Supplementary Materials for

“A Common Framework for Interactive Texture Transfer”

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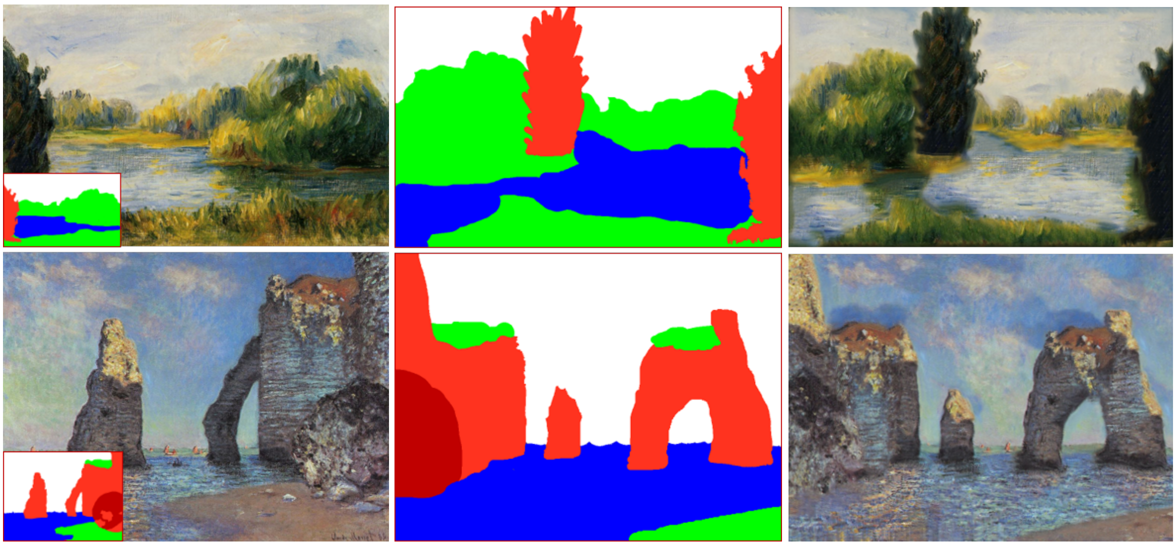
In this document we provide the following supplementary contents:

- Applications of multiple challenging interactive texture transfer tasks: turning doodles into artworks, editing decorative patterns, generating texts in special effect and swapping textures.
- Comparison of our interactive texture transfer approach with state-of-the-art methods.
- Experimental results with state-of-the-art image completion methods.
- Experimental results with drastically different semantic inputs.
- Failure cases.

