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Copy-move forgery detection using combined features and transitive matching

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Abstract

Recently, the research of Internet of Things (IoT) and Multimedia Big Data (MBD) has been growing tremendously. Both IoT and MBD have a lot of multimedia data, which can be tampered easily. Therefore, the research of multimedia forensics is necessary. Copy-move is an important branch of multimedia forensics. In this paper, a novel copy-move forgery detection scheme using combined features and transitive matching is proposed. First, SIFT and LIOP are extracted as combined features from the input image. Second, transitive matching is used to improve the matching relationship. Third, a filtering approach using image segmentation is proposed to filter out false matches. Fourth, affine transformations are estimated between these image patches. Finally, duplicated regions are located based on those affine transformations. The experimental results demonstrate that the proposed scheme can achieve much better detection results on the public database under various attacks.

Keywords Multimedia big data · Internet of things · Multimedia forensics · Region duplication detection · Copy-move forgery · Image segmentation · LIOP

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1 Introduction

In recent years, Internet of Things (IoT) [7] and Multimedia Big Data (MBD) [32, 84] represent two appealing fields for many researchers [48, 50, 76, 82]. Internet of Things (IoT) impart networked connectivity to everyday objects in the physical world [7]. Various electronic devices in IoT have generated huge multimedia data. Multimedia has become the “biggest big data”, which is MBD. There are many information security problems of IoT and MBD, i.e., the multimedia of IoT or MBD is tampered. The related research is multimedia forensics, which is a science of acquiring, analyzing, extracting, interpreting and producing an evidence from a multimedia source in civil, criminal or corporate cases of administrative nature [51].

Multimedia forensics [38, 61, 78, 80, 81] is an important domain of information security [9, 10, 12, 13, 19–24, 39]. Both IoT and MBD [17, 18, 28, 30, 42, 46, 47, 58, 62, 65–71, 75, 77, 79, 83, 85] have a lot of multimedia data. Therefore, the research of the multimedia forensics is very meaningful to IoT and MBD. The multimedia forensics can be divided into many branches, i.e., copy-move and splicing.

In a copy-move attack, one or more parts of an image are copied and pasted into another part of the same image [27]. The object of study of copy-move is multimedia data, many multimedia data make up MBD. Therefore, copy-move is an analysis and treatment of MBD. Many image Copy-Move Forgery Detection (CMFD) schemes [4, 5, 16, 25, 27, 29, 33, 34, 44, 49, 64, 72] have been proposed in recent years. According to Christlein et al. [15], commonly known copy-move detection schemes can be divided into two branches. The first one is the block-based schemes, an image is divided into fixed-size overlapping blocks, the each block is represented by a block descriptor, then those descriptors are sorted and matched. The main difference of the block-based schemes is their block features. Fridrich et al. [27] use the Discrete Cosine Transform (DCT) as block features. Popescu and Farid [53] use the Principal Component Analysis (PCA) as block features. Bashar et al. [5] propose a CMFD method using the Discrete Wavelet Transform (DWT) or the Kernel Principal Component Analysis (KPCA). An improved DCT-based method is proposed by Huang et al. [34]. Bravo-Solorio and Nandi [8] propose a CMFD scheme based on the Fourier Transform. Li et al. [41] use the Polar Cosine Transform (PCT) as block features. Ryu et al. [55, 56] propose a CMFD scheme using Zernike moment, and Locality Sensitive Hashing (LSH) matching is adopted in [55]. A histogram of orientated gradients is applied to each block in [36]. A fast Walsh-Hadamard Transform (FWHT) is adopted in [73].

The block-based schemes are not robust to scale, rotation, JPEG compression and additive noise. So keyponint-based schemes are proposed. Feature exaction methods such as the Scale-Invariant Feature Transform (SIFT) [45] and the Speeded Up Robust Features (SURF) [6] are most widely used in keypoint-based schemes. Pan and Lyu [52] propose a framework of the keypoint-based schemes, and their feature was also SIFT. Amerini et al. [3] propose a method using SIFT feature, the g2NN matching and the Agglomerative Hierarchical Clustering (AHC). Shivakumar and Baboo [57] propose a scheme based on SURF and KD-Tree. Silva et al. [59] construct a multi-scale image representation and a voting process among all detection maps. A rotation invariance scheme is proposed by Christlein et al. [14]. The Harris corner points [31] in an image are detected in [11], and their description is based on step sector statistics. Li et al. [40] propose a scheme using the Maximally Stable Color Region (MSCR). Yang et al. [74] propose a scheme using KAZE [2] and SIFT [45]. The image segmentation is adopted by Li et al. [37] and Pun et al. [54]. The image is segmented by Simple Linear Iterative Clustering (SLIC) algorithm [1] before feature extraction. Lin et al. [43] propose a Keypoint Contexts (KC) scheme to deal with duplicated regions with few keypoints. Jin and Wang [35] use OpponentSIFT and optimized J-Linkage to detect duplicated regions.

