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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

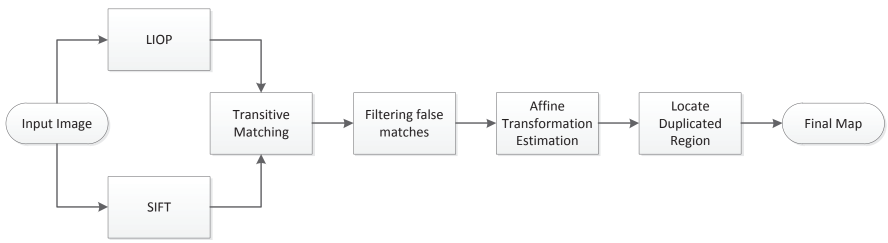

Fig. 1 The framework of the copy-move forgery detection scheme.

2.1 Combined features extraction

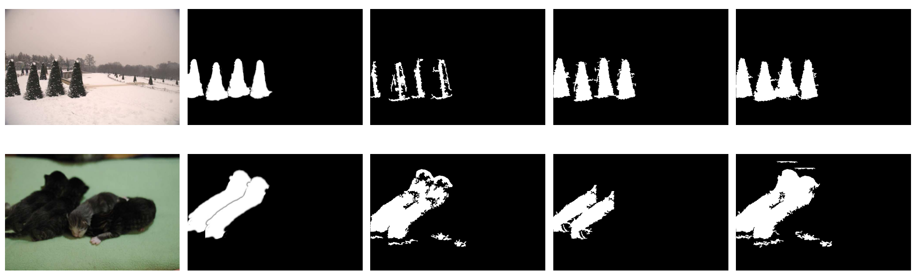

Fig. 2 Copy-move forgery detection results of the proposed scheme. Column 1: the forged images; column 2: the ground truth; column 3: the detection results only using SIFT; column 4: the detection results only using LIOP; column 5: the detection results using the proposed scheme(SIFT+LIOP).

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.

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]:

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

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

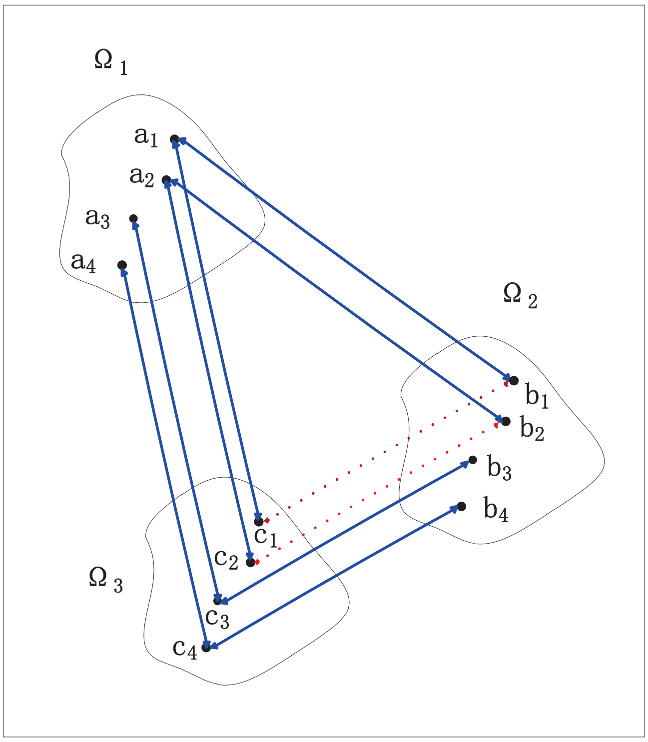

Fig. 3 The transitive matching. There are three duplicated regions, such as Ω_1, Ω_2 and Ω_3. The initial matching are connected by a solid line, for instance, (a_1, b_1) and (a_1, c_1). The transitive matching are connected by a dotted line, for instance, (b_1, c_1).

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 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

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

3000×2300 pixels. There are 1488 images on IMD. The details of the utilized image dataset are shown in Table 1.

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 Table 2 and Table 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 Table 2 and Table 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 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.

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

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 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.