1. Applications

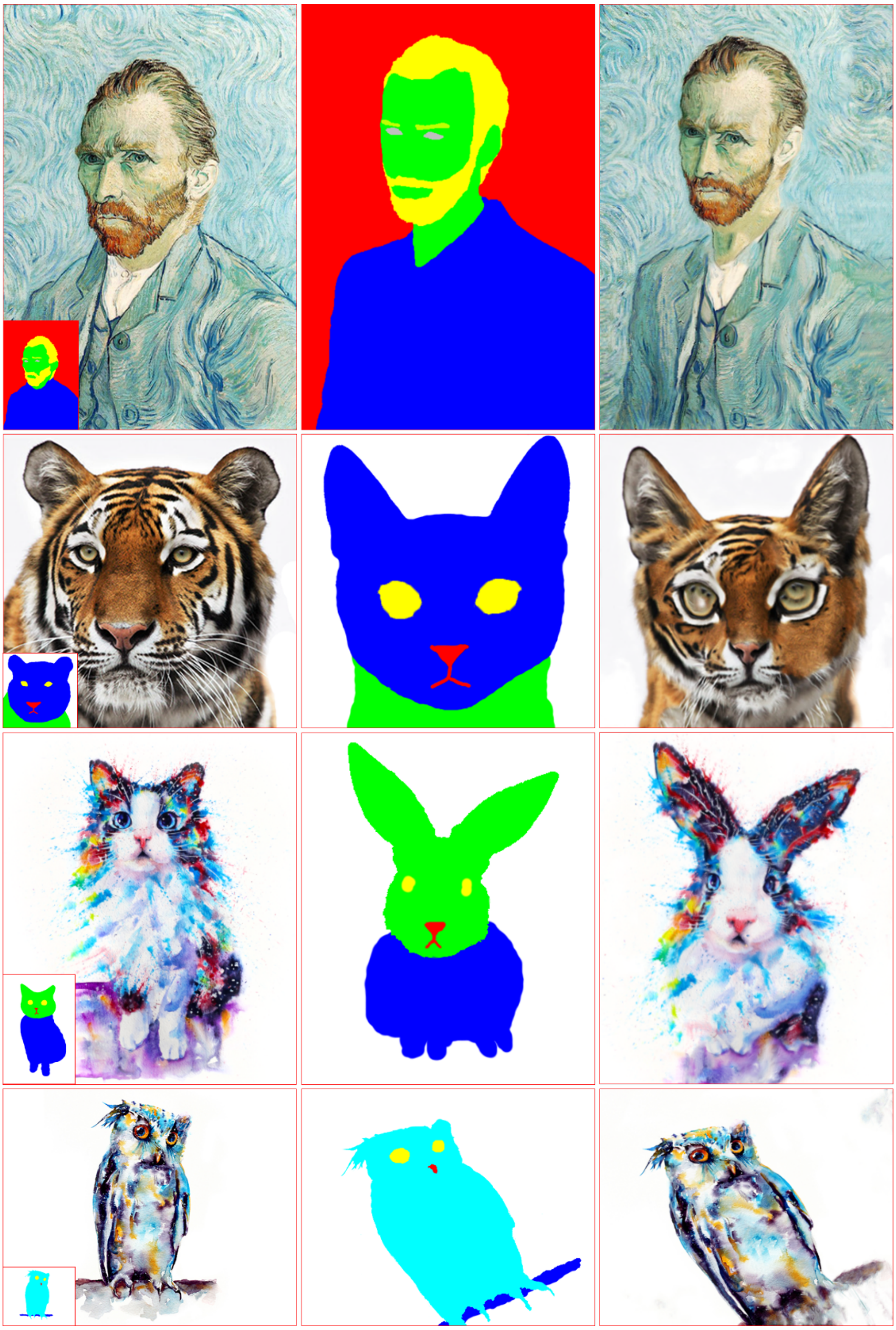
1.1. Doodles-to-artworks

This task turns doodles into paintings with various styles, including oil pastel, watercolor, colored pencils, comic and photorealism.



Input (source) Input (semantics) Output (target)

Figure 1. Doodles-to-artworks transfer results. Image courtesy of Champandard [2].



Input (source) Input (semantics) Output (target)

Figure 2. Doodles-to-artworks transfer results. Image courtesy of Van Gogh, Liao *et al.* [5] and Zcool [1].

Figure 3. Doodles-to-artworks transfer results. Image courtesy of Liao *et al.* [5] and Zcool [1].

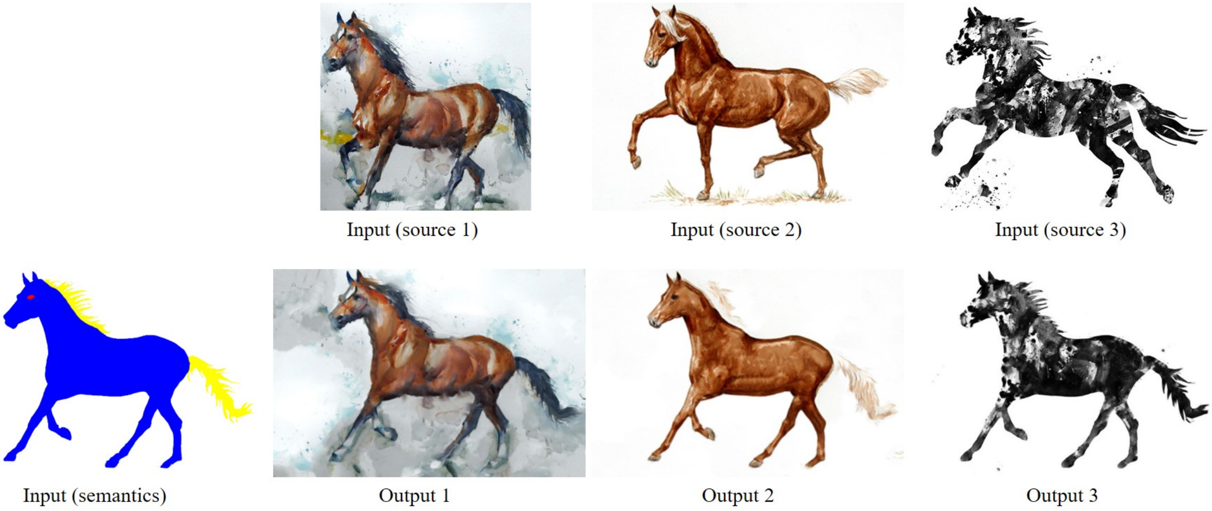


Figure 4. Results of doodles-to-artworks transfer with various styles. Image courtesy of Liao *et al.* [5].