The block-based scheme is not robust and the keypoint-based scheme cannot detect duplicated regions with few keypoints. To overcome this issue, in this paper, a novel copy-move forgery detection scheme using combined features and transitive matching is proposed.

The remainder of this paper is organized into three sections. Section 2 shows the framework of the proposed scheme and then explains each step in detail. To validate the effectiveness of the proposed scheme, the experimental results are given in Section 3. Finally, Section 4 draws conclusions.

2 The proposed scheme

2.1 Combined features extraction

A block-based scheme is good at plain copy-move, but it cannot deal with significant geometrical transformations. A keypoint-based scheme is more robust than a block-based scheme, but it cannot deal with duplicated regions with few keypoints. Therefore, a strategy of combined features is proposed by our scheme, where both the Local Intensity Order Pattern (LIOP) [63] and the Scale Invariant Feature Transform (SIFT) [45] are adopted as our combined features. The outline of the proposed scheme is shown in Fig. 1.

Now we describe the reason why we choose LIOP and SIFT as the combined features. First, SIFT is invariant to image scale, rotation, addition of noise, etc. Meanwhile, SIFT has been widely used in many CMFD schemes [3, 4, 52] and obtained good results. Second, both local and overall intensity ordinal information of the local patch are captured by the LIOP descriptor [63]. Therefore, LIOP is invariant to image scale, rotation, viewpoint change, image blur and JEPG compression. We choose combined features to deal with duplicated regions with few keypoints.

We are familiar with SIFT. So let's introduce LIOP [63]. The main idea of LIOP is that when the intensity monotonous changes, the relative order of pixel intensities remains unchanged. The steps of LIOP are as follows. First, the local patch is divided into ordinal bins using the overall intensity order. Second, for a point x, the LIOP of which is defined as follows [63]:

$$LIOP(x) = \Phi(\gamma(P(x))) \tag{1}$$

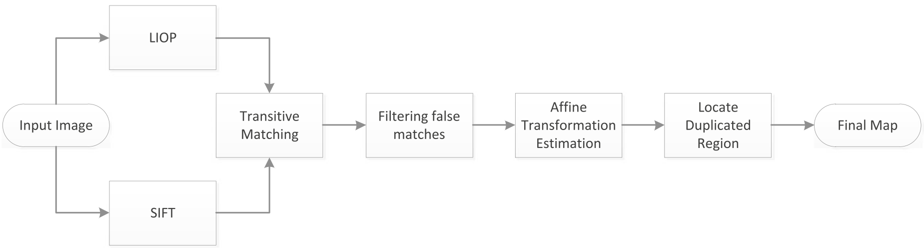

Fig. 1 The framework of the copy-move forgery detection scheme

where $P(x) = (I(x_1), I(x_2), \cdots, I(x_N)) \in P^N$ and $I(x_i)$ represent the intensity of the i-th neighboring sample point x_i. Third, for a local patch, to accumulate the LIOPs of points in each ordinal bin, we obtained the LIOP descriptor [63]:

$$\begin{aligned} D_{LIOP} &= (des_1, des_2, \cdots, des_B) \\ des_i &= \Sigma_{x \in bin_i} \omega(x) LIOP(x) \end{aligned} \tag{2}$$

where $\omega(x)$ is a weighting function and B is the number of the ordinal bins.

In some cases, the results of LIOP are better than that of SIFT. But in other cases, the results of SIFT are better than that of LIOP. Therefore, both LIOP and SIFT are integrated as our combined features, and the results of combined features are better than that of LIOP or SIFT, as shown in Fig. 2.

