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Detecting Affine-Distorted Duplicated Regions in Images by Color Histograms

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Abstract. *Region duplication is a simple method to create forgery images, where part of an image is copied and pasted somewhere else in the same image. In order to fit the scene better and hinder possible forgery detection, the copied region is often processed by affine transforms before being pasted. In order to achieve this goal, region rotation, scaling, even nonlinear local distortions can be applied. This paper presents a method to detect the region-duplication forgery under affine distortions. The image is first filtered and divided into overlapping circular blocks. Then the normalized color histogram is extracted as the block feature. The Histogram Intersection Similarity (HIS) is employed to estimate the similarities of the histogram features. A post-processing filter is proposed to reduce the false matches and the regions are located in a pixel-based manner, which we call pixel-based marking. The final detection result is obtained after morphological operations. Simulation results demonstrate the efficiency of the proposed scheme.*
Keywords: Image forensics, Region-duplication, Affine transform, Color histogram

1. **Introduction.** Digital images have been widely used as evidences in our daily life. However, the prevalence of powerful image processing software has brought great threat to the security of digital images. Actually, we have witnessed many image forgery cases through the public media. Region duplication, also known as copy-move, is a common method to create forgery images [1, 2]. In this case, part of an image is copied and pasted somewhere else in the same image, aiming to cover an unwanted object or emphasize the presence of a specific scene. The current countermeasure to detect region duplication forgery is to divide the image into blocks and find corresponding ones. It is based on a simple assumption that there are no two exactly similar regions in natural images.

In region duplication, the copied region may be processed before being pasted. These manipulations are mainly based on the following two reasons. (1) In order to fit the scene better and produce more vivid scene, the copied object may be rotated, scaled or even transformed by nonlinear local distortions. (2) The image forgers may transform the copied regions deliberately, aiming to hinder the detection of such forgeries. If the copied region is distorted by affine transforms before being pasted, it will be extremely difficult to identify and locate the tampered regions. In order to solve the problem, several methods have been proposed recently, which can be classified into: (1) keypoint matching based detection; (2) invariant transform based detection; and (3) invariant moment based method. Keypoint matching based methods commonly employ the multi-scale feature point detection techniques, which have been widely used in pattern recognition. Xu et al. proposed a SURF (Speed up Robust Features) based method in [3]. The SURF keypoints were extracted from the image and the forged regions were detected by comparing the distances of the SURF descriptors. A possible deficiency of the scheme is that it cannot generate close contours of the forged regions. Instead, the regions are marked directly by the matched keypoints. Amerini et al. proposed a scale-invariant feature transform (SIFT) based method [4]. The SIFT features were extracted from the images and the corresponding regions were determined by estimating similarities of the SIFT descriptors. Similar to [3], the detected regions are marked by the matched SIFT keypoints. Pan and Lyu also proposed a SIFT based detection method [5]. The method first estimated the transform between matched SIFT keypoints. The pixels within the duplicated regions were obtained after discounting the estimated transforms. This method can generate close contours of the detected regions. These methods can detect the region duplication forgeries when the copied region is subject to rotation and/or scaling, because the keypoints are typically invariant to the general geometric transforms. For the invariant transform based method, the block is usually transformed to form a rotation and scaling invariant representation. Block matching is then conducted based on the invariant features. Solorio et al. proposed to generate the block features using log polar mapping (LPM) [6]. The block pixels were mapped to log-polar coordinates and summed along the angle axis, producing a one-dimensional descriptor. The descriptor is invariant to rotation, and scaling corresponds to a simple translation of the descriptor. Corresponding blocks can be determined by comparing the 1-D descriptors. Bayram et al. proposed a Fourier-Mellin Transform (FMT) based detection method [7]. The block features were extracted using FMT, which had proved to be invariant to image rotation, scaling and translation (RST). Another very similar method is to extract the block features using the log-polar Fourier transform (LPFT), which is a rotation and scaling invariant feature extraction method [8]. Log-polar transform (LPT) is conducted on the block, followed by a 2-D Fourier transform. The forged regions can be determined by comparing the cross-spectra of the LPFT features. The third kind of method to deal with geometric transforms of the copied regions is to represent the block using invariant moments. Liu et al. proposed to extract geometrically invariant block features using the well-known Hu moments [9]. The experiments showed that the method can resist moderate region rotation as well as the traditional image processing operations. Ryu et al. extracted the block features using Zernike moment (ZM) [10], which is a rotation invariant feature extraction method. They built an image database containing 12 images to evaluate the performance of the scheme, and the average detection precision rate is 83.59% for region rotation of 30 degree.

