Tampering Detection using Resampling Features and Convolution Neural Networks

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| **Article Info** |  | **ABSTRACT** |
| ***Article history:***  Received Jun 9, 2018  Revised Nov 20, 2018  Accepted Jan 11, 2019 |  | The increased usage of image editing tool have resulted in ease of manipulating multimedia data such as images. These manipulation affect truthfulness and legitimacy of images, resulting in misinterpretation and may affect social stability. The image forensic technique has been utilized for detecting whether an image is tampered using certain attack such as splicing, copy-move, etc. This paper present an efficient tampering detection method using resampling features (RSF) and Convolution neural network (CNN). In RSF-CNN, during preprocessing the image is divided into homogenous patches. Then, within each patches resampling features are extracted by exploiting affine transformation and Laplacian operator. Then, feature extracted are aggregated for constructing descriptor using Convolution neural network. Extensive analysis is carried out for evaluating tampering detection and tampered region segmentation accuracies of proposed RSF-CNN based tampering detection methodologies considering various distortions and post processing attacks such as joint photographic expert group (JPEG) compression, scaling, rotations, noise additions, and multiple manipulations. From result achieved it can be seen the RSF-CNN based tampering detection model achieves much better accuracies than existing tampering detection methodologies. |
| ***Keywords:***  Deep learning  Convolution neural network  Image tampering detection  Image transformation  Resampling feature extraction |
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1. **INTRODUCTION**

With increased exposure to internet because of cheap availability of smart phones and bandwidth has led to increased usage and sharing of multimedia data on online environment such as WhatsApp, Facebook, Instagram, Youtube etc. This growth let to emergence of various digital image editing software’s leading to trust issues of photography being shared. Building well-crafted tampering is well within the reach of end-users especially with introduction of artificial intelligence (AI) enabled multimedia data editing software tool. Some of the well know software editing tool are FaceApp [1]- which is used for editing age of person and facial expressions, Adobe Sensei [2]- which is used to enhance or beautify the faces, Deep Photo Style Transfer [3]- which are used for changing the visual appearance of an image such as time-of-day hallucination, weather etc. Adobe Sky Replace [4]- which is used for matching lighting, replacing skies etc. Number of these editing technique are readily available in smart phones and devices [5]. As human fail to distinguish between genuine and fake images [6], thus it is important to develop a automating tampering detection scheme with high accuracies is utmost importance in wide range of applications and services.

The discovery of multimedia content tampering has become extremely challenging and difficult as tampered images looks very much identical with respect to authenticated image. With growth of cutting edge multimedia editing software, a picture can be tampered from multiple points of view. These tampering can be classified into following types such as content changing and content preserving [7]. The primary tampering methodologies such as object removal, splicing, copy-clone etc. alter the complete image in random manner and also semantically alters the meaningful representation of the image [7]. On the other side, the secondary tampering methodologies such as contrast enhancement, blurring, compression etc. are generally done during post-processing operation and are less problematic as they do not change semantic representation of an image. Thus, this paper focus on addressing content changing problems. The content changing tampering will lead in give misappropriate and deceptive information. As with increased use of social media platform for exchanging multimedia content has resulted in increased number of tampering; thus it is very much important to identify the tampered image for preventing users from viewing deceptive information’s. As of late, content-changing tampering detection using image or video has attained wide-attention across research community considering different surety and surveillance applications. This paper presented a new methodologies for detecting tampering and localization of tampered segment at pixel level for content changing manipulation.

Recently, extensive researches have been carried out for classifying image tampering, that is, to detect whether an image is manipulated of not [8, 9, 10]. Among them very limited research have focused on localizing tampered segments at pixel level [11, 12]. In [13, 14] addressed tampering location detection by classifying whether a patches is tampered or not. Identifying tampering location is challenging and difficult job as tampered images doesn’t provide any visual piece of information/evidence, as displayed in Figure 1. In Figure 1, copy-clone tampering is shown where a particular segment of an image is copied and pasted onto different region within same image resulting in two similar objects, one is a tampered objects and other is an original objects. The splicing tampering is shown in Fig. 2, where an object from one image is removed and placed onto another image. Majority of existing tampering detection methodologies uses the frequency domain statistical feature or characteristic of multimedia content [15, 16]. In [16, 17] use artifacts measurement from multiple JPEG compressions for detecting tampered images, though the model only works for JPEG formats. In [18] for improving resampling detection performance added noise into the JPEG compressed image. Recently, deep learning have attained good performance in computer vision such as segmentation, scene classification, and object detection [19-21].