2.2 Transitive matching

The detected keypoints are tentatively matched using their feature vectors. There are two common matching methods. The first one is the 2NN matching proposed by Pan and Lyu [52]. Given a keypoint, its distance d_1 to the nearest neighbor and the distance d_2 to the next-nearest-neighbour are compared, if d_1/d_2 is less than a threshold (often fixed to 0.5 or 0.6), a pair of keypoints is obtained. To deal with multiple keypoint matching, Amerini et al. [3] proposed the generalized 2NN (g2NN) matching.

Some duplicated regions which are copied and pasted more than once still cannot be detected by the g2NN matching, because some matched keypoints cannot be detected. Therefore, the transitive matching is proposed to improve the matching relationship. We obtain a list of matched keypoints after the g2NN matching, as shown in Fig. 3, there are three duplicated regions, which are labeled as Ω_1, Ω_2 and Ω_3. The duplicated regions Ω_1 and Ω_3 are easy to be detected for there are enough matched keypoints between them. Neither the matched keypoints between Ω_1 and Ω_2, nor the matched keypoints between Ω_2 and Ω_3 are sufficient. So the duplicated region Ω_2 cannot be detected.

In fact, keypoints are sufficient, only their matching relationship is not detected. Now the transitive matching is used to obtain the new matching relationship. We obtain the matched keypoints (a_1, c_1) between Ω_1 and Ω_3, the matched keypoints (a_1, b_1) between Ω_1 and Ω_2, which are connected by a solid line in Fig. 3. Keypoints a_1 is matched with c_1, and the same keypoints is matched with b_1, then we draw a conclusion that keypoints b_1 is matched with

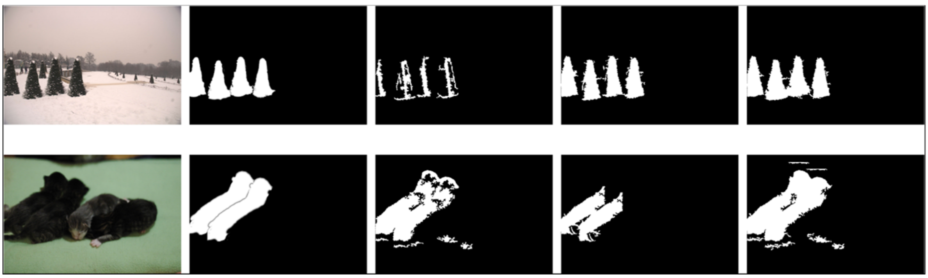

Fig. 2 Copy-move forgery detection results of the proposed scheme. Column 1: the forged images; column 2: the ground truth; column 3: the detection results only using SIFT; column 4: the detection results only using LIOP; column 5: the detection results using the proposed scheme(SIFT+LIOP)

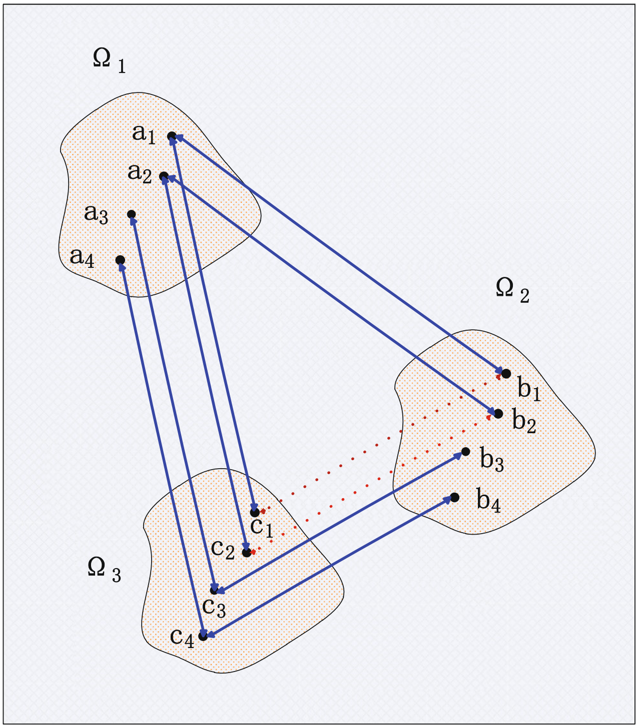

Fig. 3 The transitive matching. There are three duplicated regions, such as Ω_1, Ω_2 and Ω_3. The initial matching are connected by a solid line, for instance, (a_1, b_1) and (a_1, c_1). The transitive matching are connected by a dotted line, for instance, (b_1, c_1)

c_1, which is the transitive matching. Therefore, the transitive matching can be described as follows:

$$(K_1, K_2), (K_1, K_3) \Rightarrow (K_2, K_3) \tag{3}$$

where (K_1, K_2) indicates the matched keypoints K_1 and K_2. Then the new matched keypoints such as (b_1, c_1) and (b_2, c_2) is obtained, which are connected by a dotted line in Fig. 3. Thus, we can estimate the affine transformation between Ω_2 and Ω_3 after the transitive matching. The transitive matching try to detect a region which is copied and pasted more than once. The matching relation is improved by the transitive matching. To decrease mismatches, the transitive matching is limited to some regions which have matching relation. As shown in Fig. 3, there are matched keypoints between the three regions, which are connected by a solid line, then the transitive matching is carried out in the three regions.

2.3 Filtering false matches

In the section, the filtering algorithm to discard false matches is described. To improve the accuracy of affine transformations, those mismatched keypoints should be discarded after the transitive matching. Therefore, the Random Sample Consensus (RANSAC) algorithm [26] is adopted by Pan and Lyu [52]. The RANSAC algorithm returns with the affine transformations that lead to the largest number of matched keypoints and the smallest error.

Some mismatched keypoints can be discarded by RANSAC. But when there are lots of mismatched keypoints, the inaccurate affine transformation will be obtained by RANSAC. To overcome this issue, some false matches should be filtered, and the corresponding affine transformation will not be estimated. Considering the duplicated regions are usually meaningful regions, the input image is divided into non-overlapping image patches. It should be noted that the images are segmented by the Simple Linear Iterative Clustering (SLIC) algorithm [1]. Then N_m is adopted to represent the number of matched keypoints between the two image patches. If N_m is larger than a threshold, an affine transformation between the two image patches is estimated. Otherwise, those mismatched keypoints will be discarded. Thus some false matches can be discarded by our filtering algorithm.

2.4 Estimation of affine transformation

After the matched keypoints and the image patches are obtained, an affine transformation is estimated between the two image patches, one denotes as the source region and the other denotes as the forged region, if there are more than three matched keypoint between the two image patches. Two matched keypoints $\hat{x}_i = (x_i, y_i, 1)^T$ and $\hat{x}_i' = (x_i', y_i', 1)^T$ are from the source region and the forged region, respectively. Formally, their transformation can be expressed in matrix form as:

$$\hat{x}_i' = H\hat{x}_i = \begin{pmatrix} h_{11} & h_{12} & t_x \\ h_{21} & h_{22} & t_y \\ 0 & 0 & 1 \end{pmatrix} \hat{x}_i \tag{4}$$

where t_x and t_y are denoted as the translation factors, while h_{11}, h_{12}, h_{21} and h_{22} are denoted as rotation and scaling directions deformation. An affine transformation has six degrees of freedom, corresponding to the six matrix elements, then the transformation can be computed from three pairs of matched keypoints that are not collinear. Using RANSAC, the transformation matrix which returns the the largest number matched keypoints is obtained. Meanwhile, their total error of the affine transformation is minimized. Thus, an affine transformation between the two image patches is estimated. Then the duplicated regions are located according to the affine transformation [52].

3 Experiments and discussions

3.1 Dataset and error measures

To evaluate the efficiency of the proposed scheme, the Image Manipulation Dataset (IMD) [15] is adopted as the image dataset. The average size of an image is about 3000×2300 pixels. There are 1488 images on IMD. The details of the utilized image dataset are shown in Table 1.

Table 1 Setting of the attacks on IMD

Attacks	Criteria	Parameters
Scaling	Ratio	0.91:0.02:1.09
Rotation	Angle	2°:2°:10°
AWGN	Stand Deviation	0.02:0.02:0.1
JPEG	Quality Factor	20:10:100

In fact, the forgery is more difficult to be detected when the duplicated regions are small. Many images on the Internet are usually small, they are not as big as the images on IMD. Therefore, all the images on IMD are resized, just as Li et al. [37] did. The maximum of the width and the height of the images are set to 800 pixels. The proposed scheme is rather challenging for the duplicated regions are difficult to be detected after the images are resized.

It should be noted that the images on IMD are segmented by the SLIC algorithm [1], which is implemented by vlFeat library [60], where all the images on IMD are empirically divided into 100 image patches.