The existing methods focus on the detection of region duplication forgery with rotation. In this paper, we present a novel method for the detection of more general region duplication forgeries. We are particularly interested in detecting the forgeries when the regions are distorted by the general affine transforms, including rotation, scaling and challenging nonlinear local distortions. Unlike the existing methods, we propose to use normalized color histogram (NCH) as the block feature. The NCH feature is computed on a circular domain and it is invariant to the content-preserving affine transforms as well as traditional image processing operations. An image is first divided into overlapping circular blocks and the NCH features are computed. The Histogram Intersection Similarity (HIS) is employed to estimate the similarities of the features. The forged regions are coarsely located using the proposed Pixel Based Marking (PBM) method. A post-processing filter (PPF) is also proposed to reduce the false matches. The detection results are obtained after morphological operations. Experimental results show that the proposed method can handle region rotation, scaling, shearing etc.

2. **Normalized Color Histogram.** The histogram of an image is a statistical feature, denoting the distribution of the gray scales. It has been widely used in data hiding [11, 12]. In image processing, the histogram is obtained by first splitting the gray scales into equal-sized bins. The number of pixels is then counted. Given an image $\mathbf{F} = \{f(x, y)|x = 1, 2, \cdots, M; y = 1, 2, \cdots, N\}$, the histogram is a vector:

$$\mathbf{H} = \{h(i)|i = 1, 2, \cdots, L\}, \tag{1}$$

where $h(i)$, $h(i) \geq 0$, denotes the number of pixels in the ith bin, satisfying $\sum_{i=1}^{L} h(i) = M \times N$, L is the total number of bins. Assume that the bit depth of the image is P, then the number of bins can be calculated as:

$$L = \begin{cases} 2^P/W, & \text{if } \bmod(2^P, W) = 0 \\ \lfloor 2^P/W \rfloor + 1, & \text{otherwise,} \end{cases} \tag{2}$$

where $\lfloor \cdot \rfloor$ denotes the *floor* operation, W is the width of a bin.

In practise, most of the images are in color format. Therefore, we propose a color histogram based method to detect the region duplication forgery in images. The process for generating the normalized color histogram (NCH) feature is illustrated in Fig.1.

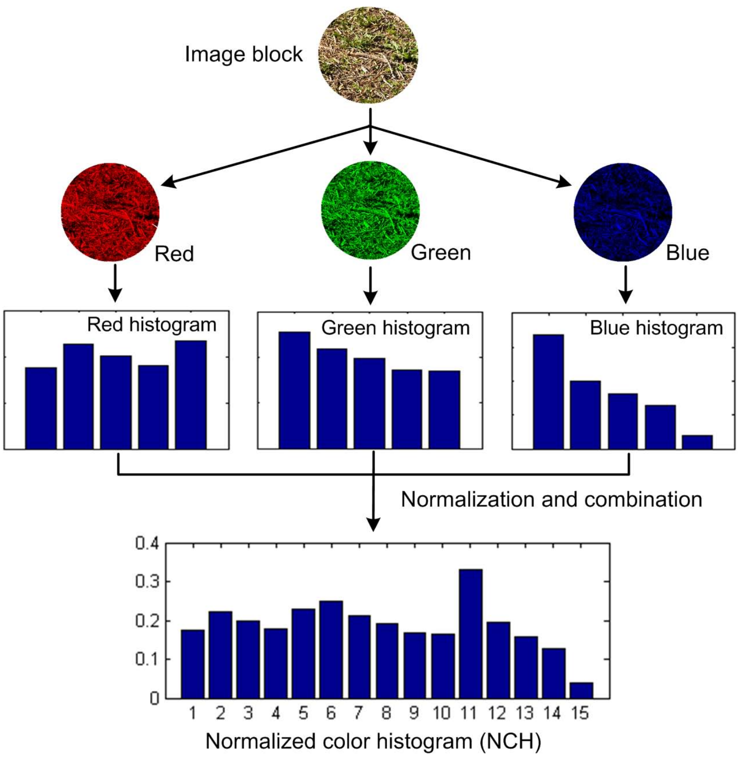

Figure 1. Generation of the NCH feature.

For a given image block $\mathbf{B}$, it is first divided into the red channel $\mathbf{B}_r$, green channel $\mathbf{B}_g$ and blue channel $\mathbf{B}_b$:

$$\mathbf{B} = \mathbf{B}_r + \mathbf{B}_g + \mathbf{B}_b. \tag{3}$$

Then, the histogram for each color channel is computed, which can be denoted as

$$\begin{aligned} \mathbf{H}_r &= \{h_r(i)|i = 1, 2, \cdots, L\} \\ \mathbf{H}_g &= \{h_g(i)|i = 1, 2, \cdots, L\} \\ \mathbf{H}_b &= \{h_b(i)|i = 1, 2, \cdots, L\} \end{aligned} \tag{4}$$

where H_r, H_g and H_b denote the red, green and blue histograms, respectively. The next step is to normalize the histograms according to the total number of pixels. Since the total number of pixels is $M \times N$, the normalized histograms can be obtained by:

$$\begin{aligned} \overline{\mathbf{H}_r} &= \left\{\tfrac{h_r(i)}{M\times N}|i = 1, 2, \cdots, L\right\} \\ \overline{\mathbf{H}_g} &= \left\{\tfrac{h_g(i)}{M\times N}|i = 1, 2, \cdots, L\right\} \\ \overline{\mathbf{H}_b} &= \left\{\tfrac{h_b(i)}{M\times N}|i = 1, 2, \cdots, L\right\} \end{aligned} \tag{5}$$