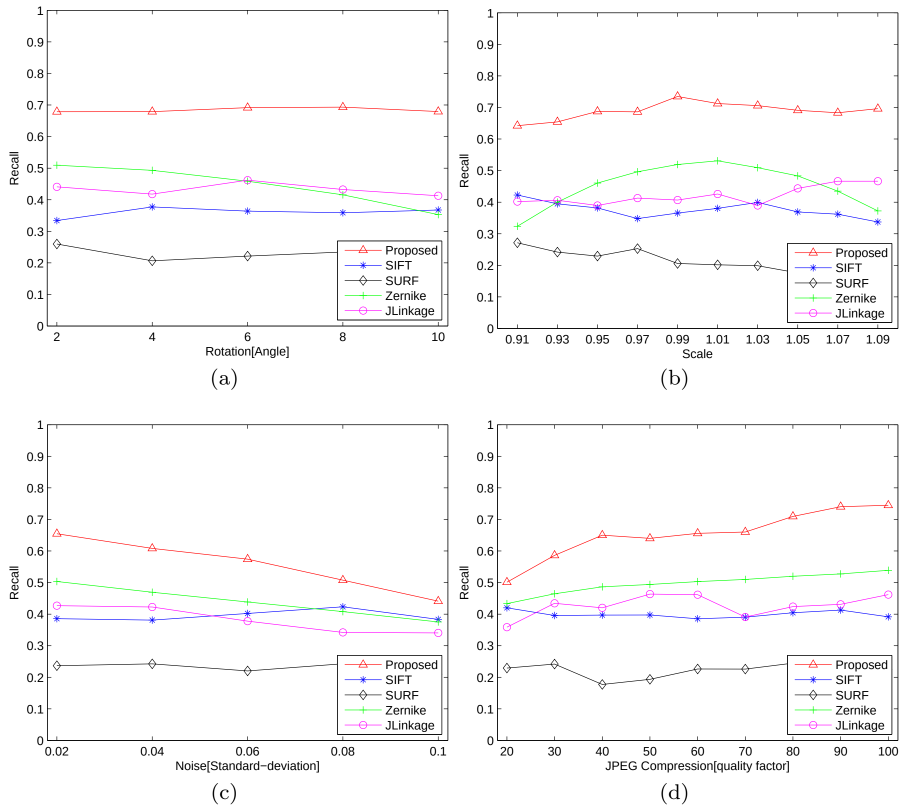

Fig. 4 *Recall* results at the pixel level. (a) Rotation, (b) Scale, (c) Adding noise, (d) JPEG compression.

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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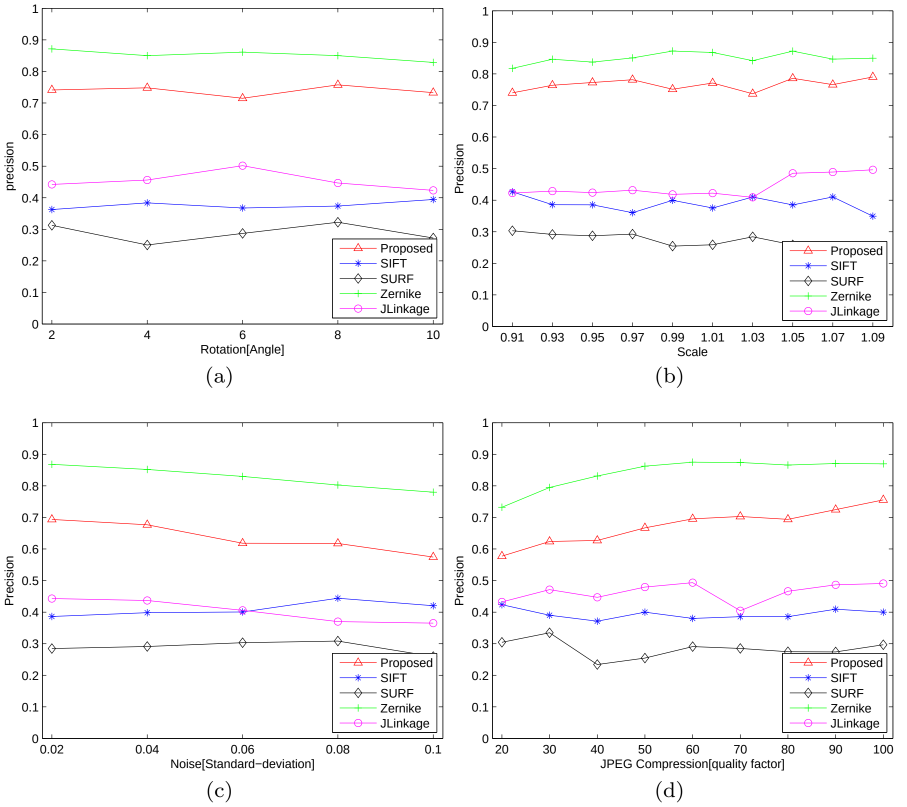

Fig. 5 *Precision* results at the pixel level. (a) Rotation, (b) Scale, (c) Adding noise, (d) JPEG compression.

