

Splicing Image and Its Localization: A Survey

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Abstract: With the rapid development of information technology, digital images have become an important medium for information transmission. However, manipulating images is becoming a common task with the powerful image editing tools and software, and people can tamper the images content without leaving any visible traces of splicing in order to gain personal goal. Images are easily spliced and distributed, and the situation will be a great threat to social security. The survey covers splicing image and its localization. The present status of splicing image localization approaches is discussed along with a recommendation for future research.

Keywords: Social security, image splicing, image splicing localization.

1 Introduction

Digital image is vulnerable to manipulation and doctoring so that people can tamper with images by image editing software, and apply tampered image in diverse areas. In addition, image tampering is a common task due to the continuous development of science and technology.

In 2013, Iran announced that they can produce fighter planes, which could be invisible, in order to enhance the military strength of their country. As shown in Fig. 1(c). Although this image was quickly confirmed to be a spliced image, it still caused bad influence in global world.

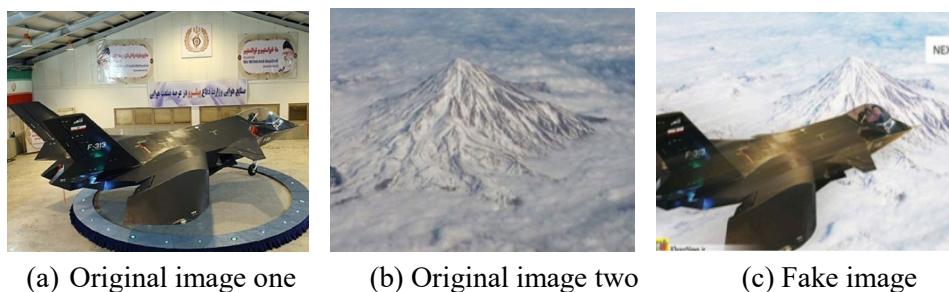


Figure 1: The event of Iranian invisible fighter planes

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In 2017, the original author of “Chinese Boys” photographs sued Taiwan artist Jimmy Lin for infringement. The reason is that without the permission of the author of the original work, Jimmy Lin synthesizes bald head photos on the basis of “Chinese Boys” and personal images of Jimmy Lin using the software of mapping without authorization, thus arousing people’s fanaticism for idols. As shown in Fig. 2.

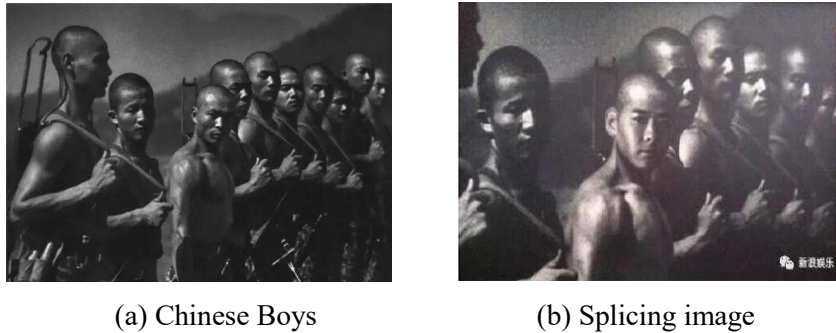


Figure 2: Chinese Boys with splicing image of Jimmy Lin

There are many influential events, such as the examples of mentioned above, which have caused negative effects in the history. Therefore, tampered images are a potential threat to social stability. In order to protecting the use of digital image, it is important to identify the authenticity of the image, and more conclusive to locate the tampered region directly in the tampered image. In general, there are two types of image tampering: image splicing [Ng and Chang (2004); Yuan and Ni (2017)] and copy-move [Arun (2015)]. However, some post-processing, including blurring, retouching, beautifying Zeng et al. [Zeng, Zhan, Kang et al. (2017)], rotating, etc., make the tampering traces in the tampered image to be eliminated. Considering the diversity of tampering operations [Asghar, Habib and Hussain (2016)], image forensics technology should adopt specific analysis solutions to improve the accuracy of forensics scheme. In this paper, image splicing, and its localization are studied and discussed.

The rest of the paper is organized as follows. Section 2 introduces the image splicing and its localization. Section 3 presents the literature survey of splicing image localization. Comparative analysis of different approaches is provided in Section 4. Finally, we conclude this paper in Section 5.

