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Replacing DWT with DTCWT in blind image rotation angle estimation

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Abstract

During the image tampering, rotation is often involved to make the forgery more convincing. Hence, estimating the rotation angle accurately and locally is of forensic importance. Recently, a novel rotation angle estimation scheme was proposed based on linear pattern (LP), achieving state of the art performance especially in the case when the rotation angle is small. However, due to the limitations of the involved discrete wavelet transform (DWT), the existing LP based method cannot always accurately detect rotated linear pattern from a rotated image. To fill this gap, we propose to extract the rotated LP using dual tree complex wavelet transform (DTCWT). Thanks to the good directional selectivity of DTCWT, the proposed method can extract the LP more accurately. Experiments show that our proposed method performs better than the state of the art in rotation angle estimation, and is also a promising forensic tool for tampering localization.

Introduction

Geometric transformations are frequently used during image tampering. For example, an imported image patch can be rotated within the host image in order to mimic a genuine photographed object. Hence, revealing a localized geometric transformation and possibly further estimating its exact parameters can provide meaningful clues for forensic analysis [1-5]. In this paper, we focus on the rotation angle estimation which is typically involved in image splicing, and can also occur in in-camera video stabilization [6, 7]. Previous methods estimate the rotation angle from interpolation artifacts detected in the Discrete Fourier Transform (DFT) domain [2, 3, 4, and 5]. However, all such methods perform poorly in estimating small angles.

In 2018, Goljan proposed a rotation angle estimation method [8] based on linear pattern (LP) [9], which is a weak weaving-like pattern (Fig. 1 (d)) introduced by in-camera image processing, e.g., color filter array interpolation, and further formed by JPEG compression. Compared to previous rotation angle estimation methods, the LP based method achieves high precision even for slightly rotated images. However, after analyzing the weaving-like nature of LP and the used filter for extracting LP in [8], we find the LP signal in rotated images often distorted during the discrete wavelet transform (DWT)-based denoising. We attribute it to the poor directional selectivity of DWT, which can ultimately result in a degradation in rotation angle estimation. To overcome this limitation, we propose to use an alternative denoising filter that is based on dual tree complex wavelet transform (DTCWT) [11] for better preserving the rotated LP signal in the noise residual. Experiments show that the proposed approach can improve upon [8] in rotation angle estimation in the full range of angles. Considering that a rotation angle inconsistency is likely involved in image tampering, the application of the proposed method can also be extended to tampering localization.

We aim at extracting the LP signal from rotated images as accurately as possible. Considering that the possible rotation angle θ involved in image tampering or video stabilization are typically small (if not zero), a high precision estimation, e.g.,$|\hat{\theta}-\theta|<0.1°$, for small angles θ, such as $\theta \in [-10°, 10°]$, is expected. For image tampering localization purpose, the algorithm needs to be applied to many local patches of the questioned image. Hence, time complexity of the algorithm must be kept in mind. A practical approach is also expected to be robust to mild JPEG compression or rescaling after rotation.

The rest of this paper is organized as follows. In the next section, we review the concept of a LP and existing image forensic works based on LP. In the third section, we analyze the limitation of the existing work in extracting LP from rotated images, then provide an alternative solution. We also extend its application into tampering localization based on rotation angle inconsistency. Experiments are presented in the fourth section. The paper is closed in the fifth section.