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References

1. Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., Süsstrunk, S.: Slic superpixels compared to state-of-the-art superpixel methods. IEEE Transactions on Pattern Analysis and Machine Intelligence **34**(11), 2274–2282 (2012)
2. Alcantarilla, P.F., Bartoli, A., Davison, A.J.: Kaze features. In: European Conference on Computer Vision(ECCV), pp. 214–227. Florence, Italy (2012)
3. Amerini, I., Ballan, L., Caldelli, R., Bimbo, A.D., Serra, G.: A SIFT-based forensic method for copy-move attack detection and transformation recovery. IEEE Transactions on Information Forensics and Security **6**(3), 1099–1110 (2011)
4. Amerini, I., Ballan, L., Caldelli, R., Bimbo, A.D., Tongo, L.D., Serra, G.: Copy-move forgery detection and localization by means of robust clustering with J-Linkage. Signal Processing: Image Communication **28**(6), 659–669 (2013)
5. Bashar, M., Noda, K., Ohnishi, N., Mori, K.: Exploring duplicated regions in natural images. IEEE Transactions on Image Processing **PP**(99), 1–1 (2010)
6. Bay, H., Ess, A., Tuytelaars, T., Gool, L.V.: SURF: Speeded up robust features. Computer Vision and Image Understanding **110**(3), 346–359 (2008)

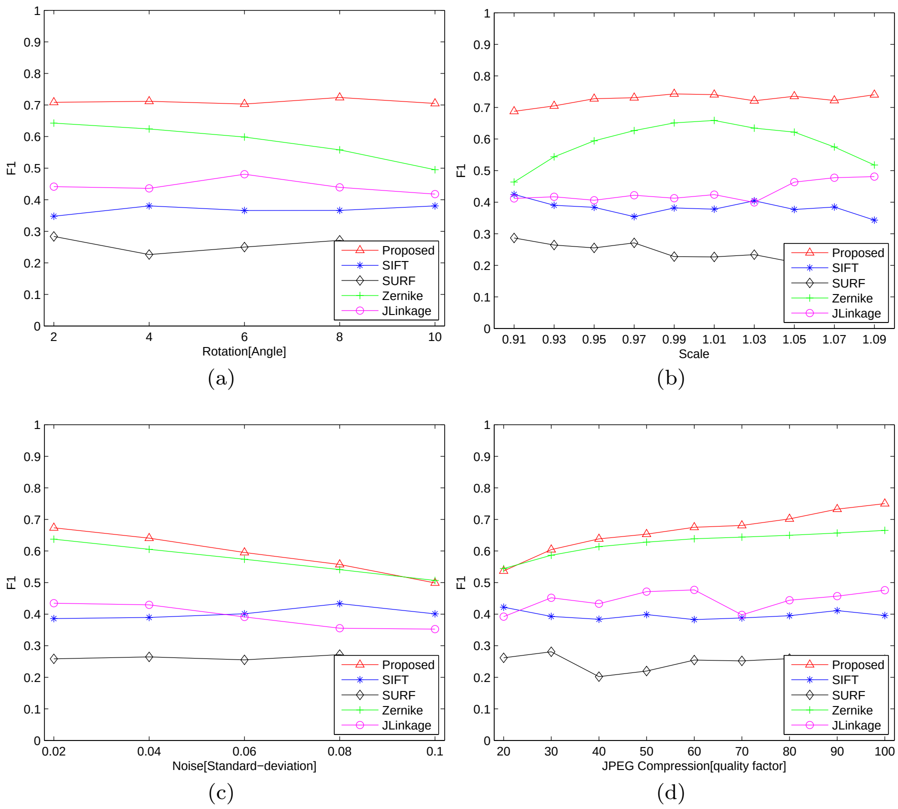

Fig. 6 F_1 results at the pixel level. (a) Rotation, (b) Scale, (c) Adding noise, (d) JPEG compression.