2 Framework of splicing image localization

Image splicing is a process in which it crops and pastes regions from the same or different images [Bharti and Tandel (2016)]. Namely, copying a part of an image and pasting it onto other images to form a new image using image editing tools like Photoshop, MEITU and so on. The processing of spliced image is shown in Fig. 3. As shown in Fig. 3, the part of the Fig. 3(b) is cropped and pasted onto the Fig. 3(a) to form the Fig. 3(c).

It is not difficult to find that in a spliced image, the difference between two image blocks from different images mainly comes from the following aspects. The first aspect is the information carried by the image itself, such as noise Pan et al. [Pan, Xing and Lyu (2012)], light, CFA algorithm Ferrara et al. [Ferrara, Bianchi, Rosa et al. (2012)], blur

type [Bahrami and Kot (2014)], camera source [Chen, Fridrich, Goljan et al. (2008)], and so on. The second aspect is the smoothness [Du, Ma, Chen et al. (2015)], which is the operation of removing abrupt edges. The last aspect is the compression characteristics of the original region and the splicing region [Piva (2011); Bianchi and Piva (2012); Bianchi and Piva (2012); Mire, Dhok, Mistry et al. (2015)]. The above aspects provide clues for image splicing localization [Wu, Zhu, Li et al. (2005); Piva (2011); Bianchi and Piva (2012); Bo and Kong (2012); Ferrara, Bianchi, Rosa et al. (2012); Amerini, Becarelli, Caldelli et al. (2014); Bahrami and Kot (2014); Mire, Dhok, Mistry et al. (2015); Asghar, Habib and Hussain (2016); Bahrami, Kot, Li et al. (2015); Cozzolino and Verdoliva (2017); Salloum, Ren and Kuo (2017); Zampoglou, Papadopoulos and Kompatsiaris (2017); Zeng, Zhan, Kang et al. (2017); Chen, Zhao, Shi et al. (2018)], and there are two approaches of image localization: active approach and passive approach [Zhou (2007); Luo, Zhenhua, Feng et al. (2008); Birajdar and Mankar (2013)].

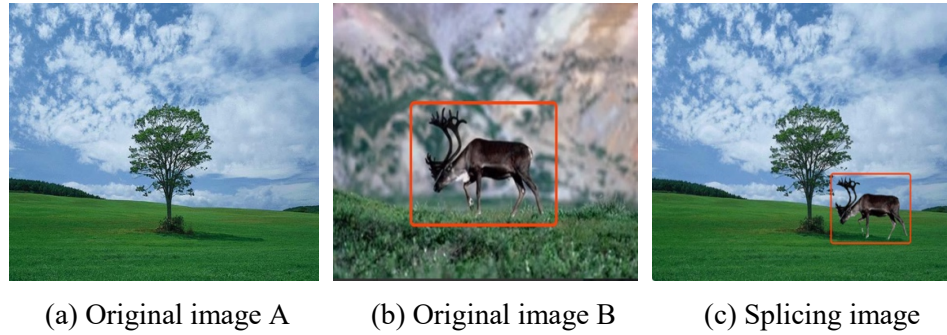


Figure 3: The processing of image splicing

The active approach is based on watermarking [Potdar, Han and Chang (2005); Yin, Lin, Qiu et al. (2005)]. The watermarking consists of fragile watermarking and semi-fragile watermarking. Both of them are sensitive to image tampering attacks, and difficult to be tampered. The watermarking will be destroyed when the image undergoes tampering, which provides important clues to the localization methods. However, it is needed to know the prior information about the image, so it is mainly used for copyright protection by embedding the digital information to the image.



Figure 4: The framework of splicing image localization

Hence, passive approach is more favored by researchers, and it is just needed to analyze the traces left on the image by image splicing. The basic framework of image splicing localization is shown in Fig. 4.

In the existing localization framework, there are four steps. Firstly, many schemes adopt pre-processing operation to extract the feature effectively, such as color space conversion, discrete wavelet transform (DWT) [He, Wei, Wei et al. (2012)], discrete cosine transform

(DCT) [Alahmadi, Hussain, Aboalsamh et al. (2013); Li, Qiang, Xiao et al. (2017)], principle component analysis (PCA) [Pyatykh, Hesser and Zheng (2013)]. Secondly, image is often divided into image blocks with small size with various segment in order to achieve high accuracy of localization. Thirdly, the designed algorithm is used to extract the feature of each image blocks. Finally, all image blocks are classified into two clusters by classification algorithm. In addition, the selection of feature is also the key of the localization.