1.2. Decorative Pattern Editing

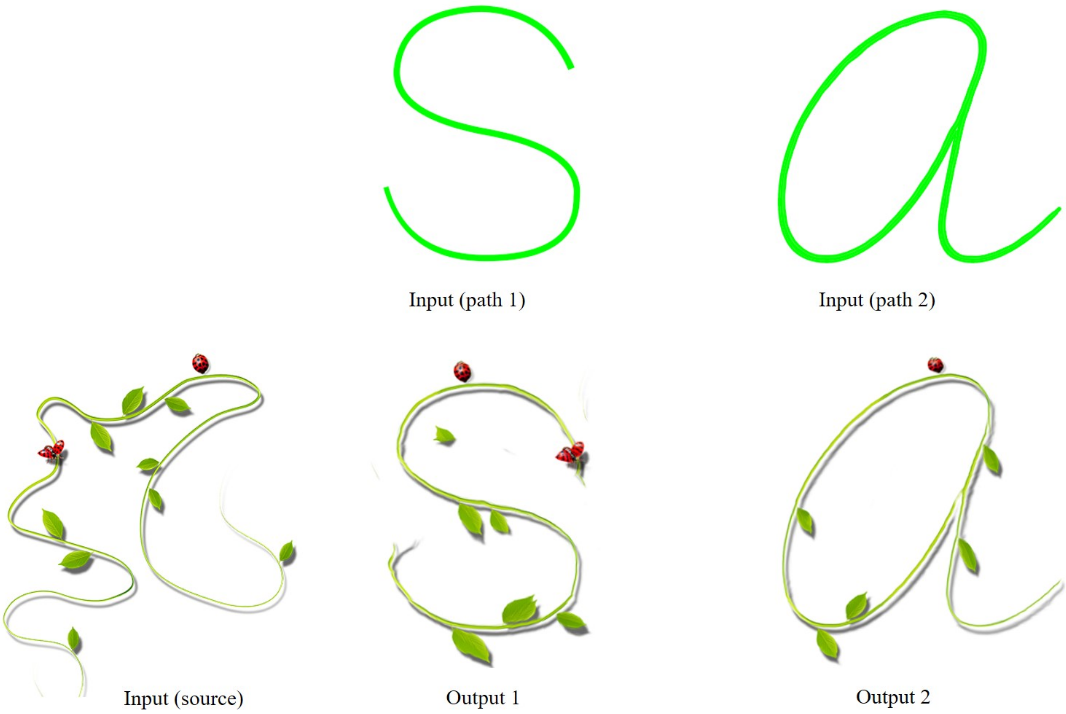


Figure 5. Decorative pattern editing results. Image courtesy of Lu *et al.* [10]