7. Bedi, G., Venayagamoorthy, G.K., Singh, R., Brooks, R., Wang, K.C.: Review of internet of things (iot) in electric power and energy systems. IEEE Internet of Things Journal **PP**(99), 1–1 (2018)
8. Bravo-Solorio, S., Nandi, A.K.: Exposing duplicated regions affected by reflection, rotation and scaling. In: IEEE International Conference on Acoustics, Speech and Signal Processing(ICASSP), pp. 1880–1883. Prague, Czech Republic (2011)
9. Chen, J., Lu, W., Fang, Y., Liu, X., Yeung, Y., Yingjie, X.: Binary image steganalysis based on local texture pattern. Journal of Visual Communication and Image Representation **55**, 149–156 (2018)
10. Chen, J., Lu, W., Yeung, Y., Xue, Y., Liu, X., Lin, C., Zhang, Y.: Binary image steganalysis based on distortion level co-occurrence matrix. Computers, Materials and Continua **55**(2), 201–211 (2018)
11. Chen, L., Lu, W., Ni, J., Sun, W., Huang, J.: Region duplication detection based on harris corner points and step sector statistics. Journal of Visual Communication and Image Representation **24**(3), 244–254 (2013)
12. Chen, X., Weng, J., Lu, W., Xu, J.: Multi-gait recognition based on attribute discovery. IEEE Transactions on Pattern Analysis and Machine Intelligence **PP**(99), 1–1 (2018)
13. Chen, X., Weng, J., Lu, W., Xu, J., Weng, J.: Deep manifold learning combined with convolutional neural networks for action recognition. IEEE Transactions on Neural Networks and Learning Systems **PP**(99), 1–15 (2017)
14. Christlein, V., Riess, C., Angelopoulou, E.: On rotation invariance in copy-move forgery detection. In: IEEE International Workshop on Information Forensics and Security (WIFS), pp. 1–6. Seattle, WA, USA (2010)

