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ORIGINAL RESEARCH

Improving the Accuracy in Copy-Move Image Detection: A Model of Sharpness and Blurriness

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Abstract

The paper suggests a model based on the sharpness and blurriness to confirm the exact tampered areas from the suspicious ones which are detected from similar regions. In copy-move image detection, most research focus on comparing and finding areas with similar properties on the image. Actually, the same areas are not certainly done by copy-move manipulation, they may be the image texture. A model from the sharpness at the collage borderlines and the blurriness inside the image area is built to determine if the areas are really caused by the copy-move manipulation. The combination of feature extraction using oriented FAST and rotated BRIEF (ORB) and tampered region confirmation using a logistic regression model with 98% on accuracy proves the efficiency of the proposed methods.

Keywords ORB (oriented FAST and rotated BRIEF) · Feature points · Copy-move detection · Sharpness · Blur · Feature descriptor · Logistic regression

Introduction

Nowadays, with the rapid development of image processing software, processing and forging images for various purposes are done so perfectly that it is difficult to distinguish whether an image is fake or not by human eyes. According to the Wall Street Journal, at least 10% of all color images published in the US have been changed and intervened since 1989. The more diverse software develops, the more complicated detections are. The image authentication becomes more challenging if there is no information about the original image.

According to statistics from the IEEE and Science Direct websites in the past 5 years (see Fig. 1), the number of publications related to blind image forgery detection, generally called image forgery detection (IFD) in which information of the original image is completely unknown, has increased about 10% per year. There are many kinds of forgery in IFD, such as splicing, copy-move or hybrid. However, the copy-move operation is the most popular because copying and pasting information on the same image are easier to do but more difficult to detect. If they are copied from other images, many complicated steps are required to make them smooth and matched. Factually, also the above statistics in Fig. 1, the number of copy-move publications, which is called copy-move forgery detection (CMFD), has been a significant number.

Feature extraction is the most important step in looking for and detecting fake areas. Many studies on image tampering detection using SIFT, SURF, and Zernike moments always give good results because they are highly appreciated feature extraction methods. In recent years, oriented FAST and rotated BRIEF (ORB) has been considered as a good candidate for feature extraction problems with the combination of directional elements and rotation. However, the application of ORB to detect the forgery is still an idea and challenge as well.

The paper proposes a method of detecting duplicated regions on the same image using ORB in which features extraction is performed by the oriented FAST (oFAST)

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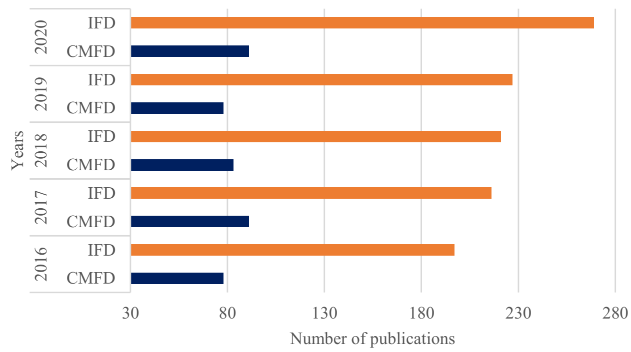


Fig. 1 Publications on image forgery detection (IFD, the orange lines) and copy-move forgery detection (CMFD, the dark-blue lines) in the recent 5 years by IEEE and Science Direct. Statistics are collected at the website of IEEE Explore and Science Direct with the keyword "Image Forgery Detection" in March 2021

with the directional element and the features description performed by the rotated BRIEF (rBRIEF) descriptor. The ORB is proved as a faster key-points and matching algorithm which is faster than SIFT two order of magnitude [1] and faster than SURF an order of magnitude [2, 3] but still being well on detection accuracy.

The main contributions of the method are:

1. Improving the processing time for detecting the cloned areas with/without the rotation compared to some algorithms using SIFT, SURF, ZMs in feature extraction.
2. Detecting copied areas with different manipulations and scales.
3. Building a model to remove the non-tampered regions to improve the accuracy in detection.

Literature review, problem statement, steps of the proposed method with related theories, simulation results, and conclusion will be presented in the following sections, respectively.

Literature Review

Image forensics is one of the remarkable fields in image security with a lot of research being carried out in recent years. The basic principle of all algorithms is to find regions with similar features and consider if those regions are duplicated.

The first prominent in the field of copy-move images is a study by Alin C. Popescu and Hany Farid published in a scientific report in the Department of Computer Science at Dartmouth College in 2004 by which demonstrated that PCA was effective in image features extraction. Each feature vector is called the basic component with values obtained from covariance matrix theory, eigenvalues, and linear bases for each small image block with the initial conditions being zero-mean [4]. These feature vectors will be the proofs for defining duplicate areas on the image. Next, the 5-component [5] or 9-component [6] vectors, the Radon transform [7], the 8z affine variable [8] Local Binary Pattern-LBP [9], SIFT [10], SUFT [11], ZMs [12], respectively, are proposed to extract and represent the features of image blocks to solve the copy-move image problem.