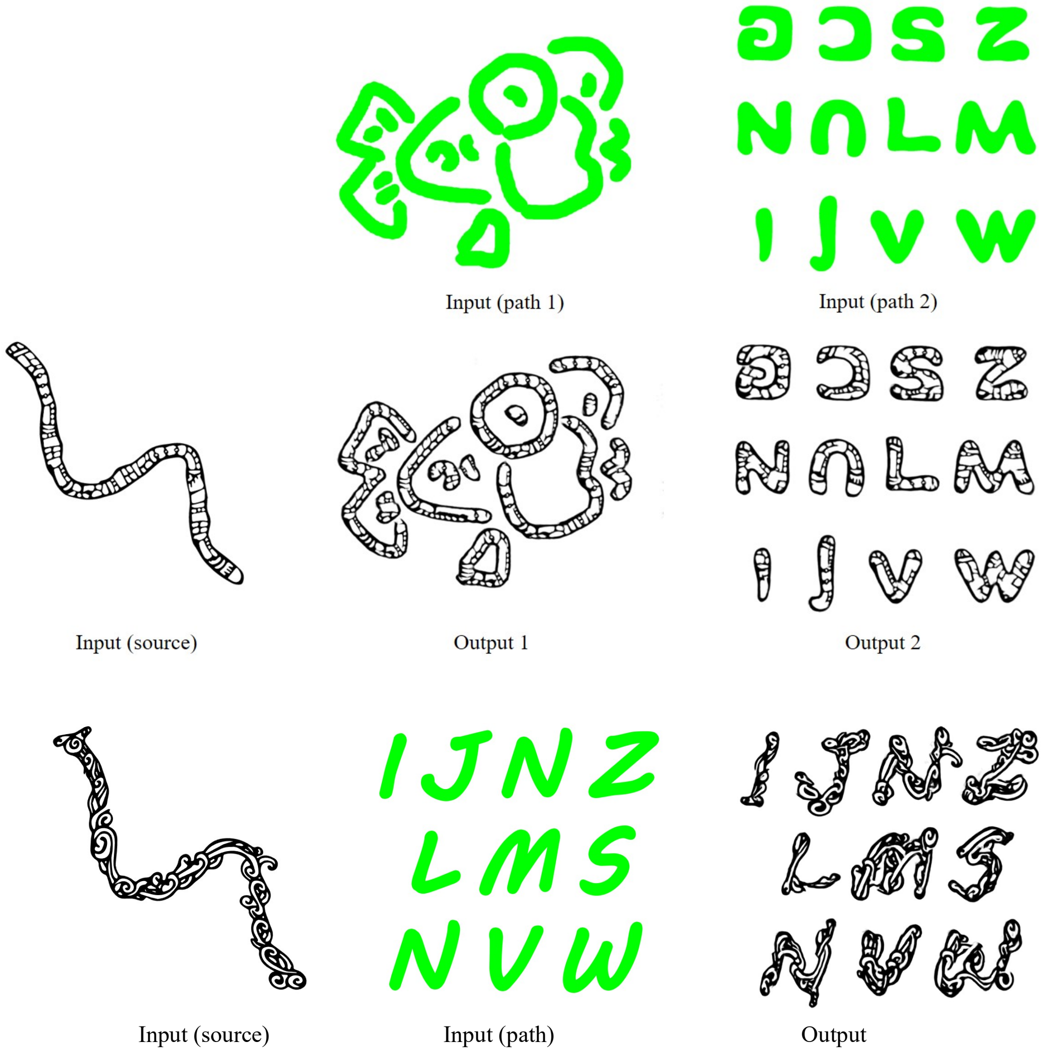
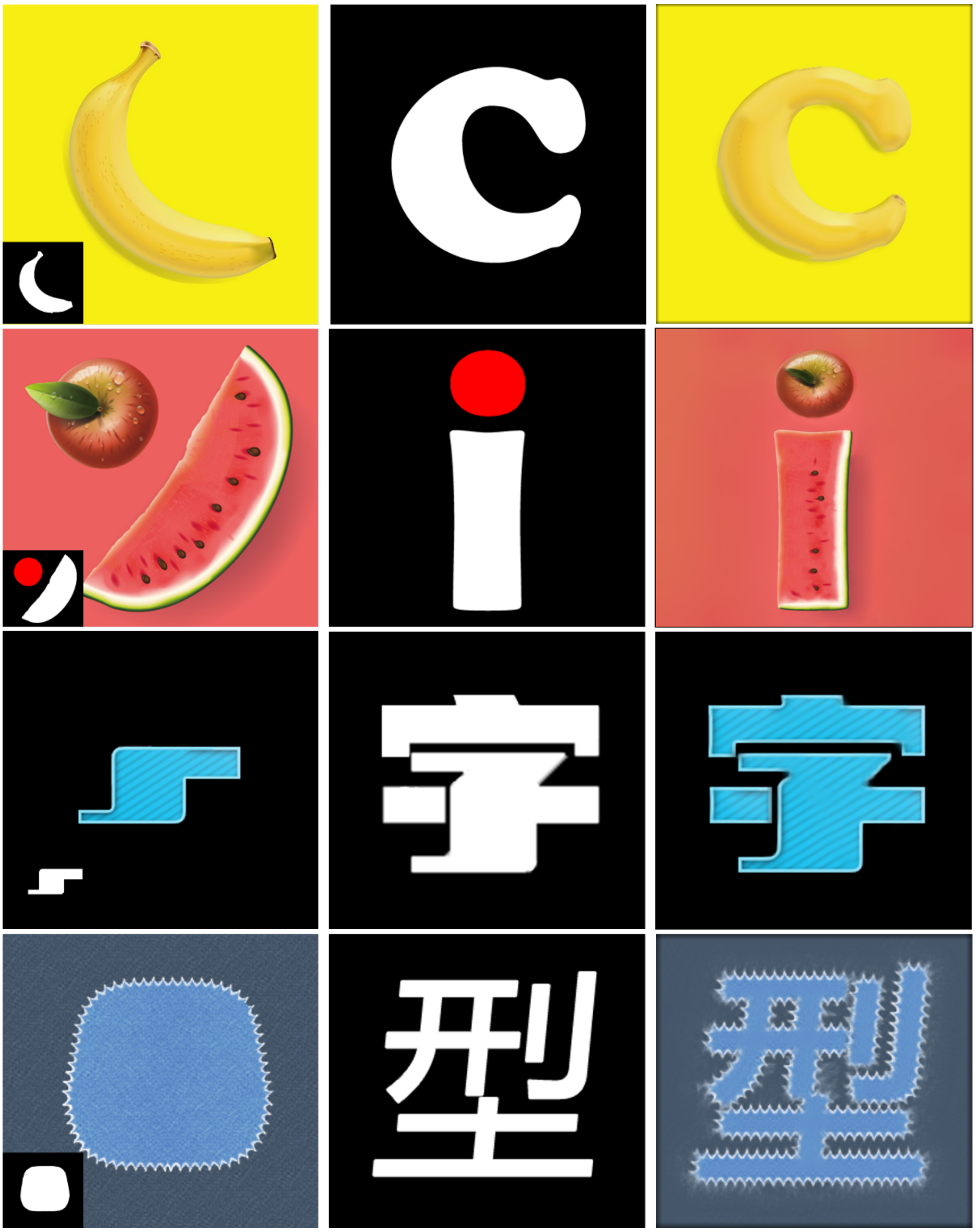