15. Christlein, V., Riess, C., Jordan, J., Riess, C., , Angelopoulou, E.: An evaluation of popular copy-move forgery detection approaches. IEEE Transactions on Information Forensics and Security **7**(6), 1841–1854 (2012)
16. Cozzolino, D., Poggi, G., Verdoliva, L.: Efficient dense-field copy-move forgery detection. IEEE Transactions on Information Forensics and Security **10**(11), 2284–2297 (2015)
17. Fang, W., Li, Y., Zhang, H., Xiong, N., Lai, J., Vasilakos, A.V.: On the throughput-energy tradeoff for data transmission between cloud and mobile devices. Information Sciences **283**(283), 79–93 (2014)
18. Fang, Y., Fang, Z., Yuan, F., Yang, Y., Yang, S., Xiong, N.N.: Optimized multioperator image retargeting based on perceptual similarity measure. IEEE Transactions on Systems Man and Cybernetics Systems **47**(11), 2956–2966 (2017)
19. Feng, B., Lu, W., Sun, W.: Secure binary image steganography based on minimizing the distortion on the texture. IEEE Transactions on Information Forensics and Security **10**(2), 243–255 (2014)
20. Feng, B., Lu, W., Sun, W.: Binary image steganalysis based on pixel mesh markov transition matrix. Journal of Visual Communication and Image Representation **26**, 284–295 (2015)
21. Feng, B., Lu, W., Sun, W.: Novel steganographic method based on generalized k-distance n-dimensional pixel matching. Multimedia Tools and Applications **74**(21), 9623–9646 (2015)
22. Feng, B., Lu, W., Sun, W., Huang, J., Shi, Y.Q.: Robust image watermarking based on tucker decomposition and adaptive-lattice quantization index modulation. Signal Processing: Image Communication **41**(C), 1–14 (2016)
23. Feng, B., Weng, J., Lu, W., Pei, B.: Steganalysis of content-adaptive binary image data hiding. Journal of Visual Communication and Image Representation **46**, 119–127
24. Feng, B., Weng, J., Lu, W., Pei, B.: Multiple watermarking using multilevel quantization index modulation. In: International Workshop on Digital Watermarking, pp. 312–326. Beijing, China (2017)
25. Ferreira, A., Felipussi, S.C., Alfaro, C., Fonseca, P., Vargasmunoz, J.E., Dos Santos, J.A., Rocha, A.: Behavior knowledge space-based fusion for copy-move forgery detection. IEEE Transactions on Image Processing **25**(10), 4729–4742 (2016)
26. Fischler, M.A., Bolles, R.C.: Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM **24**(6), 381–395 (1981)
27. Fridrich, J., Soukal, D., Lukáš, J.: Detection of copy-move forgery in digital images. In: Proceeding of Digital Forensic Research Workshop, pp. 19–23. Cleveland, OH, USA (2003)
28. Gao, L., Yu, F., Chen, Q., Xiong, N.: Consistency maintenance of do and undo/redo operations in real-time collaborative bitmap editing systems. Cluster Computing **19**(1), 255–267 (2016)
29. Ghorbani, M., Firouzmand, M., Faraahi, A.: DWT-DCT (QCD) based copy-move image forgery detection. In: International Conference on Systems, Signals and Image Processing, pp. 1–4. Sarajevo (2011)
30. Gui, J., Hui, L., Xiong, N.: A game-based localized multi-objective topology control scheme in heterogeneous wireless networks. IEEE Access **5**(99), 2396–2416 (2017)
31. Harris, C.G., Stephens, M.J.: A combined corner and edge detector. In: Alvey Vision Conference, pp. 147–151 (1988)
32. Hu, C., Xu, Z., Liu, Y., Mei, L., Chen, L., Luo, X.: Semantic link network-based model for organizing multimedia big data. IEEE Transactions on Emerging Topics in Computing **2**(3), 376–387 (2014)
33. Huang, H., Guo, W., Zhang, Y.: Detection of copy-move forgery in digital images using SIFT algorithm. In: IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application, pp. 272–276 (2008)
34. Huang, Y., Lu, W., Sun, W., Long, D.: Improved DCT-based detection of copy-move forgery in images. Forensic Science International **206**(1-3), 178–184 (2011)
35. Jin, G., Wan, X.: An improved method for SIFT-based copy-move forgery detection using non-maximum value suppression and optimized J-Linkage. Signal Processing: Image Communication **57**, 113–125 (2017)
36. Lee, J.C., Chang, C.P., Chen, W.K.: Detection of copy-move image forgery using histogram of orientated gradients. Information Sciences **321**(C), 250–262 (2015)
37. Li, J., Li, X., Yang, B., Sun, X.: Segmentation-based image copy-move forgery detection scheme. IEEE Transactions on Information Forensics and Security **10**(3), 507–518 (2015)

