Universal Deep Network for Steganalysis of Color Image based on Channel Representation

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Abstract—Up to now, most existing steganalytic methods are designed for grayscale images, and they are not suitable for color images that are widely used in current social networks. In this paper, we design a universal color image steganalysis network (called UCNet) in spatial and JPEG domains. The proposed method includes preprocessing, convolutional, and classification modules. To preserve the steganographic artifacts in each color channel, in preprocessing module, we firstly separate the input image into three channels according to the corresponding embedding spaces (i.e. RGB for spatial steganography and YCbCr for JPEG steganography), and then extract the image residuals with 62 fixed high-pass filters, finally concatenate all truncated residuals for subsequent analysis rather than adding them together with normal convolution like existing CNN-based steganalyzers. To accelerate the network convergence and effectively reduce the number of parameters, in convolutional module, we carefully design three types of layers with different shortcut connections and group convolution structures to further learn high-level steganalytic features. In classification module, we employ a global average pooling and fully connected layer for classification. We conduct extensive experiments on ALASKA II to demonstrate that the proposed method can achieve state-of-the-art results compared with the modern CNN-based steganalyzers (e.g., SRNet and J-YeNet) in both spatial and JPEG domains, while keeping relatively few memory requirements and training time. Furthermore, we also provide necessary descriptions and many ablation experiments to verify the rationality of the network design.

Index Terms—Steganalysis, Steganography, Color Images, Convolutional Neural Network (CNN).

I. INTRODUCTION

IMAGE steganography aims to embed secret information into digital image without introducing obvious visual artifacts. On the opposite side, steganalysis aims to detect covert communication established via steganography. Recently, most modern steganographic methods (1–5) are image content adaptive, which significantly enhance the steganography security. Thus, steganalysis is facing severe challenges.

Image steganalysis techniques can be divided into two categories, that is, traditional methods based on handcrafted features and CNN-based methods. Feature extraction is the key issue in traditional methods. For instance, in spatial domain, Penvy et al. [6] obtained 686-dimensional features by extracting inter-pixel relationships. Fridrich et al. [7] used several different high-pass filters and calculated the co-occurrence matrix for the obtained features to get 34671-dimensional features (called SRM). Holub et al. [8] proposed a random projection feature analysis method based on the residuals of SRM. In JPEG domain, Kodovský et al. [9] presented a rich model of JPEG to capture the changes brought by the steganographic signal more comprehensively. Holub et al. [10] proposed a DCTR feature with 64 kernels using discrete cosine transform. Later, Song et al. [11] used Gabor filters instead of SRM kernels to detect JPEG steganography, and also achieved better performance. Recently, many CNN-based steganalytic methods (e.g., [12–20]) have been proposed and achieve much better results compared with traditional ones. For instance, in spatial domain, Ye et al. [14] proposed a CNN structure and also with the help of selection channel knowledge, the model gained better detection accuracy over the SRM (called YeNet). Yedroudj et al. [16] achieved further performance improvement based on YeNet using data augmentation, batch normalization (called Yedroudj-Net). Deng et al. [19] introduced covariance pooling to the steganalysis task (we call it CovNet) and achieved better results. In JPEG domain, Xu [13] designed a 20-layer CNN-based steganalyzer called J-XuNet for detecting J-UNIWARD [21]. Boroumand et al. [17] described a universal deep steganalysis residual network (called SRNet), and showed its effectiveness in both spatial and JPEG steganography. Huang et al. [18] presented a selection-channel-aware CNN called J-YeNet by extending the YeNet [14] for JPEG steganalysis.

Note that all above mentioned methods are designed for detecting grayscale stegos, and they are not very suitable for detecting color stegos generated by some steganography methods, such as [22–27]. Recently, several traditional steganalytic methods, such as [28–31], have been proposed for color images. For instance, Goljan et al. [30] proposed an extension of the SRM [7] for steganalysis of color images (called CRM). Yang et al. [31] presented a variant of SRM feature based on the embedding change probabilities in differential channels between different color channels. In spatial domain, Zeng et al. [32] first design a wider separate-then-reunion network (called WISERNet) for steganalysis of color images, and achieve better results compared with related methods based on handcrafted features. Except for WISERNet, to our best knowledge, the recent CNN-based steganalyzers for color images are directly based on some existing methods for
grayscale images or some effective models in computer vision. For instance, in JPEG domain, Youosi et al. [33] and Chubachi [34] adjust the existing networks (i.e., SRNet) for color JPEG images. Furthermore, they introduce other improvement strategies, such as model pre-training on a big image dataset (e.g., ImageNet [35]) or ensemble model with different CNNs, to further enhance detection performances of the existing networks. Butora and Youosi et al. [36], [37] explored the effect of several variants of EfficientNet in steganalysis. Although these steganalyzers can achieve satisfactory results, some inherent steganographic artifacts within color images have not been fully exploited for steganalysis, such as the relationship between color channels. Like SRNet for grayscale images, in addition, a universal steganalytic network that is effective in both spatial and JPEG domains for color images is critically needed.