3 Splicing image localization techniques

Splicing operation may change the characteristics of the part of image, then feature used to describe the original region and splicing region may be inconsistent. The researcher can track the inconsistent between the original area and splicing area to locate the spliced image blocks. The major image splicing localization schemes fall in one of the following categories. Fig. 5 shows the various splicing image localization techniques.

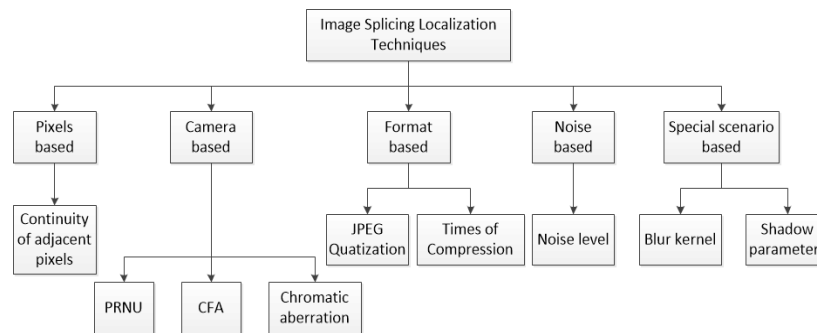


Figure 5: Splicing image localization techniques

3.1 Pixel based techniques

The splicing operation will destroy the continuity of pixels and neighborhood pixels. Wu et al. [Wu, Zhu, Li et al. (2005)] used the generalized model to construct a frame of image based on pixel level. Du et al. [Du, Ma, Chen et al. (2015)] analyzed whether the continuity between the pixels in the image and the neighborhood pixels was below the threshold, and labeled the location of the spliced region.

3.2 Camera based techniques

When a picture is taken, it involves a series of processing steps on the path from sensor to memory, and each image will carry the inherent information of the camera: camera response, sensor noise, color filter array and so on. The splicing operation will make two kinds of camera inherent information existing in one splicing image. The Photo Response Non-Uniformity (PRNU) [Lukás, Fridrich and Goljan (2006); Rosenfeld and Sencar (2009); Liu (2012); Chierchia, Poggi, Sansone et al. (2014)] is the intrinsic fingerprints of the original image, and the basic idea is to estimate a device's PRNU at first, and then evaluate whether the image under question conforms to it. If local deviations appear, the presence of a splice in the corresponding region is posited. Dehnie et al. proposed a

wavelet to filter the image in order to further enhance the difference of pattern noise from different camera source. However, calculation of PRNU needs a prior knowledge about the camera source. In addition, most shooting devices are equipped with a sensor that covers a Color Filter Array (CFA), which produces one value per pixel, and the image is then transformed into three channels using interpolation. Thus, for each channel, a number of values originate from the environment, while the rest are interpolated from them. The processing mentioned make the correlation between adjacent pixels. The splicing operation would eliminate the correlation between each pixel and neighborhood pixels by using a color filter array (CFA). The splicing region localization has been implemented by learning, the changing characteristics of the CFA caused by the spliced operation [Cao, Zhao and Ni (2009)]. In Dirik et al. [Dirik and Memon (2009)], two different features are proposed: The first attempts to detect the CFA pattern used during image capture by subsampling the image using various possible selection patterns, re-interpolating it, and comparing it to the original. Having emulated the CFA interpolation process using the estimated parameters, one could then make use of local discrepancies between the interpolated and the observed values to detect local tampering. Sun et al. [Sun, Lang, Gong et al. (2017)] believed that there was a color shift between the splicing region and the original region. The original image could be reconstructed by simulating the CFA model, and the splicing region could be located by analyzing the inconsistency between the image to be tested and the original image in the pixel neighborhood. Although this class of algorithms has gained high accuracy of localization, it needs to simulate and estimate the CFA pattern and interpolation algorithm used in the original image for feature extraction and analysis.

3.3 Format based techniques

If the splicing operation is performed in compressed image and uncompressed image, there are different compression characteristics in one splicing image. The splicing region can be located by exploiting the traces left by JPEG compression. Quantization of an image's DCT coefficients is a major step in the JPEG compression pipeline, in which the quantization factor is a function of the chosen compression quality. It has been observed that consecutive JPEG compressions at different qualities lead to specific periodicities in the DCT coefficient distribution. In Amerini et al. [Amerini, Becarelli, Caldelli et al. (2014)], author propose a splicing localization scheme based on DCT variation characteristics, and locate splicing region by analyzing DCT distribution characteristics between different image blocks. Bianchi et al. [Bianchi and Piva (2012)] proposed the idea of taking advantage of the inconsistent compression characteristics between the spliced region and the original region to realize image splicing localization.