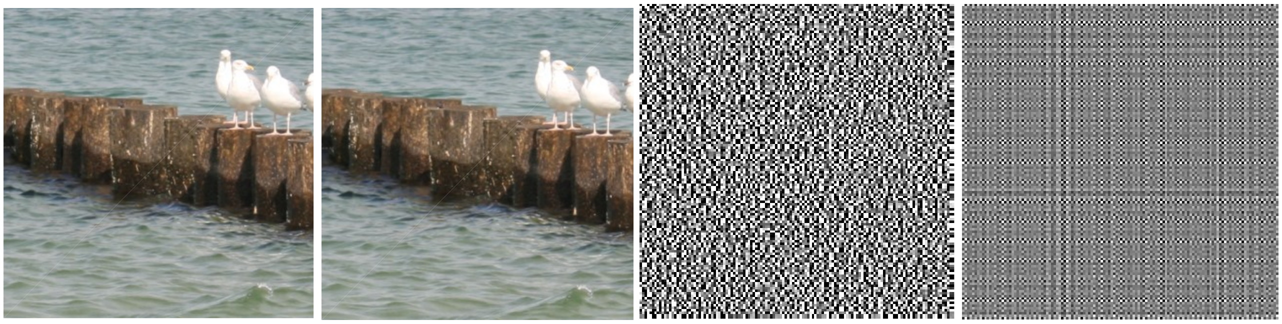
Related work

In the photo-response non-uniformity (PRNU) based camera identification, an image $\boldsymbol{I}$ is regarded as a composed signal of a clean image, the camera sensor PRNU and the LP [8] (illustrated in Fig. 1).

$$\boldsymbol{I}=\hat{\boldsymbol{I}}+PRNU+LP, \tag{1}$$

where $\hat{\boldsymbol{I}}$ is the clean image that can be estimated with a denoising filter F, i.e., $\hat{\boldsymbol{I}} \cong F(\boldsymbol{I})$. The PRNU signal, which is due to inhomogeneity of silicon wafers, is unique to every camera, and thus can be regarded as a camera fingerprint. The idea of LP is first introduced in [9] as one type of non-unique artifacts (NUA) that would increase the false alarm rate of camera identification if not subtracted from the PRNU estimate. However, LP signal itself contains useful information about in-camera processing that can be used for forensic purpose [8, 12, 13, and 14].

LP is a side product of a series of in-camera image processing steps. These LPs are typically similar for cameras of the same model and different for cameras of different models. Thus, LP can be used as an important feature for camera model identification [12]. In [13], a forgery localization method based on LP is proposed. Specifically, LP is represented in Fourier domain, and called signature. An expected signature is first estimated from the entire image, and then block signatures are estimated locally for each block. Since the signature only existed in image blocks without rotation, it is possible



(a) (b) (c) (d)

Figure 1. *An example of linear pattern. (a) A cropped image from the FAU database [10], (b) denoised version of (a), (c) estimated PRNU of (a), (d) estimated linear pattern of (a). For display purpose, the linear pattern has been zoomed in and scaled to [-0.3, 0.3].*

to identify whether an image block has been rotated or not by examining the similarity between block signatures and the expected signature. Under the assumption that the background is without rotation and the forged region may have been rotated during forgery, the forged region can be revealed. In [14], LP is used for resampling factor estimation given at least one original image is available to provide the reference LP. In [8], Goljan translates the rotation angle estimation problem to maximization of the LP energy over a range of inverse rotation angles. The basic steps of [8] can be summarized as following. First, the noise residual $\boldsymbol{W}$ is computed from a probe image $\boldsymbol{I}$ with a DWT based denoising filter [15]. Then, rotate $\boldsymbol{W}$ by sampled angles until the energy of the LP of $\boldsymbol{W}$ is maximized at $-\hat{\theta}$. More precisely.

$$\hat{\theta} = -\underset{\beta}{\operatorname{argmax}}\, e(LP(rot(\boldsymbol{W}, \beta))), \tag{2}$$

where $rot(\boldsymbol{W},\beta)$ denotes rotation of $\boldsymbol{W}$ by angle β, and e(LP()) denotes the energy of LP.

Although traces left by image rotation has been extensively studied in the image forensics, they are mostly focus on detection of the rotation operation, i.e., providing a binary result. If the specific rotation angle can be estimated, we can have a further knowledge about the history of a probe image. In [2], the authors proposed an image rotation angle estimator based on the relations between the rotation angle and the peak location of the spectrum of the image's edge map. In [3], the authors estimated the rotation angle from the cyclic spectrum of an image. By assuming no scaling involved in rotation, the method of [3] was improved in [4] by searching only four trajectory curves, instead of searching the entire cyclic spectrum. The cyclic spectrum based methods [3, 4] was further improved in [5] by denoising the spectrum before searching the peak location. The side effect of the improved methods [4, 5] is that they lack of robustness of scaling.