Finally, the three histograms are combined to generate the final NCH feature:

$$\mathbf{H}^* = \left[\overline{\mathbf{H}_r}, \overline{\mathbf{H}_g}, \overline{\mathbf{H}_b}\right]. \tag{6}$$

It is easy to know that H^* is a $3L$-dimensional vector. In this paper, the dimension of H^* is 15, namely we divide each color channel into 5 equal-size bins. As the intensity range for each channel is [0 255], we divide the ranges of the 5 bins as [1 51], [52 102], [103 153], [154 204], [205 255]. Note that the gray scale 0 is not used. Although gray scale zero is not used in the NCH feature, it would not affect the performance of the feature extraction method, because zero pixel rarely appear in natural images. The NCH feature is invariant to the general content-preserving image processing operations.

3. **Region Duplication Forgery Detection.** The proposed method operates as follows. The original image is first filtered using a loss-pass filter to reduce high frequency disturbances. Then the filtered image is divided into overlapping circular blocks, and the NCH features are extracted. Then lexicographically sorting is employed to rearrange the feature vectors, and the Histogram Intersection is employed to measure the similarities of the blocks. The matched blocks are marked in a pixel based manner, producing a coarse detection map. A Post-Processing Filter (PPF) is also proposed to reduce false matches. The final detection map is obtained by morphological operations. In the following subsections, we will illustrate each step in further detail.

3.1. **Low-Pass Filtering.** The proposed histogram feature is extracted in spatial domain. As a result, it is likely to be affected by high frequency changes in images. In order to obtain robust NCH features, we introduce the low-pass filtering before feature extraction. The low-pass filtered image is obtained by convoluting the image $\mathbf{F}(x, y)$ with a Gaussian kernel $\mathbf{G}(x, y, \sigma)$:

$$\mathbf{F}_{Low}(x, y) = \mathbf{F}(x, y) * \mathbf{G}(x, y, \sigma), \tag{7}$$

where the Gaussian function has the following form:

$$\mathbf{G}(x, y, \sigma) = \frac{1}{2\sigma^2} exp^{-\frac{x^2+y^2}{2\sigma^2}}, \tag{8}$$

where σ is the standard deviation of the Gaussian kernel. In implementation, the size of the kernel is 3×3 and the standard deviation is set to 2. The low-pass filtering operation is helpful in obtaining robust histogram features, particularly for high textured images.

3.2. **Blocking.** Most of the existing algorithms employ square blocks, and they can deal with traditional image processing operations. However, the forger may rotate, resize or warp the copied region before it is pasted, both to obtain a harmonious scene and hinder possible detection. In order to detect region rotation, the block features should be immune to region orientation changes. To this end, we employ circular blocks. For an image, we divide it into overlapping circular blocks. The diameter of the block is d, and the adjacent blocks have only one different row or column. Given an image with size $M \times N$, the number of blocks is:

$$N_{blk} = (M - d + 1) \times (N - d + 1). \tag{9}$$

3.3. **Feature Extraction and Processing.** The NCH features of the blocks are extracted in a raster scanning order. Typically, a 15-dimensional NCH feature can be extracted from each block. Therefore, N_{blk} NCH features can be generated. These features are stored in a matrix $\mathcal{S}$. The matrix has N_{blk} rows, and each row is a 15-dimensional feature vector. Before performing feature matching, the block features are first lexicographically sorted. By doing this, the similar features are arranged to locate in the neighboring rows, which is helpful for the following feature matching.

3.4. **Block Matching.** To locate the duplicated regions, the corresponding blocks should be determined. This is achieved by comparing the NCH features. In this paper, Histogram Intersection is employed to estimate the similarities of the blocks, which has been used in color indexing [13, 14]. Let $\mathcal{S}_i$ and $\mathcal{S}_j$ denote the NCH feature in the ith and jth row of $\mathcal{S}$, the HIS similarity is computed as follows.

$$\mathcal{HIS}(\mathcal{S}_i, \mathcal{S}_j) = \sum_{k=1}^{3L} min(\mathcal{S}_i(k), \mathcal{S}_j(k)). \tag{10}$$

It should be noted that for a given feature, we do not need to compute the similarities with all other features. The reason is that the similar features have been arranged to locate at the neighboring rows by lexicographically sorting. In this paper, the search range is R_{Lim}. That is to say, a feature is compared with the subsequent R_{Lim} features for possible matching.