Some other research focuses on combining transformations before feature vectors extraction in copy-move image detection. The popular transforms are discrete cosine transform (DCT) [13, 14], discrete wavelets transform (DWT) [15–18], dyadic wavelets transform (DyWT) [19], Fourier–Mellin transform (FMT) [20], undecimated dyadic wavelet transform (UDWT) [21], multi-radius polar complex exponential transform (PCET) [22], … In methods using DCTs, the quantum DCT coefficients are used to replace the pixels values from which the property vectors are generated. Correlated positions are considered in the case of multiple blocks with the same property vector. These methods are estimated to be effective in images with many copy-move areas, being blurred and noisy. Methods of using DWT aim to reduce image dimensions. The feature vectors are then determined from the approximation component LL to find similar regions. In addition, the identification of regions with different chroma/blur in sub-bands containing high-frequency components such as LH, HL and HH is also suggested to identify tampered regions.

Recently, the copy-move problem is solved by applying deep learning with a convolutional neural network architecture to learns a set of features which show the interpolation artefacts and boundary mismatched in the copy-move regions [23]. Using deep learning methods to improve the efficiency of forgery detection is also presented at the 2020 International Conference on Information Technology and Nanotechnology (ITNT) in Russia [24]. Developing an algorithm to detect the copy-move forgery in the Spatial Feature Domain is one of the newest in this field which proposes five steps to detect the tampering including: preprocessing, creating the overlapping small image blocks, mean and standard deviation estimation, feature vector lexicographically sorting and support vector machine (SVM) classifier to confirm the forgery [25].

Although published techniques can solve the specific requirements, they still have their own limitations, discretely solving for different types of copy-move images. Therefore, it is always necessary to build new or improve algorithms for copy-move problems.

Problem Statement

Considering an arbitrary in a dataset of the original and copy-move images, the problem should be able to:

- Identify copy-move images and locate tampered areas by copy-move manipulation (if any). In case of similar regions are caused by the image composition or texture, they are considered original ones.
- Detect the forgery at many positions, with scaled and rotation operations.

Problem-Solving

- Based on the published methods and survey on copy-move image forgery detection, the research group recognize that feature extraction is the important step in copy-move image detection problems. The more detailed the feature extraction, the more accurate the algorithm. The authors compare and analyze the appropriateness of the feature extraction algorithms with good results for the duplicated areas with rotation, scale manipulations such as ZMs, SIFT and SUFT and use feature extraction as a step of the proposed algorithm.
- Studying on the algorithms of identifying and extracting features using ORB and analyzing the applicability and suitability of the ORB algorithm to the problem.
- Implementing algorithm using ORB to extract features image blocks and identify similar regions for images with multiple copy regions with multiple different operations.
- Based on the principle that copied areas will have high sharpness at the collage borderlines and high blurriness inside them, build a model to identify collage areas from suspicious areas to improve the accuracy of the proposed method.
- Evaluating the performance and comparing the simulation results of the proposed algorithm with related algorithms.

Proposed Algorithm

With a given image, the proposed method extracts key-points using oriented FAST (oFAST). Adding a directional element to this step aims to enhance the orientation functionality in feature extraction because FAST itself cannot define the directional property. These key points then identify binary features vectors and are described by a rotated BRIEF (rBRIEF) descriptor. Regions with the same feature vectors will be detected using K-means clustering and the suspicious copied parts are defined.

However, for images on which there are many similar objects not being due to duplicated manipulations but by nature of the image, a question is "Among the suspicious regions detected above, how to determine whether the region is the replication or the inherent natural area of the image". If this problem is solved, the accuracy of the detection will be improved. Therefore, the paper proposes an algorithm to improve the accuracy by building a model of logistic regression with two inputs of sharpness and blurriness. At the suspicious regions, the sharpness at the collage borderlines and the blurriness inside the limited area are calculated. These values are then passed through the suggested model (SBM) to confirm if the regions are copied or texture.

The model is built based on the fact that the sharpness of the edges at the pasted positions will be higher than that belonging to the composition of the image, and the blurriness of the copied parts is also higher than the original ones.

All steps and the pseudo-code of the proposed algorithm are shown in Fig. 2 and Table 1, respectively.

ORB in Detecting Key-Points and Matching Image Regions

ORB is built on the combination of oriented FAST and oriented BRIEF. Comparing to the related feature extraction such as SIFT and SURF, ORB is considered a good alternative [2].

The oFAST Feature Points

Pixel i is defined as key-point if there are more than 8 pixels among 16 surrounding pixels i which brighter or darker than pixel i (see Fig. 3). Let I_i and I_j are respectively the intensity of pixel i and j, then pixel j is confirmed to be brighter than pixel i if I_j is greater than I_i by a predefined threshold T. Key-points are locations at which the edges are represented. Each key-point is then assigned directions which aim to determine the intensity changes around that key-point. The intensity changes are detected based on the intensity centroid [26].

Intensity centroid method Considering a pixel i having coordinates x, y and gray value $I(x, y)$. The moment and the centroid of a small image block B of pixels are defined by (1) and (2).

$$m_{pq} = \sum_{x,y \in B} x^p y^q I(x, y), \quad p, q = \{0,1\}, \tag{1}$$

$$C = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}} \right), \tag{2}$$

where m_{00} and (m_{10}, m_{01}) are the mass and the centroid of B, respectively.