Proposed method

In this section, we first analyze the limitation of the traditional DWT based filter in extracting a rotated LP signal, and propose an alternative filter that can better preserving the LP signal of a rotated image.

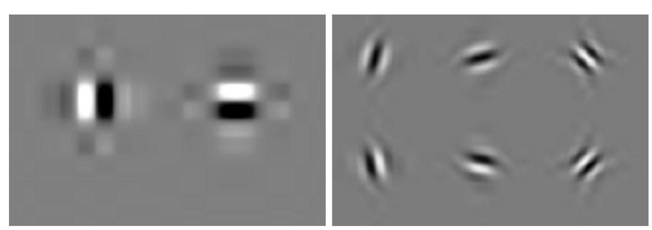
Poor directional selectivity of DWT

Even though the LP based method shows satisfactory performance in [8], the LP signal in a rotated image is likely to be distorted during the DWT-based denoising, which in turn affects the subsequent rotation angle estimation. This is because the LP signal in an unrotated image is strongly oriented at 0/90 degrees. If the image has been rotated, the corresponding LP is also rotated. However, due to the poor directional selectivity nature of DWT (see Fig. 2(a)), the rotated LP signal may not be well preserved in $\boldsymbol{W}$. To illustrate this, we first rotate the LP in Fig. 1(d) with the angle ranging from 0 to 90 degrees and add Gaussian noise to the rotated LP. Then, LP is extracted from its noisy version with DWT. The correlation coefficient with respect to the clean LP is used to evaluate the quality of the extracted LP. The red line in Fig. 3 shows the relationship between the quality of the LP extracted with DWT and the rotation angle. The quality of the estimated LP decreases significantly under rotation, reaching its minimum at θ = 45°. The limitation of the DWT based filter motivates us to find an alternative denoising filter for extracting LP in the next subsection.

Extracting linear pattern with DTCWT

To overcome the poor directional selectivity of DWT, we propose using DTCWT [11] to extract LP from a rotated image. Compared to DWT, DTCWT has better directional selectivity. A 2-D DTCWT provides six directional selective filters, which are oriented at angles of ±15°, ±45°, ±75° (see Fig. 2(b)). As a result, the noise residual extracted with DTCWT can preserve the rotated LP signal better than that extracted with DWT. To verify this, we extract rotated LPs with DTCWT from their noisy version. The correlation between the extracted LP and the clean LP is shown in Fig. 3 with the blue line. The quality of LP obtained with DTCWT measured by correlation with the original LP is notably higher than that obtained using DWT with exception of 0 and 90 degree rotation angles.

Rotation angle estimation and tampering localization



(a) (b)

Figure 2. *Impulse response of 2-D wavelet filters. (a) DWT, (b) DTCWT. DWT provides two directional selective filters, whereas DTCWT provides six directional selective filters.*

Once the noise residual $\boldsymbol{W}$ is extracted, we can search the possible rotation angle while maximizing the energy of LP as (2). Specifically, a coarse-to-fine strategy is used in this search for speed consideration. First, a coarser step s_c is used for searching the candidate angle θ_c that maximizes the energy of LP in the interval $b = [\beta_1, \beta_2]$. Second, a finer step s_f is used in the search for the final estimation of the rotation angle $\hat{\theta}$ in the interval $\hat{\theta} = [\theta_c - \Delta, \theta_c + \Delta]$.

By applying the rotation angle estimation method locally to the questioned image, it is possible to reveal the potential inconsistent rotation angle due to image tampering. Unlike the LP based forgery detection method proposed in [13], here we do not assume the background region not been rotated. Note that the method in [13] is based on the expected signature that can only be estimated from an image without rotation. Here, we only reasonably assume that the background region and the forged region have been rotated with different angles (including 0 degree). Thus, the forensic scenario considered in [13] is included in our scenario.

The proposed tampering localization method is described in steps in Algorithm 1. In short, the proposed rotation angle estimation method is performed block by block on a questioned image, and an inconsistency of the estimated rotation angles can be regarded as an indication of a forgery.