Block matching starts from the first row of matrix $\mathcal{S}$. For $\mathcal{S}_i$, the similarities with the subsequent R_{Lim} features are calculated, and the feature with the highest similarity is determined.

$$\mathcal{SD}_{i,i+K} = \sqrt{(x_i - x_{i+K}) + (y_i - y_{i+K})}. \tag{11}$$

If $\mathcal{SD}_{i,i+K} > T_d$, the ith block and the $(i+K)$th block are regarded as correctly matched. Otherwise, they are regarded as false matches. Since the neighboring circular blocks has only one different row or column, these blocks tend to have very similar NCH feature and the HIS measure tends to be very high, even bigger than T_{sim}. However, they cannot be regarded as correct matches. In implementation, we compare the spatial distance of the blocks with the threshold T_d. In this way, the false matches can be reduced.

3.5. **Pixel-Based Marking (PBM).** After obtaining the corresponding blocks, the next step is to mark the duplicated regions. The traditional method is to mark the whole block. However, marking the whole block will produce coarse boundary. In this paper, we propose to mark the duplicated regions in a pixel based manner, which we call pixel based marking.

Fig.2 illustrates how the pixels are marked. If the diameter of the circular block is even, the innermost four pixles are marked. If the diameter is odd, the innermost five pixels

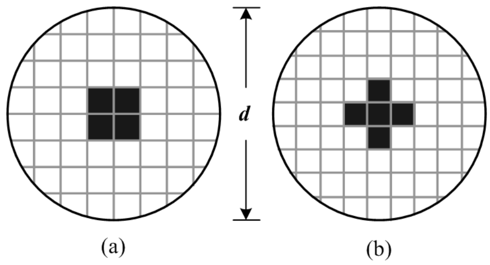

FIGURE 2. Illustration of PBM: (a) d is even, (b) d is odd.

are marked. Fig.3 shows an example of the detection maps using traditional block based marking and PBM.

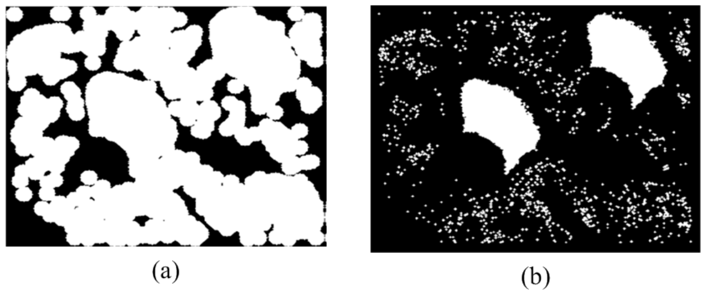

FIGURE 3. The detection maps produced by: (a) Block based marking, (b) PBM.

It is known from the figure that the proposed PBM method can generate the duplicated regions much more accurately. Meanwhile, the falsely detected regions are represented as a pattern like added noise. However, when the regions are marked in a block based manner, large area of falsely detected regions are present, which are hard to remove. It is reasonable to mark the duplicated regions in a pixel based manner, because the duplicated blocks are typically concentrated in a tight region. As a result, if we mark the regions in a pixel based manner, the duplicated regions will be readily detected, and the falsely detected blocks will be present as somewhat like added noise. Furthermore, the noise-like patterns can be easily removed.

3.6. **Post-Processing.** The detected regions are contaminated with noises, which is produced by false matches. Therefore, we have to apply a post-processing on the detection map. Having noted that the distribution of the noise pattern is scattered, we propose a new filter to handle the noises, which we call post-processing filter (PPF). The template of the filter is designed as follows

$$PPF = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 1 & 1 & \cdots & 1 \\ & & \cdots & \\ 1 & 1 & \cdots & 1 \end{pmatrix}_{N_{PPF} \times N_{PPF}} \tag{12}$$

where $N_{PPF} \times N_{PPF}$ is the size of the template. The proposed filter operates by conducting a convolution over the initial detection map. If the result of convolution at each position is denoted by R, the detection map (denoted by $\mathcal{DM}'$ here) becomes

$$\mathcal{DM}' = \begin{cases} \mathcal{DM}, & \text{if } R \geq T_{PPF} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

where $\mathcal{DM}$ is the initial detection map, T_{PPF} is a threshold, and

$$R = \mathcal{DM} * PPF \tag{14}$$

where $*$ denotes the convolution operation. The proposed filter can remove many of the noises from the detection map while preserving the correct regions. Fig.4(b) shows the result of PPF filtering.