In recent time, number of deep learning based tampering detection [34-36] such as convolutional neural networks (CNN) [22, 23, 37] and stacked auto-encoders (SAE) [24] have been presented. In media crime scene investigation, majority of state-of-art tampering detection methodologies have focused on detecting certain type tampering only such as splicing [25] and copy-clone [26]. Thus, some methodologies might work for one kind of tampering and perform badly for other types of tampering. Besides, it appears to be impracticable to know in advance the type of tampering. This work present an improved tampering detection methodologies by extending the work presented in [11] for designing a framework to detect different kind image tampering.

In contrasting with semantic object segmentation where different semantic segments are extracted, this work focusses only in identifying the tampered segments which makes it even more a challenging task. Recently, CNN based semantic segmentation methodologies [20, 27] have attained attention. In [27], used fully connected CNN for analyzing region shape and object content by extracting feature sets at different levels in hierarchical manner. The CNN based framework works very well in the area of object detection [19] and segmentation [20, 27] in learning and better understanding of content of different segments. Unlike object segmentation, tampered segments could be copied object from different region of an image or could be a removed objects. A good tampered image will have good similarities among authenticated and fake image [23]. Despite the fact that convolution neural network produces spatial maps for different segments of multimedia content, they achieve very poor performance in generalizing different artifacts induced by different tampering methodologies. As a result, tampering region segmentation using standard convolution neural network may not produces good result.

In [11], carried out comparative analysis of various existing tampering region segmentation methodologies [20, 27] and showed they do not perform well for object removal and copy-move tampering. Image forgeries creates certain artifacts such as compression, resampling, etc. which are can be better learned using resampling features [13, 28]. Due to interpolation resampling introduces periodic correlation between the pixels. The CNN shows good translational invariance to produce spatial maps across different segment of a multimedia content, and certain artifacts are well-learned using resampling feature sets [38]; which can be utilized to locate tampered segments. Thus, this paper presents efficient image tampering detection scheme using resampling features and convolution neural network. Here the resampling features are extracted by employing affine transformations and Laplacian operator. Then, descriptor are constructed using CNN for predicting whether image is tampered or not.

The contribution of research work are as follow. This paper presented efficient tampering detection scheme exploiting resampling features and convolutional neural networks. The RSF-CNN based tampering detection scheme can detect multiple tampering within image more efficiently when compared with existing tampering detection scheme. The RSF-CNN based tampering detection scheme achieves very good tampering segmentation outcomes when compared with existing tampering detection scheme. The RSF-CNN based tampering detection method achieves better recall, precision, and F1-score performance than existing tampering detection methodologies.

The manuscript is arranges as follows. The section 1, discusses about tampering detection issues and challenges, benefit of using resampling features and convolution neural network, and significance of work is discussed. In section 2, the proposed tampering detection methodologies using resampling features and convolution neural network. In section 3, the tampering detection accuracies and segmentation outcome achieved by proposed RSF-CNN based tampering detection methodologies over existing tampering detection methodologies. In section 4, the paper is concluded with research significance and future direction of work is also discussed.

1. **TAMPERING DETECTION USING RESAMPLING FEATURE AND CONVOLUTION NEURAL NETWORKS**

This section presents the image tampering methodologies using resampling features and convolution neural networks. First, present preprocessing and resampling feature extraction for tampering detection. Second, the extracted features are trained using a convolution neural network for detecting whether the image has tampered or not.

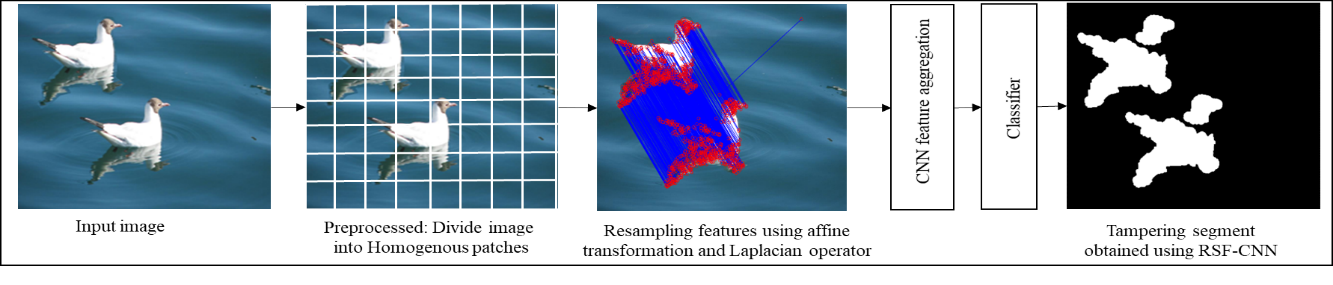


Figure 1. Proposed RSF-CNN based tampering detection methodologies.