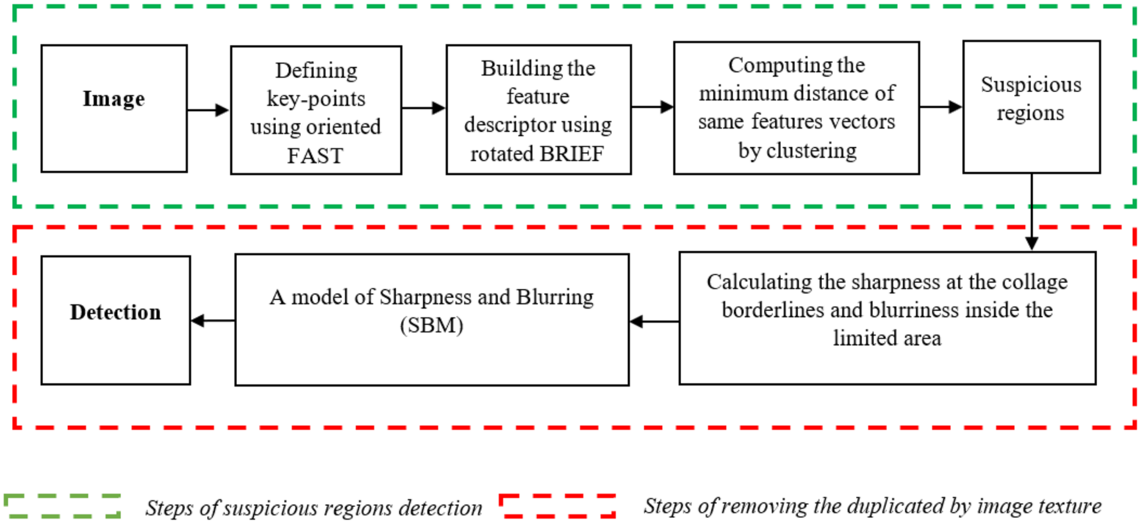


Fig. 2 Proposed algorithm

Table 1 The pseudo code of the proposed algorithm

```
Algorithm
INPUT: Image
OUTPUT: Detection
DEFINE the number of blocks N in a given image
FOR block=1 TO N DO
    DEFINE keypoint kp_block
    CALCULATE the direction to kp_block
        kp_block_di= f_θ(kp_block)
    CALCULATE the feature descriptors
        f_vec=feature_vec (kp_block,kp_direction_di)
END FOR
DETECT the suspicious regions
    sus_reg=kmeans_f (f_vec)
DEFINE the number of suspicious regions M
    M=no_f(sus_reg)
FOR region=1 TO M DO
    CALCULATE the sharpness at the collage borderlines
        sh_reg=sharpness_f(region)
    CALCULATE the blurriness on image regions
        bl_reg=blurriness_f(region)
END FOR
BUILDING a model of sharpness and blurriness
    detect_model = model_f(sh_reg,bl_reg)
DETECTION
```

The direction vector is created by the geometric center O and the centroid C, then the direction of the key-point is defined by (3) [24].

$$\theta = \arctan\left(\frac{m_{01}}{m_{10}}\right). \tag{3}$$

The rBRIEF Feature Descriptor

All key-points with assigned directions are calculated to create feature vectors or feature descriptors. BRIEF descriptor is a binary vector descriptor with vectors of 128–512 bits strings [2, 27].

BRIEF itself is not rotation invariant so the image information could be lost when rotating image. A rotation matrix

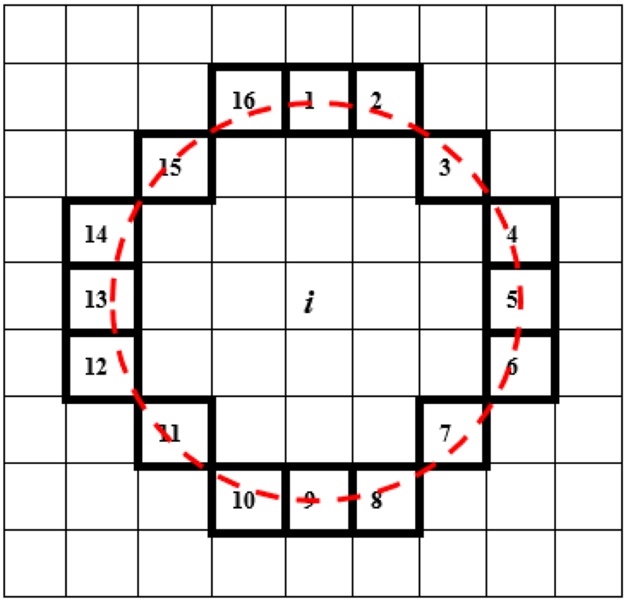


Fig. 3 Representation of 16 pixels around pixel i when defining a key-point

R_θ in (4) is suggested to calculate the main direction for each feature points which is the solution to put the direction information into the descriptor.

$$R_\theta = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix}. \tag{4}$$

The direction descriptor can be obtained by (5).

$$g_{N(p,\theta)} = f_N(p) | \left(x_i, y_i\right) \epsilon Q_\theta \tag{5}$$

where Q_θ is defined based on the rotation correction.

$$Q_\theta = R_\theta \begin{bmatrix} x_1, x_2, \ldots, x_N \\ y_1, y_2, \ldots, y_N \end{bmatrix}, \quad N \text{ is numbers of pairs of pixel points.} \tag{6}$$

Clustering

A hierarchy of clusters is applied to detect similar regions [28]. The OpenCV and Boost libraries support Kdsort in which the KD tree is used efficiently for detecting the copied parts.