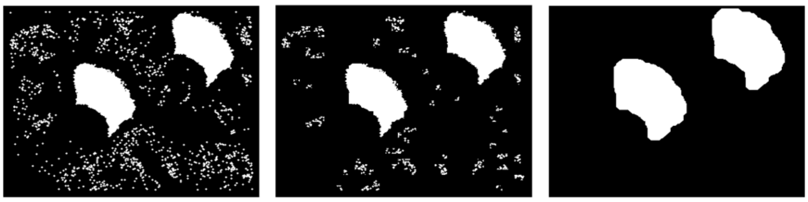

FIGURE 4. Post-processing of the detection result: (a) Initial detection map ($\mathcal{DM}$), (b) Detection map after PPF filtering ($\mathcal{DM}'$), (c) Detection map after morphological operation.

It is observed from Fig.4(b) that there are still some isolated spots in the detection map. In order to obtain a satisfactory result, we employ the morphological operations. First, corrosion is applied on the detection map. Then expansion operation is conducted. The purpose of morphological corrosion is to reduce the small isolated regions, while morphological expansion is to obtain a complete detection map. Fig.4(c) shows an example of the final detection map after PPF filtering and morphological operations.

4. **Experimental Results and Discussions.** In our experiments, the affine distortions of the copied regions are conducted using Photoshop, including rotation, scaling, shearing and local bending. Most of the test images are collected from the Internet. The UCID image database [15] is employed to evaluate the overall performances of the proposed scheme in face of signal processing attacks, which will be illustrated in section 4.3.

In experiments, the parameters are listed in Table 1. These parameters include the diameter of the circular block (d), search range of feature matching (R_{Lim}), distance threshold (T_d), similarity threshold (T_{sim}), size of the PPF (N_{PPF}) and the PPF threshold (T_{PPF}). These parameters are determined by extensive experiments and have been shown to be effective for common images.

TABLE 1. Parameters used in the experiments.

Parameter	d	R_{Lim}	T_d	T_{sim}	N_{PPF}	T_{PPF}
Value	24	30	24	2.8	8	15

The diameter (d) of the circular block should neither too big nor too small. It the blocks are too big, it will be hard to obtain fine contour of the tampered regions and some small details may not be detected. The search range R_{Lim} is a key parameter. In implementation, small values may be used for the general attacks. If powerful distortions are performed, such as severe local bending and heavy JPEG compression, the search range should be wide. We set R_{Lim} to 30, and it is efficient for the general situations. The distance threshold is set to 24 (equal to d) so that the matched blocks cannot overlap. In this way, the neighboring blocks have no chance to match so that the false matches can be greatly reduced. The similarity threshold T_{sim} is determined by experiments. The size (N_{PPF}) and threshold (T_{PPF}) of the post-processing filter are set so that the false matches can be efficiently removed while preserving the correct matches.

In order to obtain fair comparison with peer schemes, the simulation results on other two region duplication algorithms are also given in the following experiments. One is the Hu moment based detection method proposed by Liu et al. in [9], and the other is the Zernike moment based method reported by Ryu et al. in [10]. These two methods are adopted in the comparisons because they are among the few methods addressing affine-distorted region duplication detection.

4.1. **Linear Geometric Distortions.** The most common form of affine transform is the linear geometric transform, including rotation and scaling. We conduct these experiments using different parameters, including different rotation angles and different scaling factors. Simulation results on one of the test images are shown in Fig.5 and Fig.6.

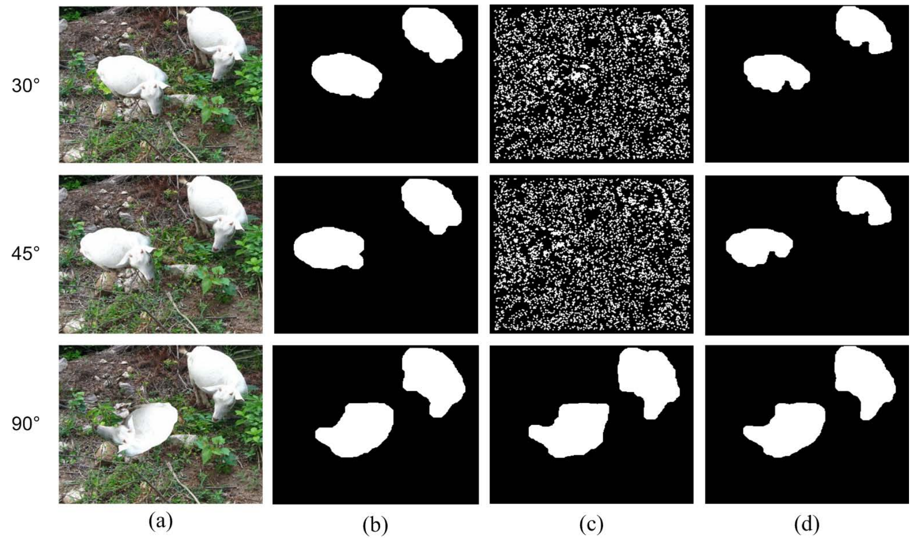

Figure 5. Detection results on region rotation: (a) Region rotation, (b) Proposed method, (c) Hu moment based method, (d) Zernike moment based method.