**2.1. Preprocessing and resampling feature detection and extraction**

In general, the images are tampered with using the following operations such as object removal, splicing, and copy-move, etc. This tampering affects the statistical feature alongside the edges of the forged segments. In [29], the resampling detection method is presented using affine transformation and Laplacian operator for extracting the resampling features for respective patches. This work uses a similar methodology for the extraction of resampling features in a given image. First, the image is segmented into a non-overlapping patch size of. When considering an image with a size of, then each patch dimension size will be. Further, for producing magnitude of linear projected error for different patches Laplacian operator is used [13]. For accumulating errors with respect to a different angle of projection this work uses affine transformation because there exist periodic correlations among resampling signals. At last, Fast Fourier Transform (FFT) is applied for identifying the resampling features periodic characteristic of the signals. Generally, the resample feature sets have the capability of identifying different resampling nature such as rotation, up- or down-sampling, and JPEG thresholding, etc.

For bringing good tradeoffs between increasing accuracy and reducing computation complexity here the image is resized to which may induce certain artifacts such as up- or down-sampling, image quality variations, etc. In [13] showed that the resampling feature can be utilized for classifying the aforementioned artifacts. Further, resampling feature sets are used for classifying patches. However, in this work, it is used for localizing at the pixel level. For obtaining a higher number of features it is important to bring good tradeoffs in choosing the patch size. This is because resampling signal can be easily established in larger patch size as it will have a higher amount of repeated features; however, identifying small tampered segments will be difficult for localizing it. The existing resampling based tampering detection methodologies extracted resampling features considering block size of. However, in this work patch size is set to for obtaining more useful information. The main factor of using resampling feature within the patches is to establish the nature of local artifacts because of different tampering.

The outcome of CNN mainly depends on the organization of the patches. It can either be ordered in vertical or horizontal directions; however, it fails to obtain relevant local feature information. This is because, if we are arranging the patches in a vertical direction, then the patch sets of different neighbors horizontally will be disconnected by a complete column of patches. Thus, takes a lot of time and CNN fails to bring good correlation among these patches. Similarly, if we traverse through horizontal direction over the rows will result in the same problem. For preserving special features of different patches, this work uses a space-filling curve [30] which is widely utilized for reducing multi-dimensional problems to one-dimensional problems [31-33].

**2.2. Feature aggregations using CNN for tampering detection**

In the feature extraction phase, we obtain a large number of features, these features are aggregated for constructing descriptor in classifying whether an image is a tamper or not and identifying and segment the forged region. Here different kind of aggregator function is considered such as minimum, maximum, mean, and mean of squares which are described below [39]. The minimum aggregation function is described below

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| --- | --- |
|  | (1) |

The maximum aggregation function is described below

|  |  |
| --- | --- |
|  | (2) |

The mean aggregation function is described below

|  |  |
| --- | --- |
|  | (3) |

The mean of square aggregation function is described below

|  |  |
| --- | --- |
|  | (4) |

where depicts the patch size considered for extracting features, represents the -component feature extracted within the path. Selection of type of averaging/pooling function depends on the type of image and type of problems to be addressed. When tampering is spread across the entire image, in such case averaging function works reasonably well, on the other side, the maximum and minimum function performs better correlative feature is focused within localized segments. Nonetheless, in this work, we use a different kind of pooling function for experiments. Finally, the spatial dependencies are eliminated after aggregating features.

An important thing to be noted here is the selection of pooling functions impacts in what way the feature information is back-propagated from the output layer for updating parameter of the feature extraction operation. For providing more detailed modeling, let be a generic parameter of convolution neural network, depicts the loss function CNN architecture, and represent the aggregated features. Then, the gradient of considering generic parameter reads

|  |  |
| --- | --- |
|  | (5) |

with

|  |  |
| --- | --- |
|  | (6) |

From Eq. (5) and (6) it can be seen, will be equal when and if the condition fails it will be, while describes a feature vector with largest component and describes a feature vector with smallest component. As a result, using minimum or maximum pooling function, only some active patches plays a major factor in the gradient, and optimize the CNN leaning model. On the other side using the mean and mean square pooling function the entire patches play a role in the gradient. Nonetheless, if different pooling functions are utilized for training at the same instance, in such case the gradient is optimized as a weighted sum of individual terms.