A Model of Sharpness and Blurriness for Removing the Mismatched Regions

In this paper, the authors apply the logistic regression [29] to detect the copied regions from the suspicious ones based on the feature extraction.

Model Description

The model of sharpness and blurriness is built from dataset of original and copy-move images. This model confirms if a region is tampered based on the combination of sharpness at its borderline and the blurriness inside it.

Inputs of the model: sharpness at the borderline and blurriness inside the area.

Output of the model: the region is confirmed by copy-move or not.

Model Training

Let $x_1^{(i)}$ and $x_2^{(i)}$ are sharpness at the borderline and blurriness inside the area of the region i; $p(x^{(i)} = 1) = \hat{y}_i$ is the probability that the model predicts the ith region to be copied; $p(x^{(i)} = 0) = 1 - \hat{y}_i$ is the probability that the model predicts the ith region to be the texture. We have:

$$p(x^{(i)} = 1) + p(x^{(i)} = 0) = 1, \tag{7}$$

where $\hat{y}_i$ is the predicted value of the real value y_i

Applying a sigmoid function in this case, linear regression is obtained by

$$\hat{y}_i = \sigma\left(w_0 + w_1 \times x_1^{(i)} + w_2 \times x_2^{(i)}\right) = \frac{1}{1 + e^{-\left(w_0 + w_1 \times x_1^{(i)} + w_2 \times x_2^{(i)}\right)}}. \tag{8}$$

Evaluate the Efficiency of the Trained Model

If the ith region is copied so $y_i = 1$, the value of $\hat{y}_i$ is as closer to 1 as possible. It also means that the higher probability of acceptance is predicted by the model, the better effective the model is.

Otherwise, if the ith regions are not copied then $y_i = 0$ so $\hat{y}_i$ is as closer to 0 as possible. In this case, the lower probability of acceptance is predicted by the model, the better effective of the model is.

Building the Loss Function

With a point $\left(x^{(i)}, y_i\right)$, the loss function L is defined by

$$L = -\left(y_i \times log\left(\hat{y}_i\right) + (1 - y) \times log\left(1 - \hat{y}_i\right)\right). \tag{9}$$

If $y_i = 1$ then $L = -log\left(\hat{y}_i\right)$, see Fig. 4

o L is gradually decreasing when $\hat{y}_i$ changes from 0 to 1.

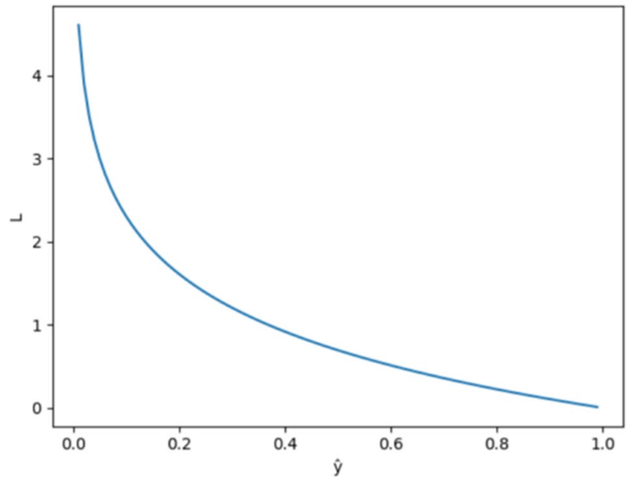


Fig. 4 Graph of loss function when $y_i = 1$

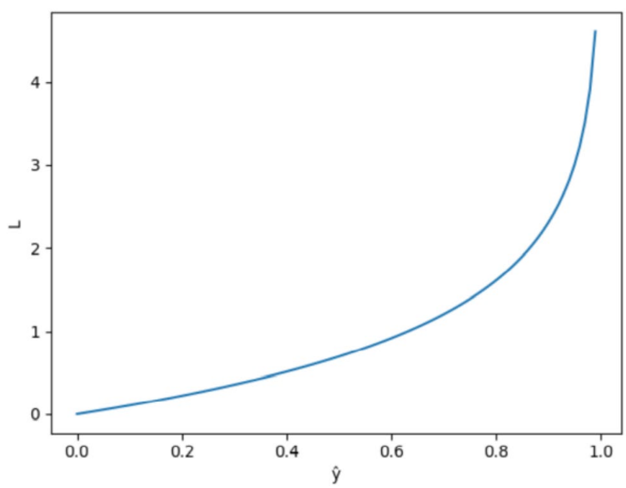


Fig. 5 Graph of loss function when $y_i = 0$

- o When the model predicts $\hat{y}_i$ being approximate to 1, the predicted value is close to actual value y_i. Therefore, L is so small, close to 0.
- o When the model predicts $\hat{y}_i$ being approximate to 0, the predicted value is opposite to actual value y_i. Therefore, L is so large.

If $y_i = 0$ then $L = -\log\left(1 - \hat{y}_i\right)$, see Fig. 5.