Region rotation is easy to conduct. However, it can be used to produce more natural image, making the forgery hard to detect. The proposed method can handle region rotation. When the region is rotated by angles integral times of 90 degree, the detection map is very accurate. However, when the region is rotated by general angles, the accuracy decreases. This is due to the interpolation error. By comparison, the proposed method performs much better than the Hu moment based method, and is comparable to the Zernike based method.

Region scaling is often employed to adapt the copied region to the scene. It is observed from Fig.6 that the proposed method is robust to region scaling, no matter the scaling factor is bigger or smaller than 1.0. Although the diameter of the circular block is fixed in the proposed method, changing the region size slightly would not affect the invariance of the NCH feature significantly.

4.2. **Nonlinear Geometric Distortions.** In some cases, the distortions applied on the copied regions may not be linear. Furthermore, the forger may transform the region intentionally in a nonlinear manner to prevent forensics analysis. Therefore, the detection method should be able to handle nonlinear distortions. Fig.7 and Fig.8 show the simulation results on region shearing and local bending.

As a statistical feature, NCH is invariant to the general content-preserving affine transforms. It can be observed from the figures that the proposed method can detect the forgery

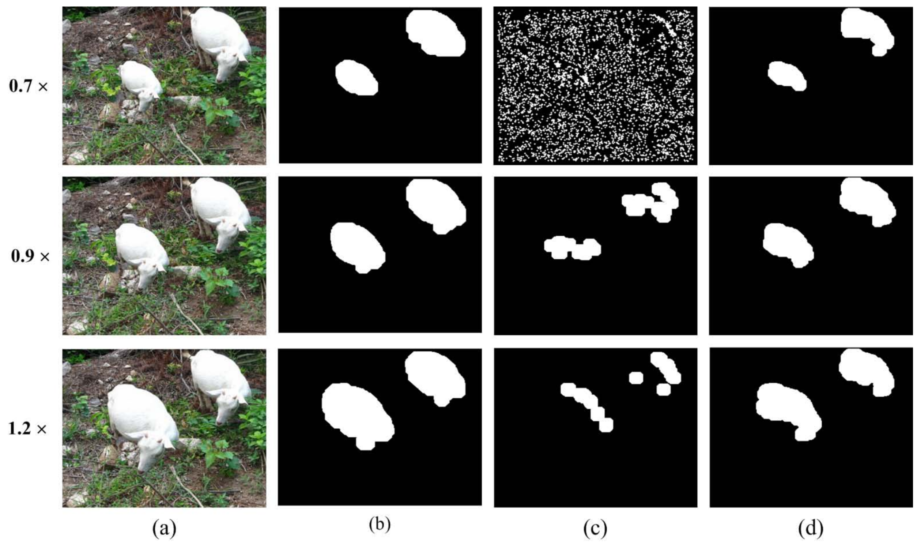

FIGURE 6. Detection results on region scaling: (a) Region scaling, (b) Proposed method, (c) Hu moment based method, (d) Zernike moment based method.

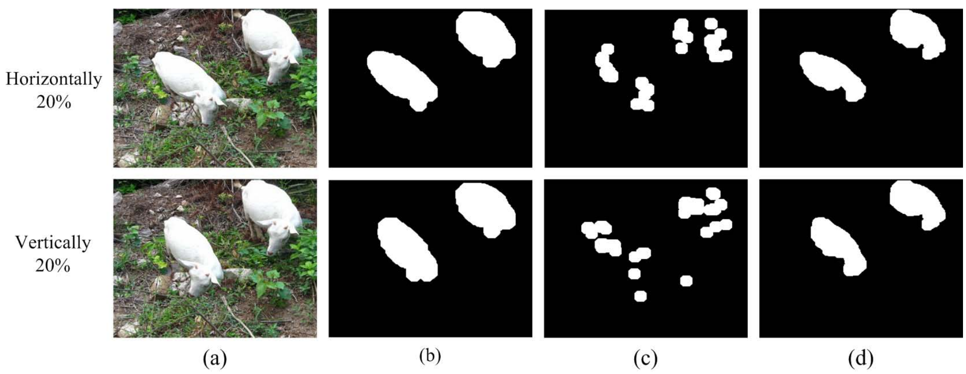

FIGURE 7. Detection results on region shearing: (a) Region shearing, (b) Proposed method, (c) Hu moment based method, (d) Zernike moment based method.

successfully when the region is subject to shearing and local bending. The Hu moment based method cannot handle these distortions. The Zernike moment based method can resist this kind of distortion to a certain extent. By comparison, the proposed method performs the best.