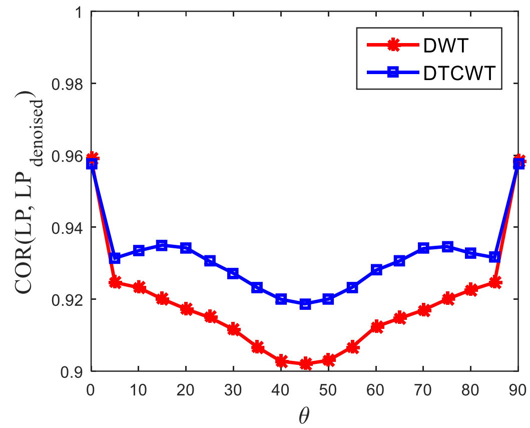


Figure 3. *The relationship between the quality of the extracted* LP *and the rotation angle.*

Algorithm 1 Tampering localization based on rotation angel inconsistency.

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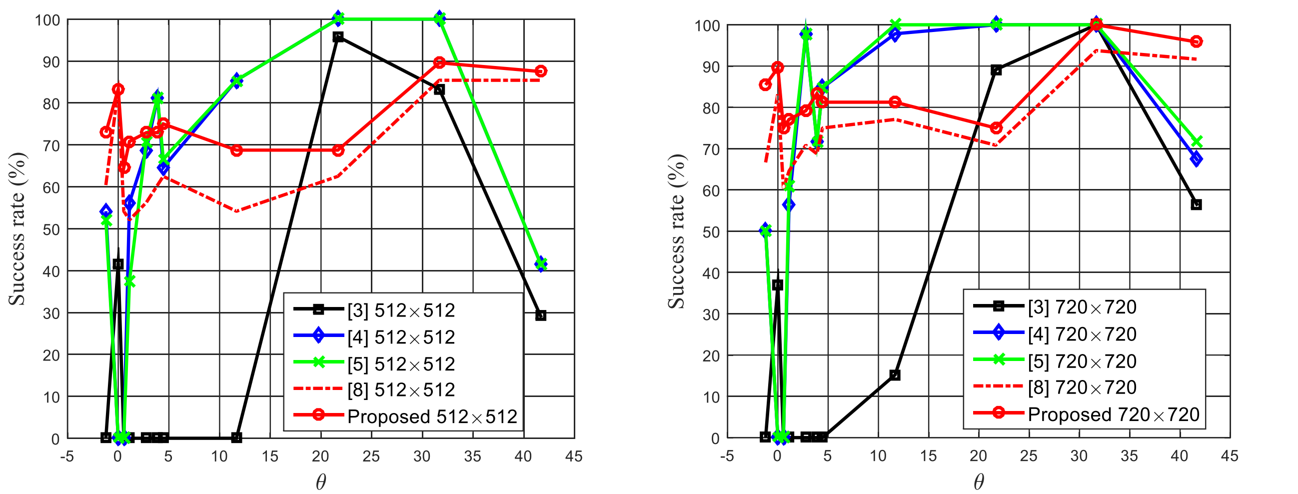
1. Compute the noise residual as $\boldsymbol{W} = \boldsymbol{I} - F(\boldsymbol{I})$, where F is the DTCWT based denoising filter described in Section 3.2.
2. Divide $\boldsymbol{W}$ into overlapping blocks of size $\omega \times \omega$, with sliding step of s.
3. Estimate the rotation angle for each block.
4. Due to the overlapping scheme, there may be more than one estimations for some pixels. We simply average them to abtain the final rotation angle estimation for each individual pixel.
5. The output is a rotation angle estimation map with the same size of $\boldsymbol{I}$, which can be used for further forensic analysis.