3.4 Noise based techniques

Assuming that the random noise in the image obeys the gaussian distribution, the noise level of the splicing region and the original region will be inconsistent. Mahdian et al. used the technique of wavelet transform to extract the local noise variance in Mahdian et al. [Mahdian and Saic (2009)]. In Pan et al. [Pan, Xing and Lyu (2012)], Pan et al. found that the coefficients of different frequency subbands present a continuous and specific

regularity in natural images. According to the clue, they proposed a two-level clustering detection scheme. Based on the research above, Lyu designed an algorithm based on the relationship between noise characteristics and kurtosis in Lyu et al. [Lyu, Pan and Xing (2014)]. The localization schemes mentioned have obtained high localization performance when the noise difference between the splicing region and the original region is large. However, those schemes fail to locate the spliced region when the noise level is quite small. Hence, a localization scheme based on PCA technology was proposed by analyzing the difference of image block noise levels in Zeng et al. [Zeng, Zhan, Kang (2017)]. To preserve the structure information of image content, Chen used the location algorithm combining super-pixel segmentation and noise features in the literature in Chen et al. [Chen, Zhao, Shi et al. (2018)].

3.5 Special scenario based techniques

For the blurred image and the shadow image, the splicing operation will make the image have two kinds of blurred kernels or different shadow parameters [Liu, Cao, Chao et al. (2011)]. Bahrami believed that there may be different types of blurring between the splicing region and the original area in the tampered blurred image, so they proposed a method of using the blur type differences to realize blurred splicing image localization [Bahrami, Kot, Li et al. (2015)].

4 Comparative analysis

All the mentioned techniques above are able to locate the spliced region in one splicing image. Tab. 1 shows the comparison of various splicing image localization techniques. It summarizes parameters, merits and demerits of the methods.

5 Research prospect

The existing localization schemes have achieved high accuracy of localization, but the accuracy can be further improved and most of these technologies are suitable for gray image. A color image is composed of color information and luminance information, and only the luminance information is used to extract the features for classification in gray images. Therefore, in the localization scheme, it is insufficient to extract the features for classification by only using the luminance information. In order to make full use of color information and improve localization accuracy, researchers should focus on the localization scheme based on color splicing images, and that is what our team has been working on.

Table 1: Comparison of different splicing image localization techniques

No.	Method	Parameters	Merits	Demerits
1	Noise level Inconsistency [Zeng, Zhan, Kang et al. (2017)]	True detection rate, Negative detection rate	Low complexity, can locate the spliced region even the difference of noise level between different source is quite small	Cannot to locate JPEG images

2	Edges smoothness [Du, Ma, Chen et al. (2015)]	Threshold	High accuracy can be achieved when splicing edges are too smooth	Only performs better in case of simple scenes
3	Feature consistency based on edge CFA interpolation[Cao, Zhao and Ni (2009)]	Threshold	Against various signal attack: JPEG compression	It needs to simulate and estimate the CFA pattern
4	Exposing blur type inconsistency [Bahrami, Kot, Li et al. (2015)]	Blur kernel	Different blurred types will be well located	It is only suitable for locating blurred splicing images.
5	Block-grained analysis of jpeg artifacts [Bianchi and Piva (2012)]	Compression characteristics	automatically computes a likelihood map, effectiveness	Aiming at localization of splicing image with JPEG compression
6	SLIC and image features [Chen, Zhao, Shi et al. (2018)]	True detection rate, negative detection rate	Can preserve the structure information of image content, high accuracy of localization	High complexity, high false detection rate

6 Conclusion

In this paper, we have discussed about the image splicing and framework of image splicing localization. The basic flow of how spliced region is located is shown. The overview of different techniques that helps us to locate the spliced region and comparison of different techniques based on different parameters with its merits and demerits are provided. Although the existing localization schemes can effectively locate the spliced region in one splicing image, image splicing localization technology also needs further development to adapt to more application scenarios.