- o L is gradually increasing when $\hat{y}_i$ changes from 0 to 1.
- o When the model predicts $\hat{y}_i$ being approximate to 0, the predicted value is close to actual value y_i. Therefore, L is so small, close to 0.
- o When the model predicts $\hat{y}_i$ being approximate to 1, the predicted value is opposite to actual value y_i. Therefore, L is so large.

Generally, function L is small when the predicted value by the model is close to the true value and very large when the model predicts incorrectly. The smaller L is, the closer the predicted value is to the true value. Therefore, finding the minimum of L means define the model.

The problem applies logistics regression as the model of sharpness and blurriness. The sharpness is calculated at the borderline and the blurriness is estimated inside the suspicious region.

At the borderline of the copied image, the sharpness is higher than in the other position and higher than that at the non-copied regions. Besides, the blurriness inside the copied image is higher than the non-copied ones.

With two rules, the model is built based on the loss function as in Fig. 5.

The Problem Representation

The problem is represented in the matrix as follows.

$$X = \begin{bmatrix} 1 & x_1^{(1)} & x_2^{(1)} \\ 1 & x_1^{(2)} & x_2^{(2)} \\ 1 & \dots & \dots \\ 1 & x_1^{(n)} & x_2^{(n)} \end{bmatrix}, \quad y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}, \quad w = \begin{bmatrix} w_0 \\ w_1 \\ w_2 \end{bmatrix},$$

where

X: set of values of sharpness at the borderline and blurriness inside the region for n regions.

y: the corresponding confirmation of n regions.

w: the weights of values, w_0 is the bias value, w_1 and w_2 weights for sharpness and blurriness. The problem set the value of $w_1 = 1$ and $w_2 = 0.5$.

The prediction and the loss function are defined by (10) and (11):

$$\hat{y} = \sigma(Xw), \tag{10}$$

$$J = -\mathrm{sum}\left(y \otimes \log\left(\hat{y}\right) + (1 - y) \otimes \log\left(1 - \hat{y}\right)\right), \tag{11}$$

$$\frac{\mathrm{d}J}{\mathrm{d}w} = X^{\mathrm{T}} \times (\hat{y} - y); \quad X^{\mathrm{T}} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ x_1^{(1)} & x_1^{(2)} & \dots & x_1^{(n)} \\ x_2^{(1)} & x_2^{(2)} & \dots & x_2^{(n)} \end{bmatrix}.$$

Sharpness Estimation [30]

At each image block at the borderline, sharpness is calculated by using gradient amplitude. The gradient at the pixel with the coordinates (x, y) in the image block I is a vector of the first derivative determined by (12).

$$\nabla I(x,y) = \left[\frac{\partial I}{\partial x}(x,y)\frac{\partial I}{\partial y}(x,y)\right], \quad (12)$$

where $\frac{\partial I}{\partial x}(x,y)$, $\frac{\partial I}{\partial y}(x,y)$ are partial derivatives along x and y.

The gradient amplitude is then calculated in (13)

$$\mathrm{GM} = |\nabla I(x,y)| = \sqrt{\left(\frac{\partial I}{\partial x}(x,y)\right)^2 + \left(\frac{\partial I}{\partial y}(x,y)\right)^2}. \quad (13)$$

Blurriness Estimation

The blurriness on image regions is estimated by performing the following three steps proposed by Hong et al. [31].

- Extracting the gradient profiles of straight edges;
- Estimating the parameter of the Point Spread Function (PSF);
- Estimating the blurriness of the image region.

Simulation Results

Environment of the Experiment

The algorithm was tested on 210 images consisting of 35 images of benchmark [32], 20 images of MICC-600 and 155 natural images created by Photoshop. Selected images for testing the proposed algorithm and comparing with related algorithms are diverse and meet the input requirements and the overall goal of the algorithms.

The algorithm is implemented in three cases of images, including:

- The copy-move images in which the copy areas are duplicated and do not resize, with/without rotation, and the same areas due to collage only (not due to image's structure).
- The copy-move images in which areas of the copied image with/without resizing, rotating and the same areas due to collage only (not due to image's structure).
- The copy-move images in which areas of the copied image are resized, rotated and the same areas may be due to the collage or image's structure.

In each case, tested images will be selected from 210 images of the dataset so that they have the corresponding characteristics of that case. With the three cases, the algorithm is tested on the whole dataset. It runs on a system of CPU Core i7-7700HQ, RAM 16 GB, SSD 512 GB, Nvidia GTX 1060 6 GB and Intel HD Graphics 630.

The algorithm was written in C for detecting key-points and matching image regions with the supporting of OpenCV; combined and integrated with Python in building a model of sharpness and blurriness to remove the mismatched regions.

Evaluation

SIFT, SURF and Zernike Moments are highly estimated in feature extraction and always the good candidates in image forgery detection. To prove the efficiency of the proposed algorithm, the authors have compared simulation results with the interested algorithms using SIFT [10], SURF [11] and Zernike moments [12] on the precision and processing time under specific image conditions. The values of precision, recall, $F1$ and processing time are calculated by the average of images in group when doing comparison.

When processing an image, the Precision, Recall and $F1$ for each image are defined by (14), (15) and (16).