4.3. **Quantitative Evaluation.** In order to evaluate the performance of the proposed method in terms of signal processing attacks, we conduct the following experiments on the UCID image database [15]. We randomly choose 100 color images from the UCID database to conduct the experiments. An image block is copied randomly and pasted to another part of the image. The same signal processing operations are applied on the forged images. We employ the correct detection ratio (F_c) and false detection ratio (F_f) to estimate the performance of the proposed method:

$$F_c = \frac{|C_1 \cap C_2| + |D_1 \cap D_2|}{|C_1| + |D_1|}, \tag{15}$$

$$F_f = \frac{|C_1 \cup C_2| + |D_1 \cup D_2| - |C_1| - |D_1|}{|C_1| + |D_1|}, \tag{16}$$

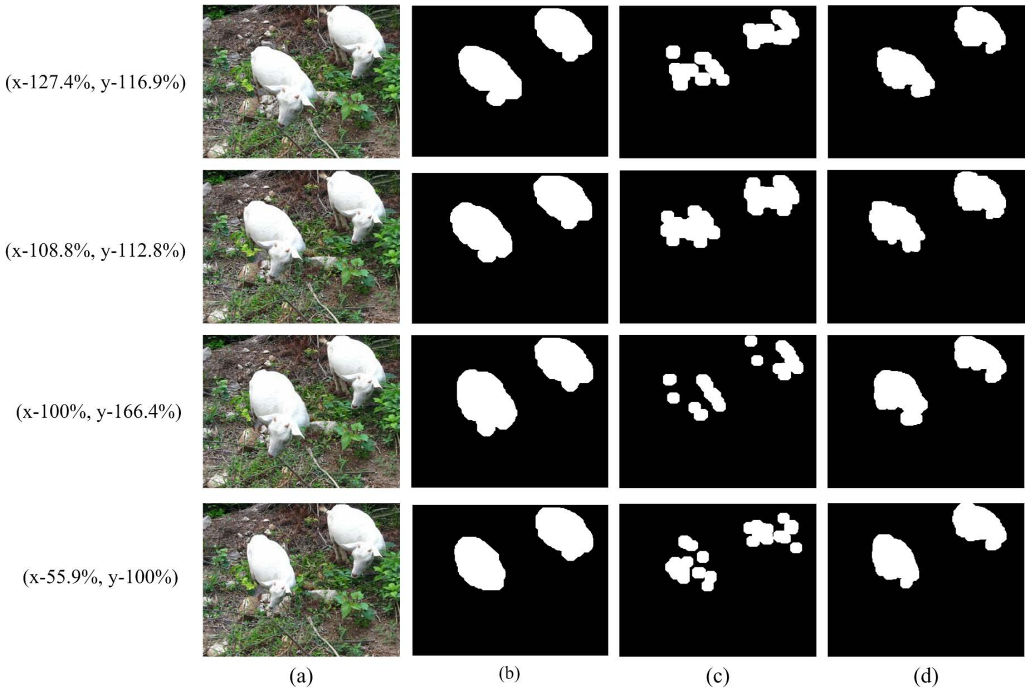

FIGURE 8. Detection results on local bending: (a) Region bending, (b) Proposed method, (c) Hu moment based method, (d) Zernike moment based method.

where C_1 and D_1 are the copy region and the tampered region, while C_2 and D_2 are the detected copy region and detected tampered region. In this experiment, we test three different region sizes, namely 60×60, 80×80 and 100×100. The simulation results are shown in Fig.9 to Fig.11.

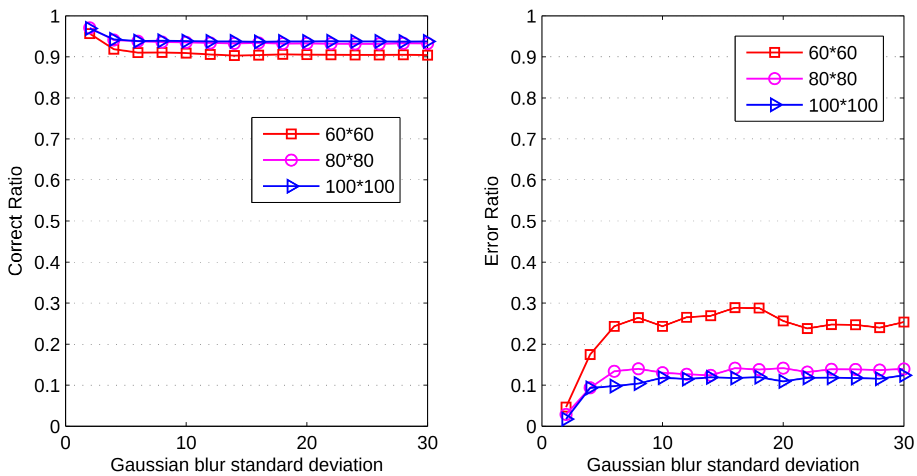

FIGURE 9. Performance on Gaussian blurring.