Aiming at color images, we design a universal deep steganalytic network based on channel representation in this paper. In the proposed method, we firstly separate the color input image into three channels according to their embedding spaces (i.e. RGB for spatial steganography and YCbCr for JPEG steganography). To enhance the steganographic noise signal in both spatial and JPEG domains, we combine 30 basic linear filters from SRM and 32 Gabor filters for calculating image residuals. To well preserve steganographic artifacts in each color channel, we then concatenate all truncated residuals for subsequent analysis instead of adding them together like existing steganalytic networks. Furthermore, we carefully design three types of layers with different shortcut connections and group convolution structures to further learn high-level steganalytic features. Extensive experimental results evaluated on ALASKA II show that the proposed method can achieve state-of-the-art results compared with some modern CNN-based steganalyzers, while maintaining lower resource requirements and number of parameters. In addition, sufficient ablation experiments are also provided to verify the rationality of the network design.

The rest of the paper is organized as follows. Section ?? describes the proposed method in detail. Section ?? shows comparative experimental results and discussions. Finally, the concluding remarks of this paper and future works are given in Section [I]

II. CONCLUSION REMARKS

Most existing steganalytic methods are originally designed for detecting grayscale images, and they are not very effective in color image steganalysis based on our experiments. In this paper, therefore, we proposed a universal deep network for steganalysis of color image based on channel representation, and demonstrate that the proposed method can achieve the best detection performances for compared with some modern steganalytic networks in both spatial and JPEG domains. The major contributions of this work are as follows:

- To well preserve the steganographic artifacts in color images, we employ the color channel separation and then concatenate feature maps instead of the convolution summation which is commonly used in existing steganalytic networks;
- To extract the high-level steganalytic features, we carefully design three new types of layers and then combined them into a continuous convolutional module. Experimental results on ALASKA II demonstrate the superiority of the proposed steganalyzer compared with the modern steganalytic networks in both spatial and JPEG domains;
- To verify the rationality of our proposed model, we give some necessary descriptions about our network design in three modules (i.e., preprocessing, convolutional, and classification). Furthermore, we provide extensive ablation experiments of the proposed model.

Our future work will focus on two aspects: 1) we will integrate selection-channel-aware into the proposed steganalyzer, and adaptively enhance the model features from different levels of network. In addition, we will design an effective strategy to improve inter-channel correlation by combining embedding probability information for each channel of color images; 2) We will further explore deep learning-based architectures for color image steganalysis using inter-channel correlation, such as introducing quaternion convolutional neural networks to preserve inter-channel dependencies and thus extract richer steganalytic features.