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}, \quad (14)$$

$$\text{Recall} = \mathrm{TP} + \mathrm{FN}, \quad (15)$$

$$F1 = 2 \times \text{Recall} \times \text{Precision}/(\text{Recall} + \text{Precision}), \quad (16)$$

where

TP*:* the number of true tampered pixels, FP: the number of false tampered pixels, FN: the number of missed tampered pixels.

Results

With the implementations on cases, the results confirm:

(i) For copy-move images in which the copy areas are duplicated and do not resize, with/without rotation, and the same areas due to collage only (not due to image's structure):in this case, 65 images are considered (including 20 images of benchmark, 20 images of MICC-600 and 30 images of natural images). The proposed algorithm only applies the step of detecting suspicious areas (see the steps belonging to the green box in Fig. 2) and confirms these are also copied areas. The results presented in Table 2 and Fig. 6 confirm that the accuracy of the algorithms is improved and the average of processing time faster than others for this image group (Fig. 7).

(ii) For copy-move images in which areas of the copied image with/without resizing, rotating and the same areas due to collage only (not due to image's structure): in this case, 35 images are considered

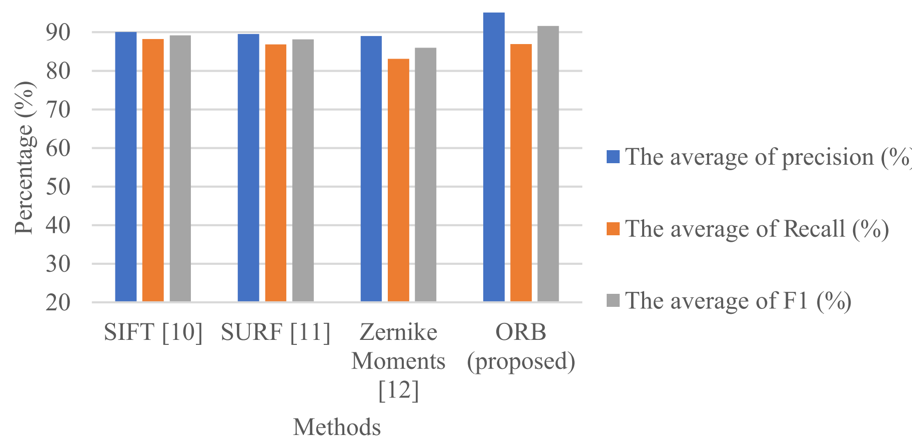


Fig. 6 Comparison of precision, recall and $F1$ for copy-move images in which the copy areas are duplicated and do not resize, with/without rotation, and the same areas due to collage only (not due to image's structure)

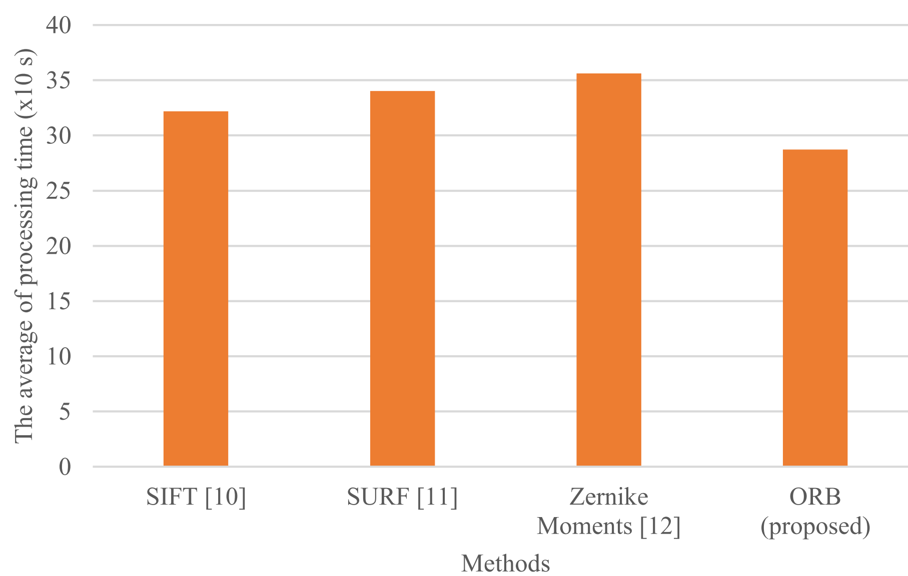


Fig. 7 Comparison of the average processing time for copy-move images in which the copy areas are duplicated and do not resize, with/without rotation, and the same areas due to collage only (not due to image's structure)