Figure 6. Decorative pattern editing results. Image courtesy of Lu *et al.* [10].

1.3. Special Effect Text Generation



Input (source) Input (plain text) Output (target)

Figure 7. Results of generating special effect text with designed textures. Image courtesy of Zcool [1].

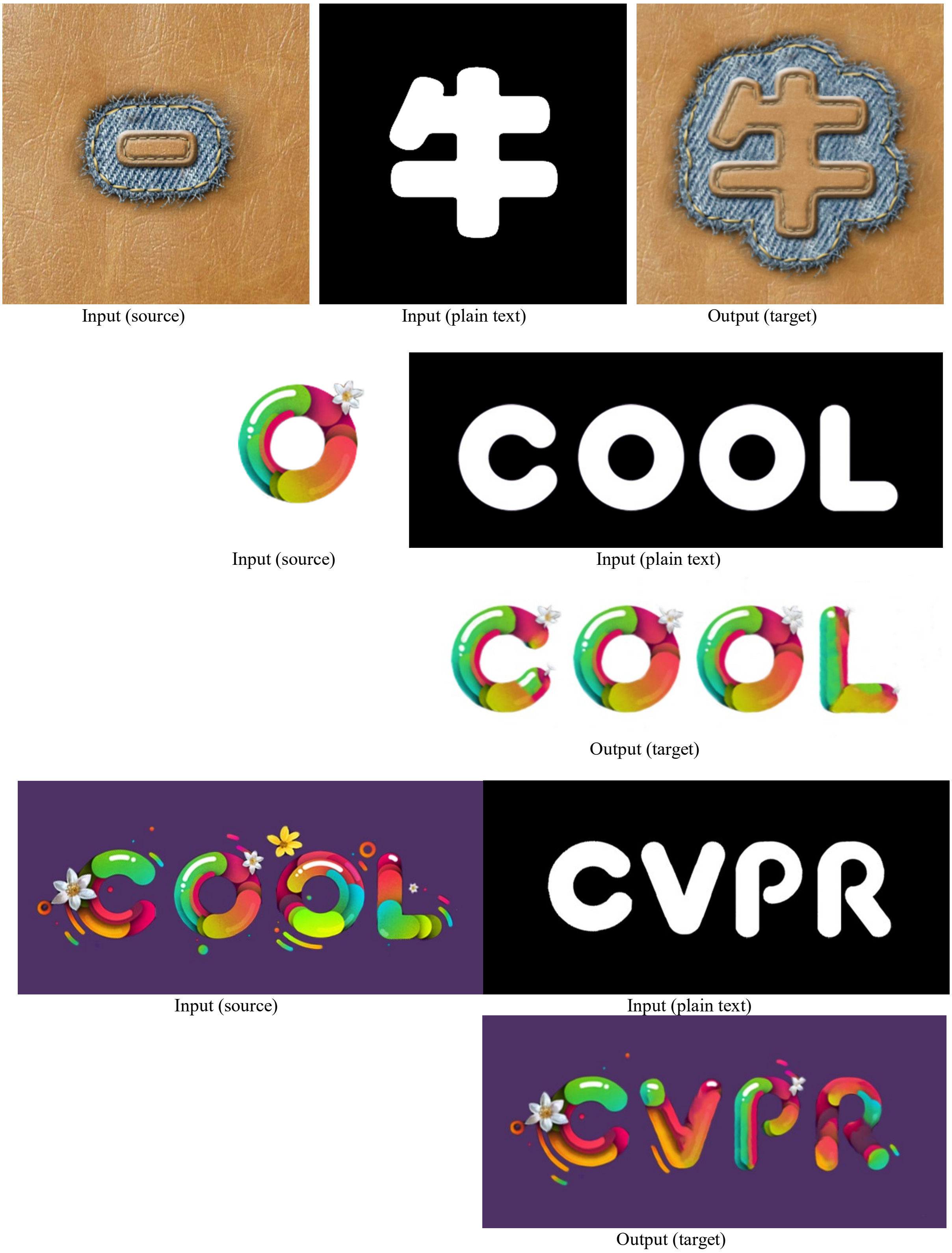


Figure 8. Results of generating special effect text with designed textures. Image courtesy of Yang *et al.* [8] and Envato [11].