Experiments

We compare the proposed method with the state of the arts [3, 4, 5, and 8] on the public FAU dataset [10], which contains 48 original images in the PNG format. The estimation is deemed successful when the difference between the estimated angle and the ground truth is smaller than 0.1°, i.e., $|\hat{\theta} - \theta| < 0.1°$. In the LP based methods, we set the coarser step $s_c = 0.05°$ in the initial search, and the finer step $s_f = 0.025°$ and interval $\Delta = 1°$ in the final search. [1]

Rotation angle estimation

In the first experiment, we compared the methods on uncompressed images of two different sizes cropped from the center of the rotated images. As in [8], the rotation angles in the experiments are unevenly distributed within the interval [-1.22°, 45°], with more attention paid to small angles. Fig. 4(a) features the results of 512×512 images and Fig. 4(b) results of 720×720



(a) (b)

Figure 4. *Success rates of the proposed method and the compared methods on FAU dataset. (a) Results of* 512×512 *images, and (b) results of* 720×720 *images*

[1] The code to reproduce our results is available at https://github.com/zengh5/RotationAngleEst_LP

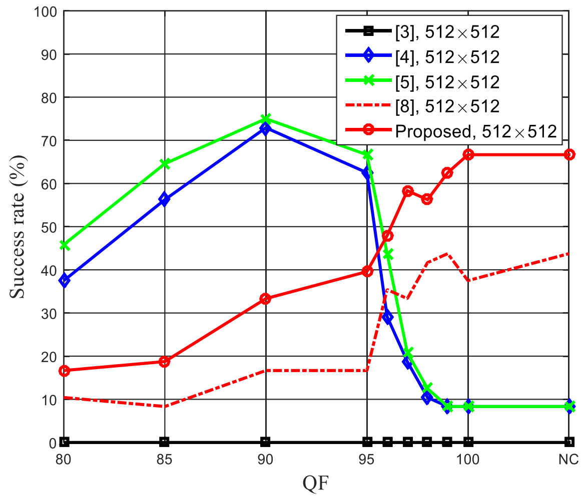


Figure 5. *Performance comparison on JPEG images with different QFs. 'NC' denotes no compression.*

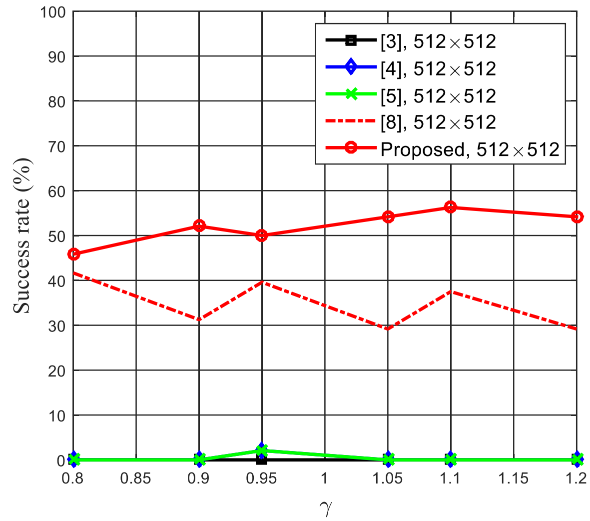


Figure 6. *Success rates for resized images*

images. It is observed that the DFT domain methods [3, 4 and 5] generally perform better for large angles except $\theta = 41.66°$. However, when θ is small, these methods deteriorate sharply. Particularly, the methods [4, 5] always fails at $\theta = 0°$ and $\theta = 0.55°$. On the other hand, the LP based methods achieve good performance for both large θ and small θ. Among the two LP based methods, the proposed method performs constantly better than [8]. Taking $\theta = 2.77°$ on 512×512 images for example, the method [8] achieves success rate of 56.25%, whereas the proposed method achieves success rate of 72.92%. We also provide the running time comparison in Table 1. Since the running time of [3, 4 and 5] are almost the same, we merge them into one row. The simulations are performed with Matlab R2015a running on a computer with a 2.6 GHz CPU and 12 GB RAM. LP based methods are much faster than the DFT domain methods.

Robustness evaluation

Next step, we evaluate the robustness of the compared methods to JPEG compression. The original images are first JPEG compressed with quality factor (QF) equal to 90 and then rotated by a small angle of 2.77° and then JPEG compressed again with QFs between 80 and 100 (or saved uncompressed). The results are plotted in Fig. 5. Again, the proposed method yields a constant improvement compared with [8]. The method of [3] is totally failed in this case because $\theta = 2.77°$ is beyond its estimation ability. The other two cyclic spectrum methods perform better than the LP based methods when $QF \leq 95$. However, when $QF > 95$, the LP based methods show obvious advantage. Note the cyclic spectrum methods does not work even the rotated images are saved uncompressed. This is because the first JPEG compression introduces similar peak values in cyclic spectrum as well as rotation, and confuse the rotation angle estimation, which means the cyclic spectrum methods are not robust to JPEG pre-processing.

