with uncompressed images (unaware case), the average test accuracy of the CNN on image patches is 93.5%, where the average is taken on the 3 manipulations, i.e., CLAHE, Corr (compression and expansion) and HS, and on all the QFs inside the training range. For the overall system, we get almost perfect classification, that is, the Area Under Curve (AUC) is 99.8%, which is in line with the state of the art [10]. A noticeable strength is that here these performance are achieved by one (generic) system only, rather than using separate systems each one specialized on one manipulation. By testing the unaware detector with JPEG compressed images, the performance drop to AUC = 56% thus showing that the CNN model is not robust to the JPEG laundering attack.

Concerning the aware case, the average accuracies that we obtained at the patch level in the range of QFs [90,100] are: 0.84 for CLAHE, 0.72 for Corr and 0.79 for HS. These accuracies are not very high; however, the performance are moderately good with respect to all the contrast adjustment operators. We also observe that specializing our network to work with one QF only, we could have obtained higher performance at the patch level; however, as said before, to be robust against common manipulations (as recompression and saving in uncompressed formats), we look for a detector of generic contrast adjustments which works well on a range of QFs. The overall performance of the detector on full images are reported in Table I in terms of AUC, for both matched and mismatched processing parameters. The CLAHE manipulation is the easiest to detect (the AUC is always above 98%), the most difficult case corresponds to γ Corr, where the AUC is below 90% for QF ≤ 95. This behavior is due to the fact that such kind of adjustment is difficult to detect by itself and above all to the fact that the CNN is simultaneously trained with values smaller and larger than 1, corresponding to a compression and an expansion of the contrast. These results significantly improve those achieved by the unaware detector. Expectedly, performance decrease as QF decreases. However, good robustness to JPEG compression is achieved (at least for CLAHE and HS) also when the QF is 85 and 80, which are outside the training range, whereas, below 80, performance become poorer. It is worth observing that, for a fixed false alarm rate, the threshold on the aggregated score changes by varying the QF: specifically, for a false alarm of 5%, the threshold ranges in [0.56 : 0.71]. Note that, since the last compression QF is always known (or it can be estimated), such a variability of the threshold is not a problem. Table II shows the results under various contrast/brightness adjustment performed with Photoshop. Based on these results, we can argue that the CNN-based detector scales well with respect to the adjustment type maintaining good performance when the tones of the image are adjusted in different ways and, possibly, selectively in different tonal ranges (Curve_S), and when the adjustment operates differently on the color channels (the Auto processing). The AUC is large with respect to all the QFs for some of the processing (AutoTone, Curve_S, HistEq) and, in general, it remains above 90% in most of the cases.

### IV. CONCLUSIONS

We proposed a JPEG-aware CNN-based approach to cope with the well known problem of detection of contrast adjusted images in the presence of JPEG post-processing. To accomplish this task, and build a detector which works well for generic contrast adjustment, we trained the CNN with a certain number of adjustments of different nature. Results show that our detector achieves good performance over a wide range of QFs and generalizes well to unseen tonal adjustments. As further research, it would be interesting to see if the performance with respect to the most difficult cases can be improved by refining the composition of the training, i.e., the types of contrast adjustments considered and their proportions, and also the fusion strategy at the final stage. As a future work, we would like to improve the performance at the patch level to move from detection to localization.

### V. ACKNOWLEDGMENTS

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### Table I. Performance (AUC) of the detector under matched processing. The matched parameters are in bold.

| QF  | no jpg  | 100 | 98 | 95 | 90 | 85 | 80 | 75 |
|-----|---------|-----|-----|-----|-----|-----|-----|-----|
| 0.005 | 100 | 99.9 | 99.9 | 98.9 | 97.6 | 97.1 | 96.8 | 96 |
| 0.005 | 100 | 99.9 | 99.9 | 99.4 | 98.9 | 98.8 | 98.5 | 98 |
| 0.007 | 100 | 99.9 | 100 | 99.6 | 99.1 | 98.9 | 98.7 | 98.5 |

### Table II. Performance (AUC) of the detector for different tonal adjustments.

| QF  | no jpg  | 100 | 98 | 95 | 90 | 85 | 80 | 75 |
|-----|---------|-----|-----|-----|-----|-----|-----|-----|
| HistEq | 100 | 99.9 | 99.9 | 99.5 | 98.3 | 96.9 | 94.8 |
| Brightness+ | 97.5 | 97.7 | 95.2 | 93.6 | 91.2 | 87.8 | 85.6 |
| Contrast+ | 99.1 | 100 | 99.6 | 97.9 | 94.7 | 91.9 | 87.1 |
| Brightness- | 98.7 | 97.3 | 93.3 | 90.1 | 84.2 | 78.8 | 75.6 |
| Contrast- | 98.8 | 99.6 | 96.4 | 91.2 | 87 | 82 | 80 |
| Curve_S | 99.6 | 99.8 | 99.3 | 91.1 | 97.5 | 94.8 |
| AutoContrast | 95.9 | 94.7 | 93 | 91.9 | 90.2 | 89 | 86.5 |
| AutoColor | 98.2 | 98.6 | 96.8 | 95.3 | 93.7 | 91.8 | 89.1 |
| AutoTone | 99.5 | 99.5 | 99 | 98.2 | 97.2 | 96.1 | 94.5 |
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