REFERENCES

[1] W. Luo, F. Huang, and J. Huang, “Edge adaptive image steganography based on lsb matching revisited,” IEEE Transactions on Information Forensics and Security, vol. 5, no. 2, pp. 201–214, 2010.
[2] T. Filler and J. Fridrich, “Gibbs construction in steganography,” IEEE Transactions on Information Forensics and Security, vol. 5, no. 4, pp. 705–720, 2010.
[3] B. Li, M. Wang, J. Huang, and X. Li, “A new cost function for spatial image steganography,” in IEEE International Conference on Image Processing, pp. 4206–4210, 2014.
[4] V. Sedighi, R. Cognanne, and J. Fridrich, “Content-adaptive steganography by minimizing statistical detectability,” IEEE Transactions on Information Forensics and Security, vol. 11, no. 2, pp. 221–234, 2016.
[5] L. Guo, J. Ni, W. Su, C. Tang, and Y.-Q. Shi, “Using statistical image model for JPEG steganography: Uniform embedding revisited,” IEEE Transactions on Information Forensics and Security, vol. 10, no. 12, pp. 2669–2680, 2015.
[6] T. Pevny, P. Bas, and J. Fridrich, “Steganalysis by subtractive pixel adjacency matrix,” IEEE Transactions on Information Forensics and Security, vol. 5, no. 2, pp. 215–224, 2010.
[7] J. Fridrich and J. Kodovsky, “Rich models for steganalysis of digital images,” IEEE Transactions on Information Forensics and Security, vol. 7, no. 3, pp. 868–882, 2012.
[8] V. Holub and J. Fridrich, “Random projections of residuals for digital image steganalysis,” IEEE Transactions on Information Forensics and Security, vol. 8, no. 12, pp. 1996–2006, 2013.
[9] J. Kodovsky and J. Fridrich, “Steganalysis of JPEG images using rich models,” in Media Watermarking, Security, and Forensics, vol. 8303, pp. 81–93, 2012.
[10] V. Holub and J. Fridrich, “Low-complexity features for JPEG steganalysis using undecimated dct,” IEEE Transactions on Information Forensics and Security, vol. 10, no. 2, pp. 219–228, 2015.
[11] X. Song, F. Liu, C. Yang, X. Luo, and Y. Zhang, “Steganalysis of adaptive JPEG steganography using 2D gabor filters,” in ACM Workshop on Information Hiding and Multimedia Security, pp. 15–23, 2015.
[12] Y. Qian, J. Dong, W. Wang, and T. Tan, “Deep learning for steganalysis via convolutional neural networks,” in Media Watermarking, Security, and Forensics, vol. 9409, p. 94090J, 2015.
[13] G. Xu, “Deep convolutional neural network to detect j-uniform,” in ACM Workshop on Information Hiding and Multimedia Security, pp. 67–73, 2017.
[14] J. Ye, J. Ni, and Y. Yi, “Deep learning hierarchical representations for image steganalysis,” IEEE Transactions on Information Forensics and Security, vol. 12, no. 11, pp. 2545–2557, 2017.
[15] M. Chen, V. Sedighi, M. Boroumand, and J. Fridrich, “JPEGL phase-aware convolutional neural network for steganalysis of JPEG images,” in *ACM Workshop on Information Hiding and Multimedia Security*, pp. 75–84, 2017.

[16] M. Yedroudj, F. Comby, and M. Chaumont, “Yedroudj-Net: An efficient CNN for spatial steganalysis,” in *IEEE International Conference on Acoustics, Speech and Signal Processing*, pp. 2092–2096, 2018.

[17] M. Boroumand, M. Chen, and J. Fridrich, “Deep residual network for steganalysis of digital images,” *IEEE Transactions on Information Forensics and Security*, vol. 14, no. 5, pp. 1181–1193, 2019.

[18] J. Huang, J. Ni, L. Wan, and J. Yan, “A customized convolutional neural network with low model complexity for JPEG steganalysis,” in *ACM Workshop on Information Hiding and Multimedia Security*, pp. 198–203, 2019.

[19] X. Deng, B. Chen, W. Luo, and D. Luo, “Fast and effective global covariance pooling network for image steganalysis,” in *ACM Workshop on Information Hiding and Multimedia Security*, pp. 230–234, 2019.

[20] R. Zhang, F. Zhu, J. Liu, and G. Liu, “Depth-wise separable convolutions and multi-level pooling for an efficient spatial CNN-based steganalysis,” *IEEE Transactions on Information Forensics and Security*, vol. 15, pp. 1138–1150, 2020.

[21] V. Holub, J. Fridrich, and T. Denemark, “Universal distortion function for steganography in an arbitrary domain,” *EURASIP Journal on Information Security*, vol. 2014, no. 1, pp. 1–13, 2014.

[22] M. Boroumand, B. Li, W. Luo, and J. Huang, “Clustering steganographic modification directions for color components,” *IEEE Signal Processing Letters*, vol. 23, no. 2, pp. 197–201, 2015.

[23] X. Qin, B. Li, S. Tan, and J. Zeng, “A novel steganography for spatial color images based on pixel vector cost,” *IEEE Access*, vol. 7, pp. 8834–8846, 2019.

[24] Y. Wang, W. Zhang, W. Li, X. Yu, and N. Yu, “Non-additive cost functions for color image steganography based on inter-channel correlations and differences,” *IEEE Transactions on Information Forensics and Security*, vol. 15, pp. 2081–2095, 2020.

[25] T. Taburet, L. Filstroff, P. Bas, and W. Sawaya, “An empirical study of steganography and steganalysis of color images in the JPEG domain,” in *International Workshop on Digital Watermarking*, pp. 290–303, 2018.

[26] R. Cogranne, Q. Giboulot, and P. Bas, “The ALASKA steganalysis challenge: A first step towards steganalysis,” in *ACM Workshop on Information Hiding and Multimedia Security*, pp. 125–137, 2019.