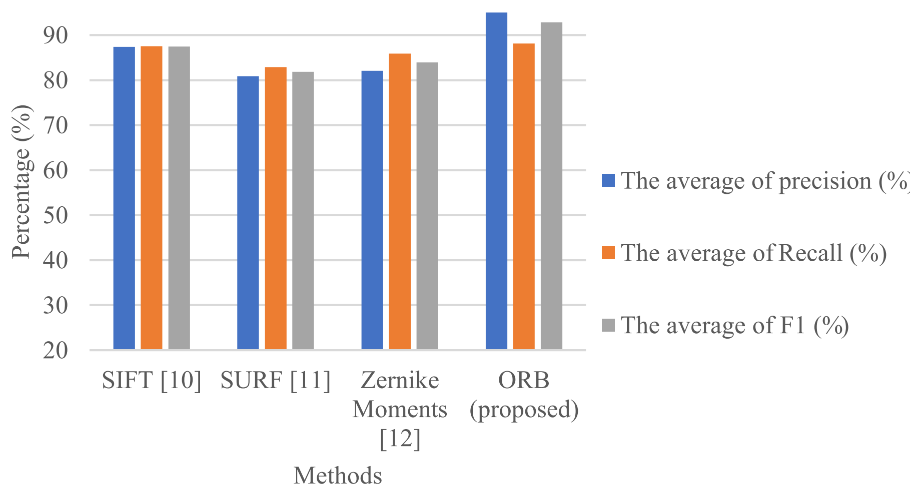
Table 2 The simulation results for copy-move images in which the copy areas are duplicated and do not resize, with/without rotation, and the same areas due to collage only (not due to image's structure)

Methods	The average of precision (%)	The average of recall (%)	The average of $F1$ (%)	The average of processing time ($\times 10$ s)
SIFT [10]	90.07	88.25	89.15	32.19
SURF [11]	89.52	86.87	88.17	34.01
Zernike moments [12]	88.96	83.08	85.92	35.62
ORB (proposed)	96.8	86.9	91.58	28.72

Table 3 The simulation results for copy-move images in which areas of the copied image with/without resizing, rotating and the same areas due to collage only (not due to image's structure)

Methods	The average of precision (%)	The average of recall (%)	The average of F (%)	The average of processing time ($\times 10$ s)
SIFT [10]	87.35	87.52	87.43	37.25
SURF [11]	80.87	82.86	81.85	36.93
Zernike moments [12]	82.06	85.91	83.94	39.17
ORB (proposed)	98.07	88.15	92.85	38.95

Fig. 8 Comparison of precision, recall and $F1$ for copy-move images in which areas of the copied image with/without resizing, rotating, and the same areas due to collage only (not due to image's structure)



(including 15 images of benchmark and 20 of natural images). The proposed algorithm performs all steps as shown in Fig. 2. The results presented in Table 3 and Fig. 8 show that the accuracy of the algorithms is different in the case of this image group. The proposed algorithm gives the highest accuracy at 98.07% and the relative processing time (Fig. 9).

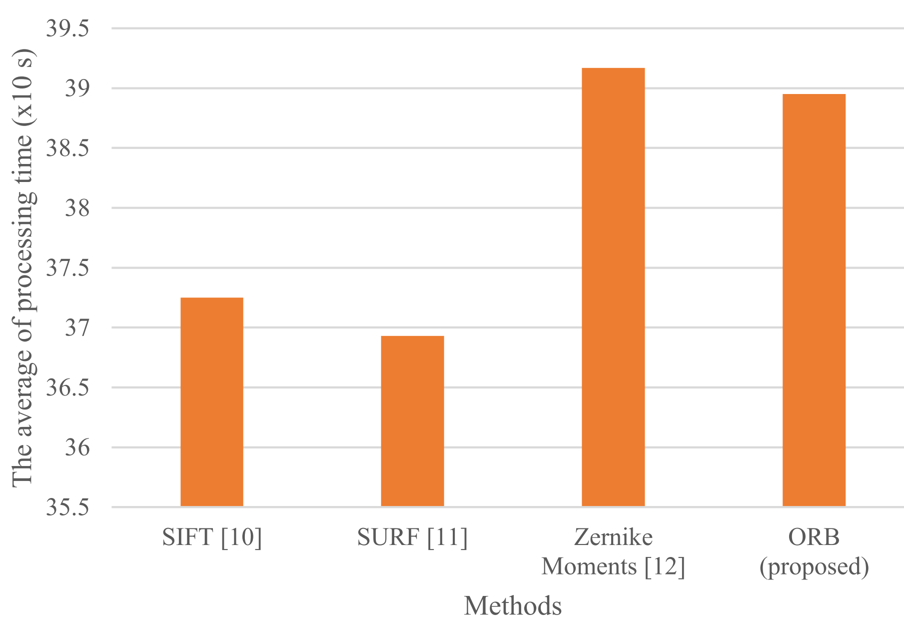
(iii) For copy-move images in which areas of the copied image are resized, rotated and the same areas may be due to collage or image's structure: in this case, only 40 natural images with the Photoshop operations are considered. The authors do not use the dataset of benchmark and MICC-600 image sets for this kind of images because their images do not meet the input requirements. The methods of using SIFT, SURF and Zernike moments published have not yet seen mentioning the identification of similar areas in case of image's structure. Therefore, only the proposed algorithm is applied to this case with positive results. The average precision of 98.67% proves the effectiveness of the algorithm.

Some simulation results of the algorithm for case (i) and (ii) are shown in Fig. 10 and for case (iii) are shown in Fig. 11.

The images in the above row: tested images, the images in the under row: detection.