To assess the proposed scheme, we should test the detection error at two different levels, namely the image level and the pixel level. The detection error are measured by the *recall*, the *precision*, and the F_1 score [15], which are calculated as follows:

$$precision = \frac{|\{Forged\ pixels\} \bigcap \{Detected\ pixels\}|}{|\{Detected\ pixels\}|} \tag{5}$$

$$recall = \frac{|\{Forged\ pixels\} \bigcap \{Detected\ pixels\}|}{|\{Forged\ pixels\}|} \tag{6}$$

$$F_1 = \frac{2 * precision * recall}{precision + recall} \tag{7}$$

3.2 Comparisons with other relevant methods

In the section, the proposed scheme is compared with several state-of-the-art existing schemes, for instance, SIFT [3, 52], SURF [57], JLinkage [4] and Zernike [56]. The results of SIFT, SURF and Zernike are different with Christlein et al. [15] because of the image resizing. The process of resizing will make the duplicated regions smaller than before. Therefore, it will difficult to be detected for all the CMFD schemes. The proposed scheme combines both LIOP and SIFT. Some detection results of the proposed scheme in comparison with only SIFT or LIOP are shown in Fig. 2. Obviously, the most duplicated regions can be detected by the the proposed scheme.

3.2.1 Detection results under plain copy-move

In this section, we evaluate the proposed scheme under ideal conditions. There are 48 original images and 48 forgery images, in which a one-to-one copy-move is implemented. The experimental results under plain copy-move at the image level and the pixel level are shown in Tables 2 and 3, respectively. It should be noted that all the images on IMD are resized and the experimental results are different with Christlein et al. [15]. From Tables 2 and 3, it can be observed easily that the *recall* of the proposed scheme is the best among all the test schemes. The *precision* of the proposed scheme is better than that of SIFT, SURF

Table 2 Detection results for plain copy-move at the image level

Methods	Recall (%)	Precision (%)	F_1 (%)
SIFT [3, 52]	47.92	74.19	58.23
SURF [57]	43.75	72.41	54.55
JLinkage [4]	62.50	78.95	69.77
Zernike [56]	79.17	88.37	83.52
Proposed	93.75	81.82	87.38

Table 3 Detection results for plain copy-move at the pixel level

Methods	Recall (%)	Precision (%)	F_1 (%)
SIFT [3, 52]	37.93	36.79	37.35
SURF [57]	25.81	31.44	28.35
JLinkage [4]	47.47	48.12	47.79
Zernike [56]	53.92	87.37	66.68
Proposed	75.41	73.44	74.42

and JLinkage, all of which are keypoint-based schemes. Meanwhile, the F_1 score of the proposed scheme is much better than that of the existing state-of-the-art schemes. As a comprehensive evaluation, the F_1 score combines both the $recall$ and the $precision$ into a single value. Therefore, the proposed scheme is the best among the existing state-of-the-art schemes.

3.2.2 Detection results under other attackers

This section presents the comparison of the proposed method with other schemes under various attacks. The proposed scheme is evaluated by the $recall$, the $precision$ and the F_1