[27] R. Cogranne, Q. Giboulot, and P. Bas, “Steganography by minimizing statistical detectability: The cases of JPEG and color images,” in *ACM Workshop on Information Hiding and Multimedia Security*, pp. 161–167, 2020.

[28] X. Liao, G. Chen, and J. Yin, “Content-adaptive steganalysis for color images,” *Security and Communication Networks*, vol. 9, no. 18, pp. 5756–5763, 2016.

[29] H. Abdurrahman, M. Chaumont, P. Montesinos, and B. Magnier, “Color images steganalysis using rgb channel geometric transformation measures,” *Security and Communication Networks*, vol. 9, no. 15, pp. 2945–2956, 2016.

[30] M. Goljan, J. Fridrich, and R. Cogranne, “Rich model for steganalysis of color images,” in *IEEE International Workshop on Information Forensics and Security*, pp. 185–190, 2014.

[31] C. Yang, Y. Kang, F. Liu, X. Song, J. Wang, and X. Luo, “Color image steganalysis based on embedding change probabilities in differential channels,” *International Journal of Distributed Sensor Networks*, vol. 16, no. 5, p. 1550147720917826, 2020.

[32] J. Zeng, S. Tan, G. Liu, B. Li, and J. Huang, “WISERNet: Wider separate-then-reunion network for steganalysis of color images,” *IEEE Transactions on Information Forensics and Security*, vol. 14, no. 10, pp. 2735–2748, 2019.

[33] Y. Yousfi, J. Butora, E. Khvedchenya, and J. Fridrich, “ImageNet pre-trained CNNs for JPEG steganalysis,” in *IEEE International Workshop on Information Forensics and Security*, pp. 1–6, 2020.

[34] K. Chubachi, “An ensemble model using CNNs on different domains for ALASKA2 image steganalysis,” in *IEEE International Workshop on Information Forensics and Security*, pp. 1–6, 2020.

[35] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “ImageNet: A large-scale hierarchical image database,” in *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 248–255, 2009.

[36] J. Butora, Y. Yousfi, and J. Fridrich, “How to pretrain for steganalysis,” in *ACM Workshop on Information Hiding and Multimedia Security*, pp. 143–148, 2021.

[37] Y. Yousfi, J. Butora, J. Fridrich, and C. Fuji Tsang, “Improving EfficientNet for JPEG steganalysis,” in *ACM Workshop on Information Hiding and Multimedia Security*, pp. 149–157, 2021.

[38] J. Butora and J. Fridrich, “Reverse JPEG compatibility attack,” *IEEE Transactions on Information Forensics and Security*, vol. 15, pp. 1444–1454, 2019.

[39] S. Xie, R. Girshick, P. Dollár, Z. Tu, and K. He, “Aggregated residual transformations for deep neural networks,” in *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1492–1500, 2017.

[40] G. Xu, H.-Z. Wu, and Y. Q. Shi, “Ensemble of CNNs for steganalysis: An empirical study,” in *Proceedings of the 4th ACM Workshop on Information Hiding and Multimedia Security*, pp. 103–107, 2016.

[41] “ALASKA homepage.” [https://alaska.utt.fr](https://alaska.utt.fr)

[42] T. Denemark and J. Fridrich, “Improving steganographic security by synchronizing the selection channel,” in *ACM Workshop on Information Hiding and Multimedia Security*, pp. 5–14, 2015.

[43] B. Li, M. Wang, X. Li, S. Tan, and J. Huang, “A strategy of clustering modification directions in spatial image steganography,” *IEEE Transactions on Information Forensics and Security*, vol. 10, no. 9, pp. 1905–1917, 2015.

[44] L. Gao, J. Ni, and Y. Q. Shi, “Uniform embedding for efficient JPEG steganography,” *IEEE transactions on Information Forensics and Security*, vol. 9, no. 5, pp. 814–825, 2014.

[45] Y. Bengio, J. Louradour, R. Collobert, and J. Weston, “Curriculum learning,” in *International Conference on Machine Learning*, pp. 41–48, 2009.

[46] M. Tan and Q. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in *International Conference on Machine Learning*, pp. 6105–6114, 2019.

[47] Y. Yousfi, J. Butora, J. Fridrich, and Q. Giboulot, “Breaking ALASKA: Color separation in JPEG domain,” in *ACM Workshop on Information Hiding and Multimedia Security*, pp. 138–149, 2019.