Acknowledgments: This work was supported in part by the Natural Science Foundation of China under Grants (Nos. 61772281, U1636219, 61502241, 61272421, 61232016, 61402235 and 61572258), in part by the National Key R&D Program of China (Grant Nos. 2016YFB0801303 and 2016QY01W0105), in part by the plan for Scientific Talent of Henan Province (Grant No. 2018JR0018), in part by the Natural Science Foundation of Jiangsu Province, China under Grant BK20141006, and in part by the Natural Science Foundation of the Universities in Jiangsu Province under Grant 14KJB520024, the PAPD fund and the CICAET fund.

References

Alahmadi, A. A.; Hussain, M.; Aboalsamh, H.; Muhammad, G.; Bebis, G. (2013): Splicing image forgery detection based on DCT and local binary pattern. *Global Conference on Signal & Information Processing*.

Amerini, I.; Becarelli, R.; Caldelli, R.; Mastio, A. D. (2014): Splicing forgeries localization through the use of first digit features. *IEEE International Workshop on Information Forensics & Security*, pp. 143-148.

Arun, A. M. (2015): Image forgery and its detection: a survey. *International Conference on Innovations in Information*.

Asghar, K.; Habib, Z.; Hussain, M. (2016): Copy-move and splicing image forgery detection and localization techniques: a review. *Australian Journal of Forensic Sciences*, vol. 49, no. 3, pp. 281-307.

Bahrani, K.; Kot, A. C. (2014): Image splicing localization based on blur type inconsistency. *IEEE International Symposium on Circuits & Systems*, pp. 2654-2658.

Bahrani, K.; Kot, A. C.; Li, L.; Li, H. (2015): Blurred Image Splicing Localization by Exposing Blur Type Inconsistency. *IEEE Transactions on Information Forensics & Security*, vol. 10, no. 5, pp. 999-1009.

Bharti, C. N.; Tandel, P. (2016): A survey of image forgery detection techniques. *IEEE International Conference on Wireless Communications*.

Bianchi, T.; Piva, A. (2012): Detection of nonaligned double JPEG compression based on integer periodicity maps. *IEEE Transactions on Information Forensics & Security*, vol. 7, no. 2, pp. 842-848.

Bianchi, T.; Piva, A. (2012): Image forgery localization via block-grained analysis of jpeg artifacts. *IEEE Transactions on Information Forensics & Security*, vol. 7, no. 3, pp. 1003-1017.

Birajdar, G. K.; Mankar, V. H. (2013): Digital image forgery detection using passive techniques: a survey. *Digital Investigation*, vol. 10, no. 3, pp. 226-245.

Bo, W.; Kong, X. (2012): Image splicing localization based on re-demosaicing. *Lecture Notes in Electrical Engineering*, vol. 136, pp. 725-732.

Cao, G.; Zhao, Y.; Ni, R. (2009): Image splicing detection based on edge CFA interpolation feature consistency. *Journal of Southeast University (Natural Science Edition)*, vol. 39, no. 3, pp. 459-463.

Chen, H.; Zhao, C.; Shi, Z.; Zhu, F. (2018): An image splicing localization algorithm based on SLIC and image features. *Cham, Springer International Publishing*, pp. 725-732.

Chen, M.; Fridrich, J.; Goljan, M.; Lukas, J. (2008): Determining image origin and integrity using sensor noise. *IEEE Transactions on Information Forensics & Security*, vol. 3, no. 1, pp. 74-90.

Chierchia, G.; Poggi, G.; Sansone, C.; Verdoliva, L. (2014): A bayesian-MRF approach for PRNU-based image forgery detection. *IEEE Transactions on Information Forensics & Security*, vol. 9, no. 4, pp. 554-567.

Cozzolino, D.; Verdoliva, L. (2017): Single-image splicing localization through autoencoder-based anomaly detection. *IEEE International Workshop on Information Forensics & Security*.

Dirik, A. E.; Memon, N. (2009): Image tamper detection based on demosaicing artifacts. *IEEE International Conference on Image Processing*.