Table 1. Running time (s) comparison of rotation angle estimation methods

Method	512 × 512	720 × 720
[3, 4, 5]	47.7	92.8
[8]	6.8	12.5
Proposed	7.5	13.7

Considering the fact that rescaling is one of the most common processing during or after rotation, we also compare the rotation angle estimation methods on the robustness to rescaling. In this experiment, the original images are first rotated by 4.44° and then rescaled with factors (γ) between 0.8 and 1.2. More attention is paid to the scenario of $\gamma \approx 1$, because it is more common in tampering and also most challenging in forensics. The results of the compared methods are plotted in Fig. 6. All the cyclic spectrum methods are failed in this case, which verified the limitation of [4, 5] of not robust to rescaling. Among the two LP based methods, the proposed method achieves average success rate of 52.08%, outperforms that of [8] which is 34.72%.

Tampering localization using rotation angle inconsistency

Based on the good performance of the proposed method in rotation angle estimation, we extend its application to tampering localization and show two toy examples in this subsection. As stated in previous, we focus on the scenario where both the background and the forged region have been rotated here. The parameters involved in Algorithm 1 are set as $\omega = 512$ and $s = 128$.

Fig. 7 shows two image tampering examples. The example in the first row is a copy-move forgery, where a statue is rotated by 10° and pasted into the background which has been rotated by 5°. The second example is an image splicing forgery, where a wild goose is rotated 10° and pasted into the background which has been rotated by 7.5°. Even a subtle inconsistence between the pristine region and forged region can be revealed by the proposed method. The proposed method can provide meaningful clues about the forgery in both examples. More extensive testing is still needed in order to evaluate performance of this method in forgery detection. We leave it to future efforts

Conclusion

By analyzing the nature of the LP signal, we determined that DWT is not the best choice for extracting LP from a rotated image. To this end, we propose using DTCWT in LP based rotation angle estimation. Thanks to the good directional selectivity of DTCWT,

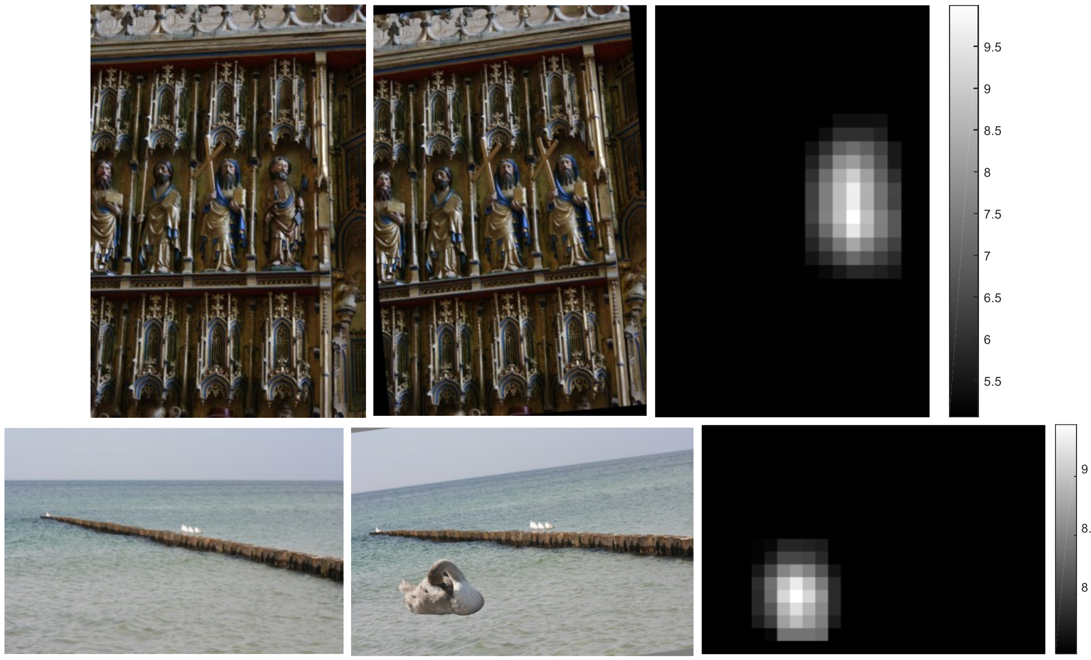


Figure 7. *Examples of tampering localization with the proposed method. From left to right are the original images, the forged images and the localization results.*