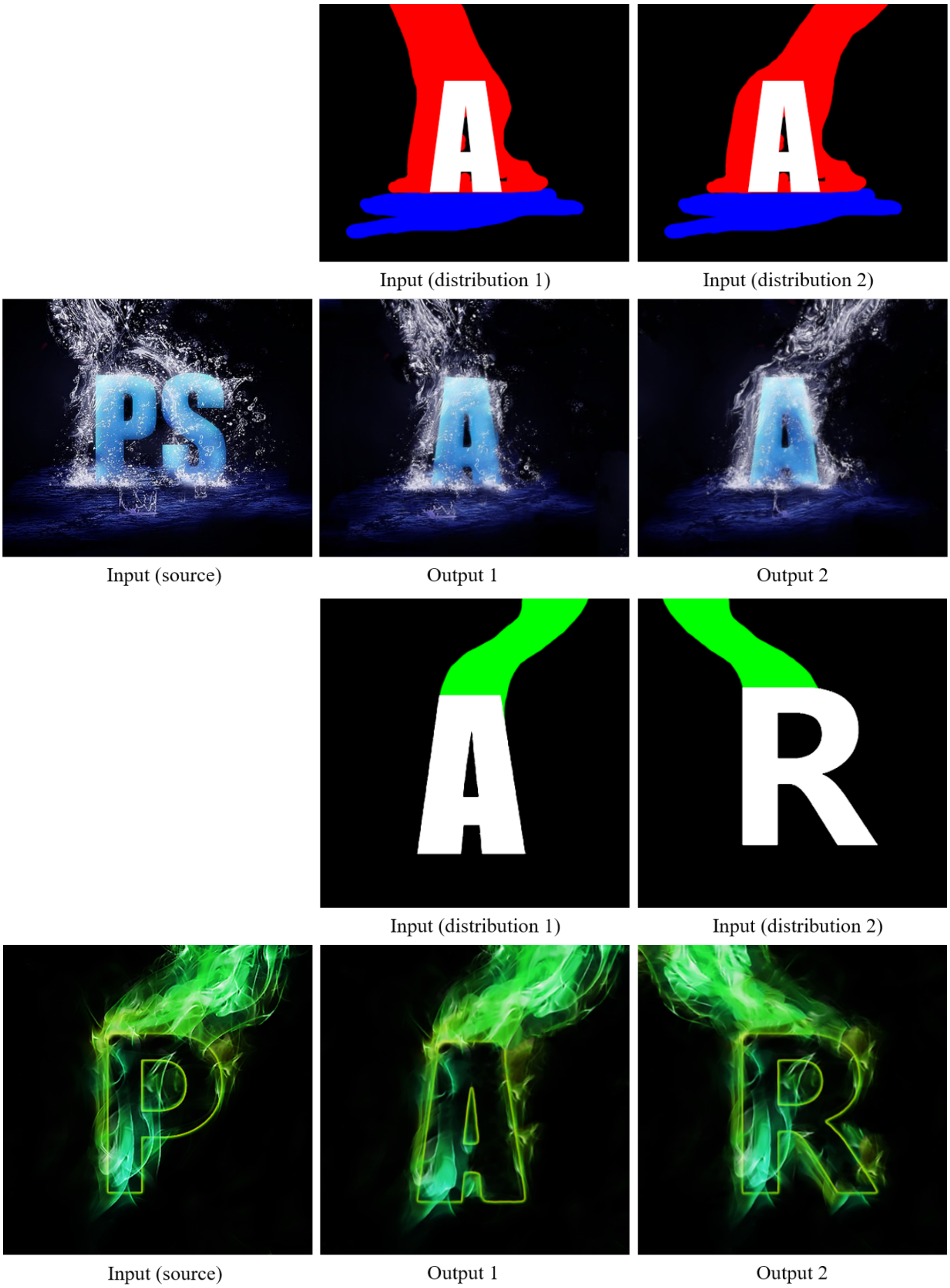


Figure 9. Results of generating complex text with controlling the effect distribution. Image courtesy of Yang *et al.* [8].