- Du, J; Ma, Q; Chen, G; Yang, Q.** (2015): Blind forensics algorithm for image splicing localization based on edge smoothness. *Computer Engineering and Design*, no. 2, pp. 330-334.
- Ferrara, P.; Bianchi, T.; Rosa, A. D.; Piva, A.** (2012): Image forgery localization via fine-grained analysis of CFA artifacts. *IEEE Transactions on Information Forensics & Security*, vol. 7, no. 5, pp. 1566-1577.
- He, Z.; Wei, L.; Wei, S.; Huang, J.** (2012): Digital image splicing detection based on markov features in DCT and DWT domain. *Pattern Recognition*, vol. 45, no. 12, pp. 4292-4299.
- Li, C.; Qiang, M.; Xiao, L.; Ming, L.; Zhang, A.** (2017): Image splicing detection based on markov features in QDCT domain. *Neurocomputing*, vol. 228, pp. 29-36.
- Liu, J.** (2012): *Natural Image and Computer Generated Image Source Forensics Based on PRNU (Ph.D. Thesis)*. Hunan University.
- Liu, Q.; Cao, X.; Chao, D.; Guo, X.** (2011): Identifying image composites through shadow matte consistency. *IEEE Transactions on Information Forensics & Security*, vol. 6, no. 3, pp. 1111-1122.
- Lukás, J.; Fridrich, J.; Goljan, M.** (2006): Detecting digital image forgeries using sensor pattern noise. *Proceedings of SPIE-the International Society for Optical Engineering*, vol. 6072, pp. 362-372.
- Luo, W.; Zhenhua, Q. U.; Feng, P.; Huang, J.** (2008): A survey of passive technology for digital image forensics. *Academic Abstracts of Chinese Institutions of Higher Learning-Computer Science*, vol. 1, no. 2, pp. 166-179.
- Lyu, S.; Pan, X.; Xing, Z.** (2014): Exposing region splicing forgeries with blind local noise estimation. *International Journal of Computer Vision*, vol. 110, no. 2, pp. 202-221.
- Mahdian, B.; Saic, S.** (2009): Using noise inconsistencies for blind image forensics. *Image & Vision Computing*, vol. 27, no. 10, pp. 1497-1503.
- Mire, A. V.; Dhok, S. B.; Mistry, N. J.; Porey, P. D.** (2015): Factor histogram based forgery localization in double compressed JPEG images. *Procedia Computer Science*, vol. 54, pp. 690-696.
- Ng, T. T.; Chang, S. F.** (2004): A model for image splicing. *International Conference on Image Processing*.
- Pan, X.; Xing, Z.; Lyu, S.** (2012): Exposing image splicing with inconsistent local noise variances. *IEEE International Conference on Computational Photography*.
- Piva, A.** (2011): Improved DCT coefficient analysis for forgery localization in JPEG images. *IEEE International Conference on Acoustics*.
- Potdar, V. M.; Han, S.; Chang, E.** (2005): A survey of digital image watermarking techniques. *IEEE International Conference on Industrial Informatics Perth*.
- Pyatykh, S.; Hesser, J.; Zheng, L.** (2013): Image noise level estimation by principal component analysis. *IEEE Transactions on Image Processing a Publication of the IEEE Signal Processing Society*, vol. 22, no. 2, pp. 687-699.

Rosenfeld, K.; Sencar, H. T. (2009): A study of the robustness of PRNU-based camera identification. *Proceedings of SPIE-the International Society for Optical Engineering*, pp. 7254.

Salloum, R.; Ren, Y.; Kuo, C. C. J. (2017): Image splicing localization using a multi-task fully convolutional network (MFCN). *Journal of Visual Communication & Image Representation*, vol. 51, pp. 201-209.

Sun P.; Lang Y.; Gong J.; Shen J. (2017): Colour offset inconsistency forensics for splicing images. *Journal of Computer Aided Design and Graphics*, vol. 29, no. 8, pp. 1408-1415.

Wu, J.; Zhu, B. B.; Li, S.; Lin, F. (2005): A secure image authentication algorithm with pixel-level tamper localization. *International Conference on Image Processing*, vol. 3, pp. 1573-1576.

Yin, H.; Lin, C.; Qiu, F.; Ding, R. (2005): Summary of digital watermarking technology. *Computer Research and Development*, vol. 42, no. 7, pp. 1093-1099.

Yuan, R.; Ni, J. (2017): A deep learning approach to detection of splicing and copy-move forgeries in images. *IEEE International Workshop on Information Forensics & Security*.

Zampoglou, M.; Papadopoulos, S.; Kompatsiaris, Y. (2017): Large-scale evaluation of splicing localization algorithms for web images. *Multimedia Tools and Applications*, vol. 76, no. 4, pp. 4801-4834.

Zhou, L. (2007): *Research on Blind Forensics Technology of Digital Image (Ph.D. Thesis)*. Beijing University of Posts and Telecommunications.

Zeng, H.; Zhan, Y.; Kang, X.; Lin, X. (2017): Image splicing localization using PCA-based noise level estimation. *Multimedia Tools and Applications*, vol. 76, no. 4, pp. 4783-4799.