**2.3. Decision**

After aggregating the feature from different patches of an image of a descriptor, this is done using few fully-connected layers similar to deep networks. For bringing good tradeoffs between achieving higher accuracy with reduced computation complexities just two-layer is used in this work.

**2.4. Training of CNN**

Here the work focuses on the post-training functions, the resampling feature-based CNN (RSF-CNN) framework is very similar to standard methodologies based on patch-based feature extraction, aggregation, and classification. However, the major difference is that the RSF-CNN model can be trained end-to-end. Thus, there is no need to train the classification model with features extracted using the fixed network. Rather, the model can be trained as a whole framework on the complete image to classify whether the image has tampered or not. The loss function back-propagates within the net up to distinct patch sets, which aids feature extractor to learn which feature is more correlated for the final decision, and the makes and CNN model to work jointly with resampling feature extractor in an adaptive manner. The proposed tampering detection method using resampling features and CNN attain superior performance when compared with the existing tampering detection method which is experimentally shown in the below section.

1. **RESULTS AND DISCUSSIONS (10 PT)**

The discussion can be made in several sub-chapters. This section presents a performance evaluation of the proposed RSF-CNN based tampering detection method over the existing tampering detection method. The RSF-CNN based tampering detection method is implemented using Python, C++, and Matlab library. The experiment is conducted on MICC-600, MICC-Multi, and D0 dataset. The dataset description used for experiment analysis is shown in Table 1. The performance of RSF-CNN and the existing tampering detection method are evaluated in terms of the following metrics such as True positive rate (TPR) (i.e., recall), F1 score, and False Positive rate (FPR). To verify the performance of the proposed RSF-CNN based image forensics, the experimental results are compared to existing tampering detection methodologies [40, 41] to perform the forgeries, including copying and translations, scaling, rotation, and compression.

Table 1. Dataset considered for experiment analysis

|  |  |  |  |
| --- | --- | --- | --- |
| Dataset | Number of images | JPEG compression | Scaling and rotation |
| MICC | 600 | No | Yes |
| D0 | 50 | yes | Yes |

**3.1. Performance evaluation on MICC dataset**

The experiment is conducted using the MICC dataset. MICC-600 consists of 600 images: 300 images have tampered images and 300 are originals. The size of the forged patch covers, on average, 1.2% of the whole image. The outcome achieved using the proposed RSF-CNN based tampering detection method is shown in Figure 2. Further, the accuracy performance of the proposed RSF-CNN based tampering detection method over the existing tampering detection method is carried is shown in Table 2. Further, from Figure. 3 it can be seen the proposed RSF-CNN model achieves a better segmentation outcome of the tampered region. From the result achieved it can be seen the proposed RSF-CNN based tampering detection method achieves a much superior outcome than the existing tampering detection method in terms of Recall/TPR, FPR, and F1-Score for the MICC dataset. Thus, the proposed RSF-CNN based tampering detection method is robust in detecting forged segments considering rotation and scaling.

|  |  |
| --- | --- |
| (a) | (b) |
| (c) | (d) |

Figure 2. The output of the proposed RSF-CNN tampering detection method.

|  |  |
| --- | --- |
| (a) original image | (b) Ground Truth |
| (c) Existing tampering region segmentation method [26] | (d) RSF-CNN based tampering region segmentation method |

Figure 3. Comparative analysis of proposed RSF-CNN based tampering detection method over existing tampering detection methodology.

Table 2. Comparative analysis of proposed RSF-CNN based tampering detection method over existing tampering detection method for MICC dataset

|  |  |  |  |
| --- | --- | --- | --- |
|  | Recall/TPR | FPR | F1-Score |
| Raju et al., 2018 [40] | 89.14 | - | 92.6 |
| RSF-CNN | 97.5 | 1.4 | 97.7 |