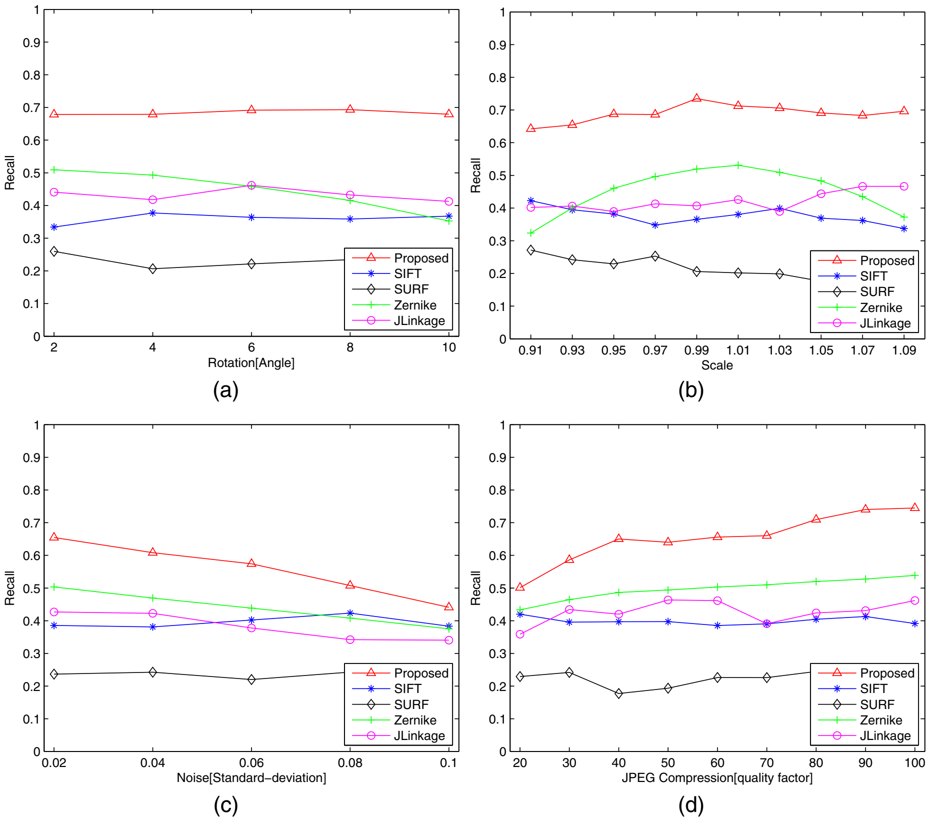

Fig. 4 *Recall* results at the pixel level. **a** Rotation, **b** Scale, **c** Adding noise, **d** JPEG compression

at the pixel level. It should be noted that the results of SIFT, SURF and Zernike are different with Christlein et al. [15] because of the image resizing. In the experiments, all the images are resized to no more than 800 pixels, just as Li et al. [37] did.

Figure 4 shows the *recall* results of the proposed scheme compared with the test schemes. It can be observed easily that the *recall* of the proposed scheme is the best among all the test schemes, which means that more number of duplicated regions can be obtained by the proposed scheme.

Figure 5 shows the *precision* results of the proposed scheme compared with the test schemes. The *precision* results of the proposed scheme is better than that of SIFT, SURF and JLinkage, all of which are keypoint-based schemes. As a block-based scheme, the *precision* results of Zernike is the best among all the test schemes. Therefore, the *precision* results of the proposed scheme is the best among all the keypoint-based schemes.

Figure 6 shows the F_1 results of the proposed scheme compared with the test schemes. Obviously, the proposed scheme outperforms the prior arts in terms of F_1 criterion. The F_1 score combines both the *precision* and the *recall* into a single value, it is a comprehensive evaluation. Therefore, the proposed scheme is better than the existing state-of-the-art schemes under various attacks.