It can be seen from the curves that bigger duplicated regions are easier to detect than smaller ones. For most of the simulations, the regions with size 100×100 are detected with the highest correct ratios as well as the lowest false ratios. For Gaussian blurring, the correct ratio decreases with increased standard derivation of the Gaussian kernel. Meantime, the correct ratios are all higher than 0.9, which are relatively high. The correct ratios are very satisfactory for blurring, because we have included a low pass filtering before feature extraction. For added Gaussian white noise and JPEG compression, we

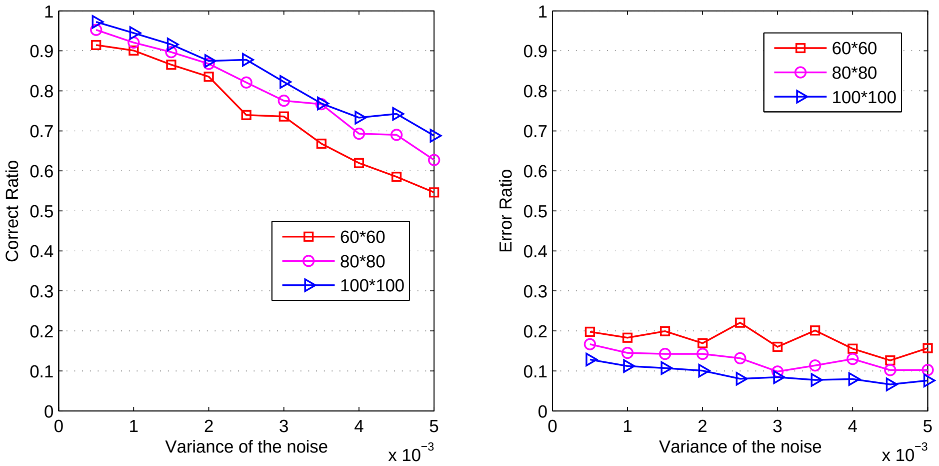

FIGURE 10. Performance on added Gaussian noise.

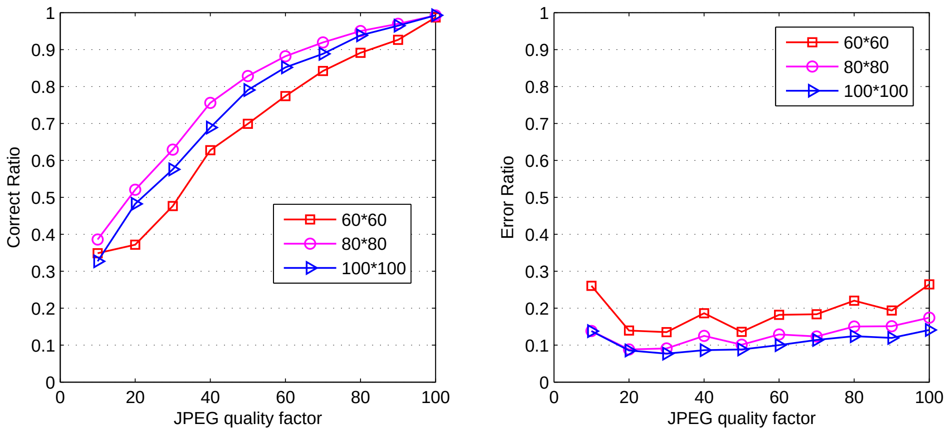

FIGURE 11. Performance on JPEG compression.

obtain similar results. For added Gaussian noise, the correct detection ratio decreases with increasing variance of the noise. For JPEG compression, the correct detection ratio increases with increased quality factors. Furthermore, the false ratios are mostly below 0.2 for these two kinds of distortions.

5. **Conclusion.** In this paper, we investigate the problem of detecting region duplication forgeries in images. Particularly, we focus on the cases that the copied region is subject to affine distortions before being pasted. An effective algorithm is addressed based on normalized color histograms. A new similarity measure, namely Histogram Intersection Similarity, is adopted to achieve feature matching. We have also proposed the pixel based marking method to obtain the detection map. A post-processing filter is also proposed to reduce the false matches. Simulations and comparisons demonstrate the efficiency of the proposed scheme.

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