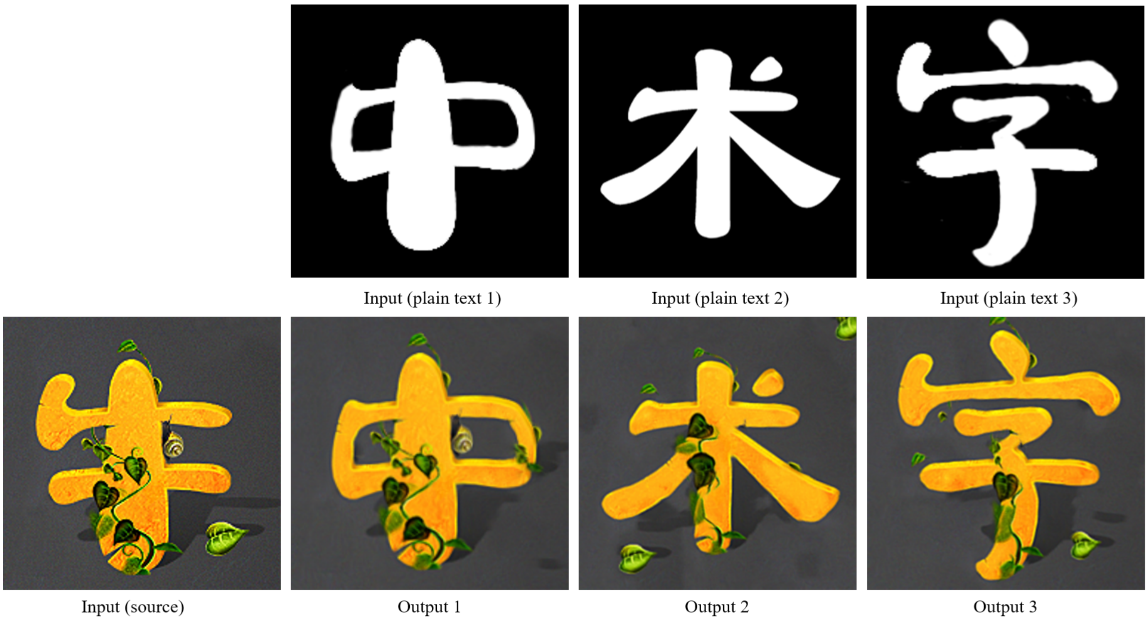


Figure 10. Results of generating complex text with salient structure. Image courtesy of Zcool [1].

1.4. Texture Swap

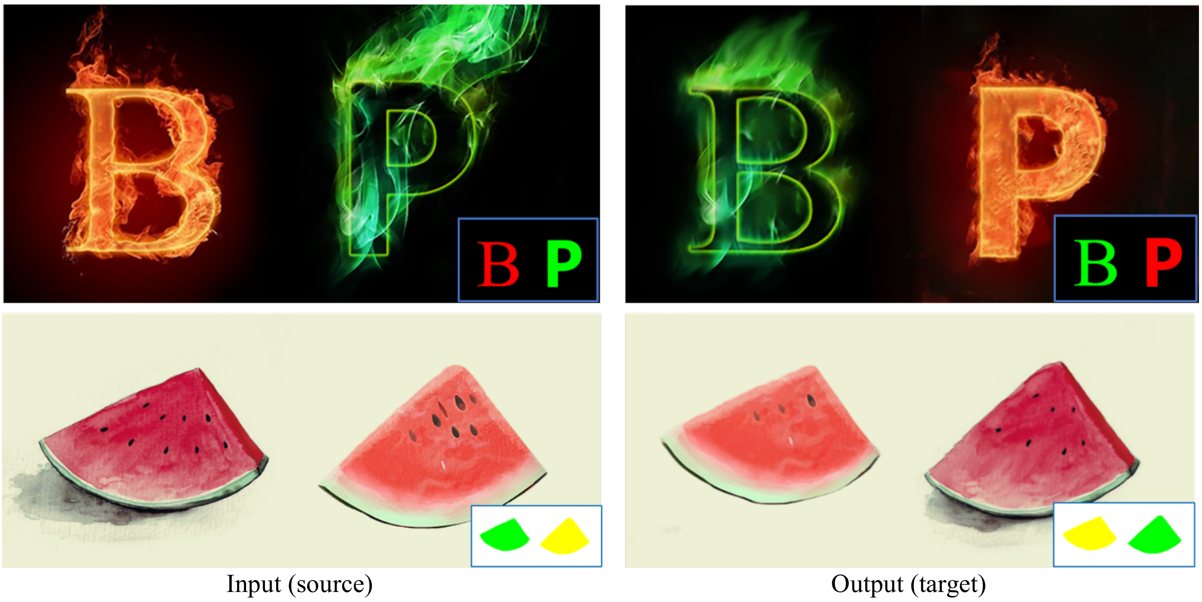


Figure 11. Texture swap results. Image courtesy of Yang *et al.* [8] and Zcool [1].