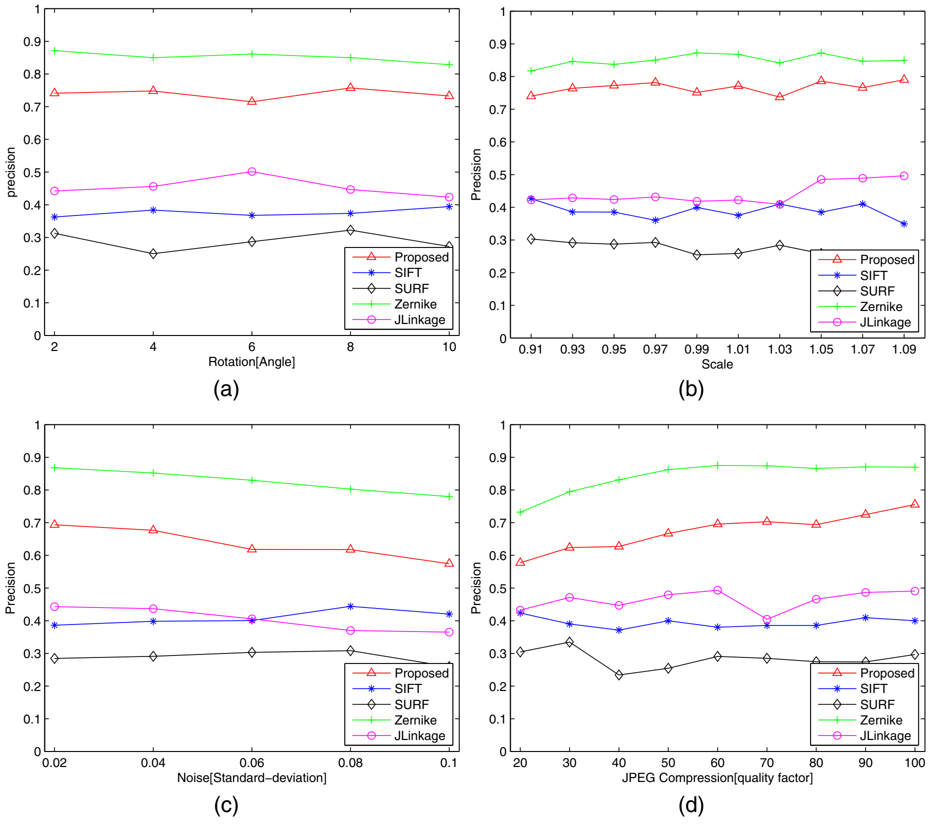

Fig. 5 *Precision* results at the pixel level. **a** Rotation, **b** Scale, **c** Adding noise, **d** JPEG compression

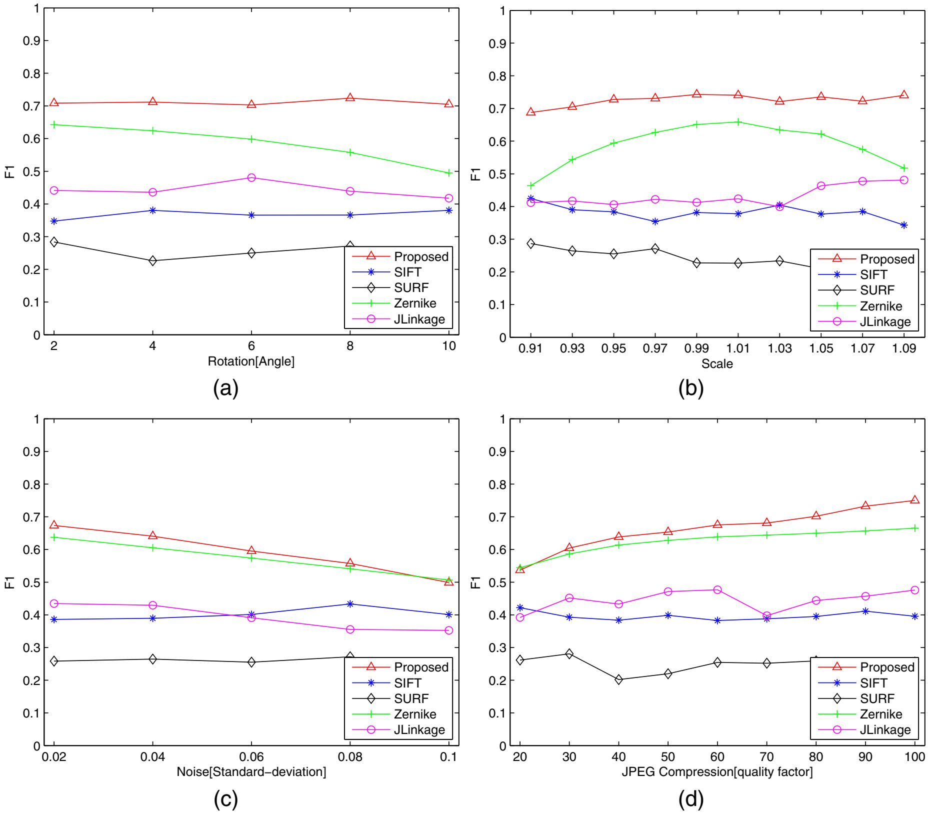

Fig. 6 F_1 results at the pixel level. **a** Rotation, **b** Scale, **c** Adding noise, **d** JPEG compression

4 Conclusions

In this paper, a novel copy-move forgery detection scheme using combined features and transitive matching is proposed. The specific contributions are summarized as follows. First, combined features which are composed of LIOP and SIFT are proposed. Thus, some duplicated regions with few keypoints can be detected. Second, transitive matching is used after the g2NN matching, then the matching relationship is improved. Third, to discard the false matches, a new filtering approach based on image segmentation is proposed. Experimental results show that the proposed scheme can achieve the best *recall* and the best F_1 score under challenging conditions.

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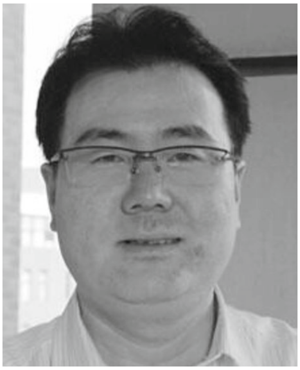

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