In Fig. 10, the images at the first and the fourth column are created by copy-move operation with rotation while the images at the second and the third column are created by cloning. In these images, one of the similar regions is the original and the others are faked by copy-move. However, regardless of the rotation, resized or clone when carrying

Fig. 9 Comparison of the average processing time for copy-move images in which areas of the copied image with/without resizing, rotating and the same areas due to collage only (not due to image's structure)



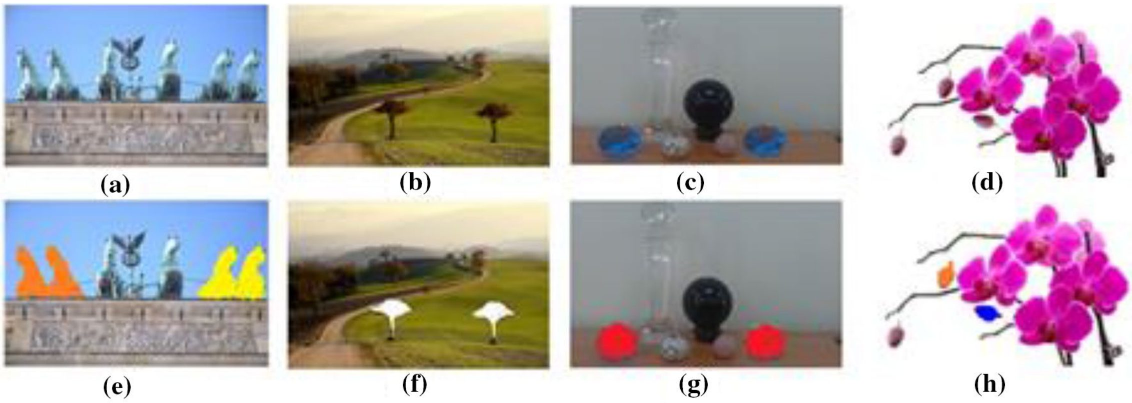


Fig. 10 Some results by the proposed method for images in case (i) and (ii)

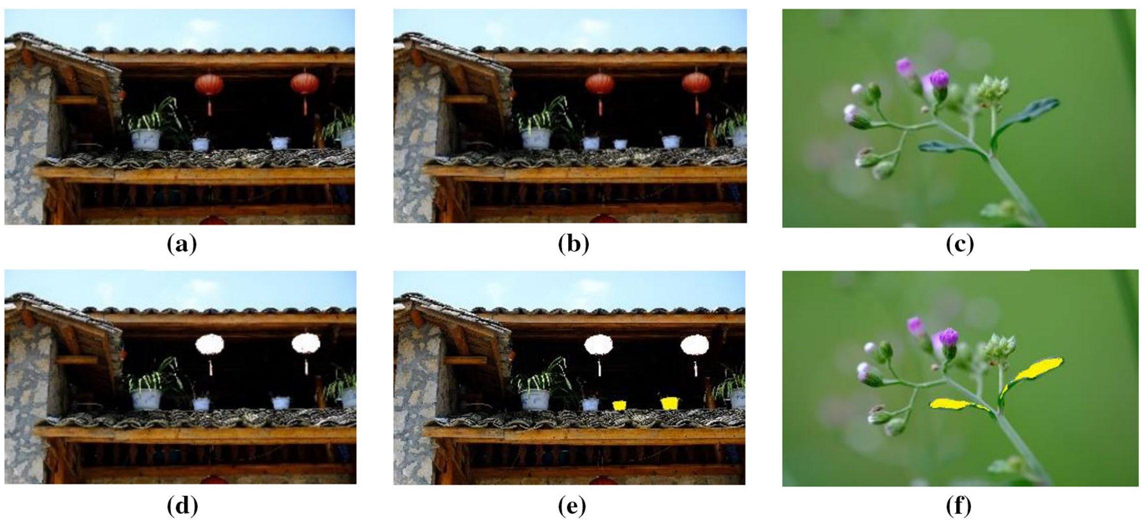


Fig. 11 Some results by the proposed method for image in case (iii). The images in the above row: tested images, the images in the under row: detection

out the copy-move, the detection of forged regions in these images is detected efficiently. Figure 10 demonstrates for the case (i) and (ii).

In Fig. 11, image (a) is a forged image in which the red lantern on the right is the clone of the left one and the two white-small pots are original. The image (b) is a modified version of (a) in which a small pot in the middle is copied and resized from the right one. The image (c) is also a forged image in which the left leaf is copied and resized from the right one. In these images, many objects are similar due to the image's structure, not being faked and forged regions are created by Photoshop operations. The forgery detections of image (a), (b), (c) are shown in image (d), and (f) respectively. The simulation results from these images and others in the dataset of case (iii) prove the efficiency with high accuracy of the algorithm.

Conclusion

The paper suggests a method using ORB to extract similar features which are clues of copy-move manipulations and apply the logistic regression model to remove the duplicated regions due to the texture so that the copied region detection is exact. The results of simulation in three different cases give the accuracy improved. The method can detect the copied regions which are scaled, rotated before copying to a place in the same image. The model to remove the non-copied regions from the suspicious regions is built by the combination of sharpness in the borderline and blurriness inside the image regions. Experiments are carried out in images with different kinds of operation in forging. With the simulation results and comparisons with related algorithms, the proposed method gives the average of accuracy at least 95% for image groups. This proves that ORB is an efficient extraction method for detecting copy-move regions with scale and rotation in image forensics and the model is good for copy-move manipulation confirmation. Applying deep learning to build a general model for copy-move forgery detection is one of the future works.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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