38. Li, J., Lu, W.: Blind image motion deblurring with L0-regularized priors. Journal of Visual Communication and Image Representation **40**, 14–23 (2016)
39. Li, J., Lu, W., Weng, J., Mao, Y., Li, G.: Double jpeg compression detection based on block statistics. Multimedia Tools and Applications pp. 1–16 (2018)
40. Li, J., Yang, F., Lu, W., Sun, W.: Keypoint-based copy-move detection scheme by adopting mscrs and improved feature matching. Multimedia Tools and Applications **76**(20), 1–15 (2016)
41. Li, Y.: Image copy-move forgery detection based on polar cosine transform and approximate nearest neighbor searching. Forensic Science International **224**(1-3), 59 (2013)
42. Lin, B., Guo, W., Xiong, N., Chen, G., Vasilakos, A.V., Zhang, H.: A pretreatment workflow scheduling approach for big data applications in multicloud environments. IEEE Transactions on Network and Service Management **13**(3), 581–594 (2016)
43. Lin, C., Lu, W., Sun, W., Zeng, J., Xu, T., Lai, J.H.: Region duplication detection based on image segmentation and keypoint contexts. Multimedia Tools and Applications (11), 1–18 (2017)
44. Liu, G., Wang, J., Lian, S., Wang, Z.: A passive image authentication scheme for detecting region-duplication forgery with rotation. Journal of Network and Computer Applications **34**(5), 1557–1565 (2011)
45. Lowe, D.G.: Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision **60**(2), 91–110 (2004)
46. Lu, X., Tu, L., Zhou, X., Xiong, N., Sun, L.: Vimedianet: an emulation system for interactive multimedia based telepresence services. Journal of Supercomputing **73**(8), 3562–3578 (2017)
47. Lu, Z., Lin, Y.R., Huang, X., Xiong, N., Fang, Z.: Visual topic discovering, tracking and summarization from social media streams. Multimedia Tools and Applications **76**(8), 1–25 (2017)
48. Ma, Y., Luo, X., Li, X., Bao, Z., Zhang, Y.: Selection of rich model steganalysis features based on decision rough set α-positive region reduction. IEEE Transactions on Circuits and Systems for Video Technology **PP**(99), 1–1 (2018)
49. Mahdian, B., Saic, S.: Detection of copy-move forgery using a method based on blur moment invariants. Forensic Science International **171**, 180–189 (2007)
50. Melro, L.S., Jensen, L.R.: Influence of functionalization on the structural and mechanical properties of graphene. Computers Materials and Continua **53**(2), 111–131 (2017)
51. Nelson, B., Phillips, A., Steuart, C.: Guide to Computer Forensics and Investigations. Delmar Learning (2015)
52. Pan, X., Lyu, S.: Region duplication detection using image feature matching. IEEE Transactions on Information Forensics and Security **5**(4), 857–867 (2010)
53. Popescu, A.C., Farid, H.: Exposing digital forgeries by detecting duplicated image regions. Tech. Rep. TR2004-515, Department of Computer Science, Dartmouth College (2004)
54. Pun, C.M., Yuan, X.C., Bi, X.L.: Image forgery detection using adaptive over-segmentation and feature points matching. IEEE Transactions on Information Forensics and Security **10**(8), 1705–1716 (2015)
55. Ryu, S.J., Kirchner, M., Lee, M.J., Lee, H.K.: Rotation invariant localization of duplicated image regions based on Zernike moments. IEEE Transactions on Information Forensics and Security **8**(8), 1355–1370 (2013)
56. Ryu, S.J., Lee, M.J., Lee, H.K.: Detection of copy-rotate-move forgery using Zernike moments. In: IEEE International Workshop on Information Hiding(IH), pp. 51–65. Springer, Berlin,Germany (2010)
57. Shivakumar, B.L., Baboo, S.: Detection of region duplication forgery in digital images using SURF. International Journal of Computer Science Issues **8**(4), 199–205 (2011)
58. Shu, L., Fang, Y., Fang, Z., Yang, Y., Fei, F., Xiong, N.: A novel objective quality assessment for super-resolution images. International Journal of Signal Processing **9**(5), 297–308 (2016)
59. Silva, E., Carvalho, T., Ferreira, A., Rocha, A.: Going deeper into copy-move forgery detection: Exploring image telltales via multi-scale analysis and voting processes. Journal of Visual Communication and Image Representation **29**(C), 16–32 (2015)
60. Vedaldi, A., Fulkerson, B.: Vlfeat: an open and portable library of computer vision algorithms. In: International Conference on Multimedea, pp. 1469–1472. Firenze, Italy (2010)
61. Wang, J., Li, T., Shi, Y.Q., Lian, S., Ye, J.: Forensics feature analysis in quaternion wavelet domain for distinguishing photographic images and computer graphics. Multimedia Tools and Applications **76**(22), 1–17 (2016)