the proposed method can extract the LP more accurately, and thus achieves better performance in rotation angle estimation which can benefit subsequent forensic analysis, e.g., image splicing localization or, possibly, reversing in-camera video stabilization for camera identification.

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References

[1] S. Pfennig and M. Kirchner, “Spectral methods to determine the exact scaling factor of resampled digital images,” in *International Symposium on Communications Control and Signal Processing, ISCCSP 2012*, 2012.

[2] W. Wei, S. Wang, X. Zhang, and Z. Tang, “Estimation of image rotation angle using interpolation related spectral signatures with application to blind detection of image forgery,” *IEEE Transactions on Information Forensics and Security*, 5(3): 507–517, 2010.

[3] D. Vázquez-Padín, C. Mosquera, and F. Pérez-González. “Two-dimensional statistical test for the presence of almost cyclostationarity on images,” In *2010 IEEE International Conference on Image Processing*, pp. 1745–1748, 2010.

[4] C. Chen, J. Ni, and Z. Shen, “Effective estimation of image rotation angle using spectral method,” *IEEE Signal Processing Letters*, 21(7): 890–894, 2014.

[5] S. Dai, Y. Zhang, W. Song, et al. “Rotation Angle Estimation of JPEG Compressed Image by Cyclic Spectrum Analysis,” *Electronics*, 2019, 8(12):1431.

[6] S. Taspinar, M. Mohanty, and N. Memon, “Source camera attribution using stabilized video,” In *2016 IEEE International Workshop on Information Forensics and Security (WIFS)*, pp. 1–6, 2016.

[7] S. Mandelli, P. Bestagini, L. Verdoliva, and S. Tubaro, “Facing Device Attribution Problem for Stabilized Video Sequences,” *IEEE Transaction on Information Forensics and Security*, 2020, 15: 14–27.

[8] M. Goljan, “Blind Detection of Image Rotation and Angle Estimation,” in *IS&T International Symposium on Electronic Imaging 2018, Media Watermarking, Security, and Forensics*. 2018, 158: 1–10.

[9] M. Chen, J. Fridrich, and M. Goljan, “Digital imaging sensor identification (further study),” In *Proceedings of SPIE, Electronic Imaging, Security, Steganography, and Watermarking of Multimedia Contents IX*, pages 0P 1–13, 2007.

[10] https://www5.cs.fau.de/research/data/image-manipulation

[11] I. W. Selesnick, R. G. Baraniuk, and N. Kingsbury, “The dual-tree complex wavelet transform,” *IEEE Signal Processing Magazine*, 2005, 22(6): 123–151.

[12] T. Filler, J. Fridrich, M. Goljan, "Using Sensor Pattern Noise for Camera Model Identification," in *2008 IEEE International Conference on Image Processing*, pp. 1296–1299.

[13] M. Goljan, J. Fridrich, and M. Kirchner, "Image Manipulation Detection using Sensor Linear Pattern," in *IS&T International Symposium on Electronic Imaging 2018, Media Watermarking, Security, and Forensics*. 2018, 119: 1–10.

[14] M. D. M. Hosseini, M. Goljan, and H. Zeng, "Semi-Blind Image Resampling Factor Estimation for PRNU Computation", in *Proc. SPIE, Electronic Imaging, Media Forensics and Security*. 2020.

[15] M. K. Mihcak, I. Kozintsev, and K. Ramchandran, "Spatially adaptive statistical modeling of wavelet image coefficients and its application to denoising," In *Proceedings IEEE, International Conference on Acoustics, Speech, and Signal Processing*, pp. 3253–3256, 1999.