**3.2. Performance evaluation on D0 dataset**

An experiment is conducted using the D0 dataset to detect whether an image has tampered or not using the proposed RSF-CNN based tampering detection method using resampling features and CNNs. The dataset includes the tampered images in which every copy-pasted area is transformed according to the following transformations: rotation in the range of [-25°, 25°] with step 5°, rotation in the range of [0°, 360°] with a step of 30°, rotation in the range of [-5°, 5°] with a step of 1°, scaling in the range of [0.25, 2] with step 0.25, and scaling in the range of [0.75, 1.25] with step 0.05. The outcome achieved using the proposed RSF-CNN based tampering detection method is shown in Figure 4. Further, the accuracy performance of the proposed RSF-CNN based tampering detection method over the existing tampering detection method is carried is shown in Table 3. From the result achieved it can be seen the proposed resampling feature-based tampering detection method achieves a much superior outcome than the existing tampering detection method in terms of precision, recall, and FPR, and F1-score for the D0 dataset. Thus, the proposed RSF-CNN based tampering detection method is robust in detecting forged segments considering rotation and scaling. To estimate the robustness of our approach against false positive detection, we used an untampered dataset (D3 dataset) to verify our approach.

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| G:\WS_PHD\FogeryDetection\C1\cv reports in order\SLIC_CMFD_F600_\EE734_Term-master\data\MICC_F600\im1_t.bmp | D:\ForgeryDet\05Chandrakala\Image_Forgery\Dataset\Copy-Move Forgery Dataset\dataset\Dataset 0\im1_t_mask.bmp | G:\WS_PHD\FogeryDetection\J1\FinalDelv\BackUP\Sunita_Image_result\im1_t.tif | G:\WS_PHD\FogeryDetection\J1\FinalDelv\BackUP\Sunita_Image_result\im1_t_result.tif |
| D:\ForgeryDet\05Chandrakala\Image_Forgery\Dataset\Copy-Move Forgery Dataset\dataset\Dataset 0\im10_t.bmp | D:\ForgeryDet\05Chandrakala\Image_Forgery\Dataset\Copy-Move Forgery Dataset\dataset\Dataset 0\im10_t_mask.bmp | G:\WS_PHD\FogeryDetection\J1\FinalDelv\BackUP\Sunita_Image_result\im10_t_8544.tif | G:\WS_PHD\FogeryDetection\J1\FinalDelv\BackUP\Sunita_Image_result\im10_t_res.tif |
| D:\ForgeryDet\05Chandrakala\Image_Forgery\Dataset\Copy-Move Forgery Dataset\dataset\Dataset 0\im15_t.bmp | D:\ForgeryDet\05Chandrakala\Image_Forgery\Dataset\Copy-Move Forgery Dataset\dataset\Dataset 0\im15_t_mask.bmp | G:\WS_PHD\FogeryDetection\J1\FinalDelv\BackUP\Sunita_Image_result\im15_t_9263.tif | G:\WS_PHD\FogeryDetection\J1\FinalDelv\BackUP\Sunita_Image_result\im15_t_res.tif |
| Input image | Ground truth image | Feature extraction and detection | Forged segment |

Figure 3. Comparative analysis of proposed RSF-CNN based tampering detection method over existing tampering detection methodology.

Table 3. Comparative analysis of proposed RSF-CNN based tampering detection method over existing tampering detection method for D0 dataset

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Recall | Precision | FPR | F1 |
| Huang et al. 2019 | 84.88 | 92.81 | 3.39 | 88.67 |
| RSF-CNN | 98.08 | 98.84 | 1.68 | 99.28 |

1. **CONCLUSION**

This paper present a tampering detection method using resampling features (RSF) and convolution neural network (CNN). The RSF-CNN based tampering detection methodologies can effectively classify forged and non-forged segments and can semantically segment the forged region. The RSF-CNN model can retain spatial features by using resampling features among different patches and establish a correlation between tampered and non-tampered patches. Then, these resampling features are aggregated for eliminating spatial dependencies, and a descriptor is built for the whole image. An experiment is conducted on standard MICC and D0 datasets which includes different copy-clone, scaling, rotation, and compression. From the results attained it can be seen the RSF-CNN based tampering detection model achieves a much superior True positive rate, F1 score, and False Positive rate when compared with the existing tampering detection model.

Despite very good results attained, the model can be further improved by improving the quality of feature extraction with a reduced outlier. Then, develop a new CNN framework for mitigating the effects of noise affecting the spatial relationship. Thus, future work would consider the aforementioned problems in developing improved tampering detection methodologies. Further, performance evaluation will be considered more diverse tampering attack datasets.

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**BIOGRAPHIES OF AUTHORS (10 PT)**

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| --- | --- |
| First author’s  Photo (3x4cm) | Xxxx (9 pt) |
|  |  |
| Second author’s photo(3x4cm) | Xxxx (9 pt) |
|  |  |