62. Wang, Y., Chen, K., Yu, J., Xiong, N., Leung, H., Zhou, H., Zhu, L.: Dynamic propagation characteristics estimation and tracking based on an em-ekf algorithm in time-variant mimo channel. Information Sciences **408**(C), 70–83 (2017)
63. Wang, Z., Fan, B., Wu, F.: Local intensity order pattern for feature description. In: IEEE International Conference on Computer Vision (ICCV), pp. 603–610 (2011)
64. Warif, N.B.A., Wahab, A.W.A., Idris, M.Y.I., Salleh, R., Othman, F.: SIFT-symmetry: A robust detection method for copy-move forgery with reflection attack. Journal of Visual Communication and Image Representation **46**, 219–232 (2017)
65. Wu, P., Xiao, F., Sha, C., Huang, H., Wang, R., Xiong, N.: Node scheduling strategies for achieving full-view area coverage in camera sensor networks. Sensors **17**(6), 1303 (2017)
66. Xia, Z., Wang, X., Sun, X., Liu, Q., Xiong, N.: Steganalysis of lsb matching using differences between nonadjacent pixels. Multimedia Tools and Applications **75**(4), 1947–1962 (2016)
67. Xia, Z., Xiong, N.N., Vasilakos, A.V., Sun, X.: Epcbir: An efficient and privacy-preserving content-based image retrieval scheme in cloud computing. Information Sciences **387**, 195–204 (2017)
68. Xiong, N., Jia, X., Yang, L.T., Vasilakos, A.V., Li, Y., Pan, Y.: A distributed efficient flow control scheme for multirate multicast networks. IEEE Transactions on Parallel and Distributed Systems **21**(9), 1254–1266 (2010)
69. Xiong, N., Liu, R.W., Liang, M., Wu, D., Liu, Z., Wu, H.: Effective alternating direction optimization methods for sparsity-constrained blind image deblurring. Sensors **17**(1), 1–27 (2017)
70. Xiong, N., Vasilakos, A.V., Yang, L.T., Song, L., Pan, Y., Kannan, R., Li, Y.: Comparative analysis of quality of service and memory usage for adaptive failure detectors in healthcare systems. IEEE Journal on Selected Areas in Communications **27**(4), 495–509 (2009)
71. Xiong, N., Vasilakos, A.V., Yang, L.T., Wang, C.X., Kannan, R., Chang, C.C., Pan, Y.: A novel self-tuning feedback controller for active queue management supporting tcp flows. Information Sciences **180**(11), 2249–2263 (2009)
72. Xu, B., Wang, J., Liu, G., Dai, Y.: Image copy-move forgery detection based on SURF. In: International Conference on Multimedia Information Networking and Security(MINES), pp. 889–892. Nanjing, China (2010)
73. Yang, B., Sun, X., Chen, X., Zhang, J., Li, X.: An efficient forensic method for copy-move forgery detection based on dwt-fwht. Radioengineering **22**(4), 1098–1105 (2013)
74. Yang, F., Li, J., Lu, W., Weng, J.: Copy-move forgery detection based on hybrid features. Engineering Applications of Artificial Intelligence **59**, 73–83 (2017)
75. Yang, Y., Tong, S., Huang, S., Lin, P.: Dual-tree complex wavelet transform and image block residual-based multi-focus image fusion in visual sensor networks. Sensors **14**(12), 22,408–22,430 (2014)
76. Yang, Z., Ma, L., Ma, Q., Cui, J., Nie, Y., Dong, H., An, X.: Multiscale nonlinear thermo-mechanical coupling analysis of composite structures with quasi-periodic properties. Computers Materials and Continua **53**(3), 219–248 (2017)
77. Zhang, C., Wu, D., Liu, R.W., Xiong, N.: Non-local regularized variational model for image deblurring under mixed gaussian-impulse noise. Journal of Internet Technology **16**(7), 1301–1319 (2015)
78. Zhang, F., Lu, W., Liu, H., Xue, F.: Natural image deblurring based on l0-regularization and kernel shape optimization. Multimedia Tools and Applications pp. 1–19 (2018)
79. Zhang, H., Liu, R.W., Wu, D., Liu, Y., Xiong, N.N.: Non-convex total generalized variation with spatially adaptive regularization parameters for edge-preserving image restoration. Journal of Internet Technology **17**(7), 1391–1403 (2016)
80. Zhang, Q., Lu, W., Wang, R., Li, G.: Digital image splicing detection based on markov features in block dwt domain. Multimedia Tools and Applications pp. 1–22 (2018)
81. Zhang, Q., Lu, W., Weng, J.: Joint image splicing detection in dct and contourlet transform domain. Journal of Visual Communication and Image Representation **40**, 449–458 (2016)
82. Zhang, Y., Qin, C., Zhang, W., Liu, F., Luo, X.: On the fault-tolerant performance for a class of robust image steganography. Signal Processing **146**, 1–1 (2018)
83. Zheng, H., Guo, W., Xiong, N.: A kernel-based compressive sensing approach for mobile data gathering in wireless sensor network systems. IEEE Transactions on Systems Man and Cybernetics Systems **PP**(99), 1–13 (2017)
84. Zhou, P., Zhou, Y., Wu, D., Jin, H.: Differentially private online learning for cloud-based video recommendation with multimedia big data in social networks. IEEE Transactions on Multimedia **18**(6), 1217–1229 (2016)

85. Zhou, Y., Zhang, D., Xiong, N.: Post-cloud computing paradigms: A survey and comparison. Tsinghua Science and Technology **22**(6), 714–732 (2017)