2. Comparisons with State-of-the-Art Methods

Here we compare our algorithm with state-of-the-art interactive texture transfer methods in different scenarios. We apply synthesis constraint without structure restrain to original optimized-based method [6, 7] to build our baseline. our approach is capable of synthesizing higher-quality content-specific stylization with well-preserved structures.

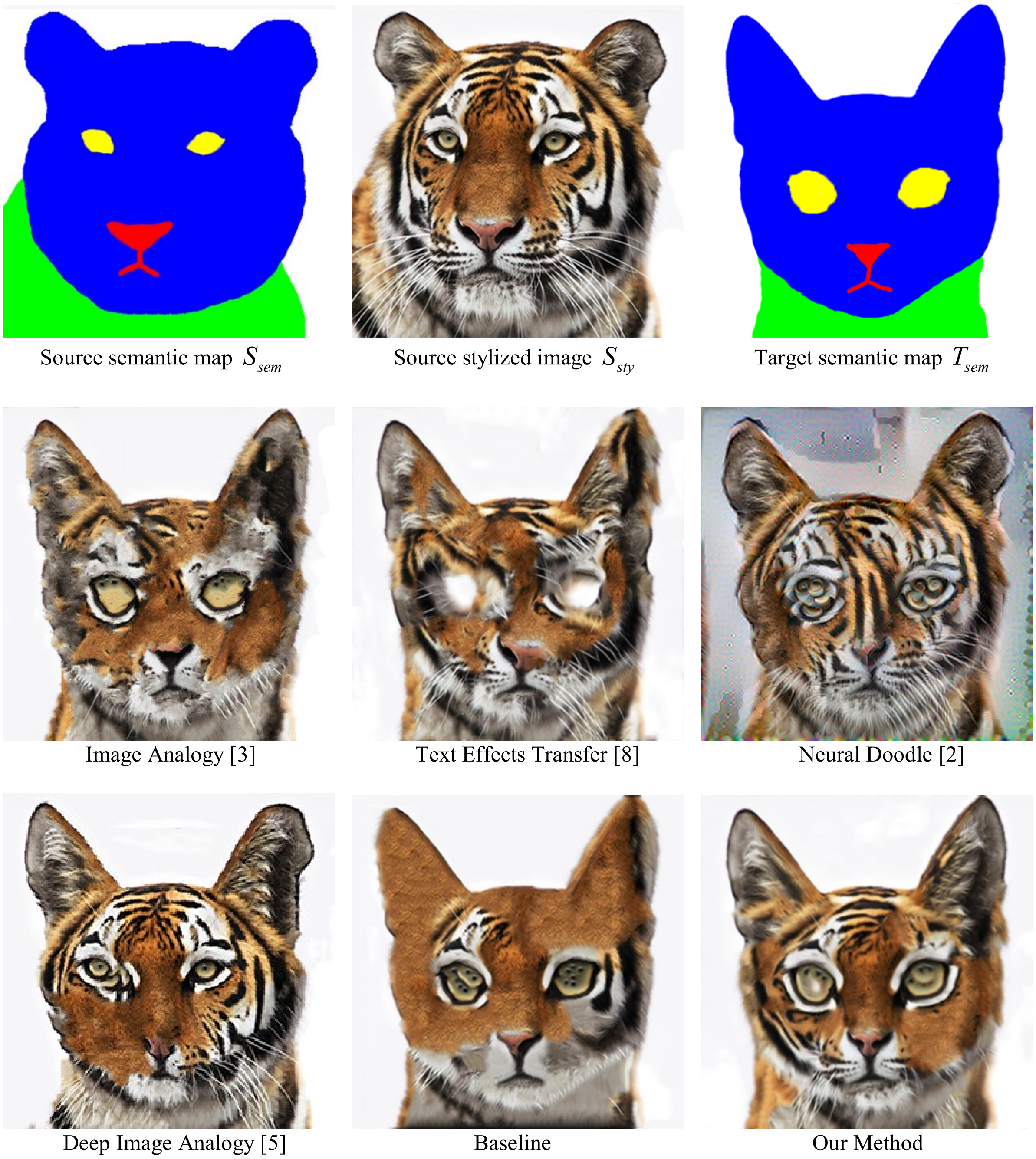


Figure 12. Comparison with state-of-the-art methods on the doodles-to-artworks task.

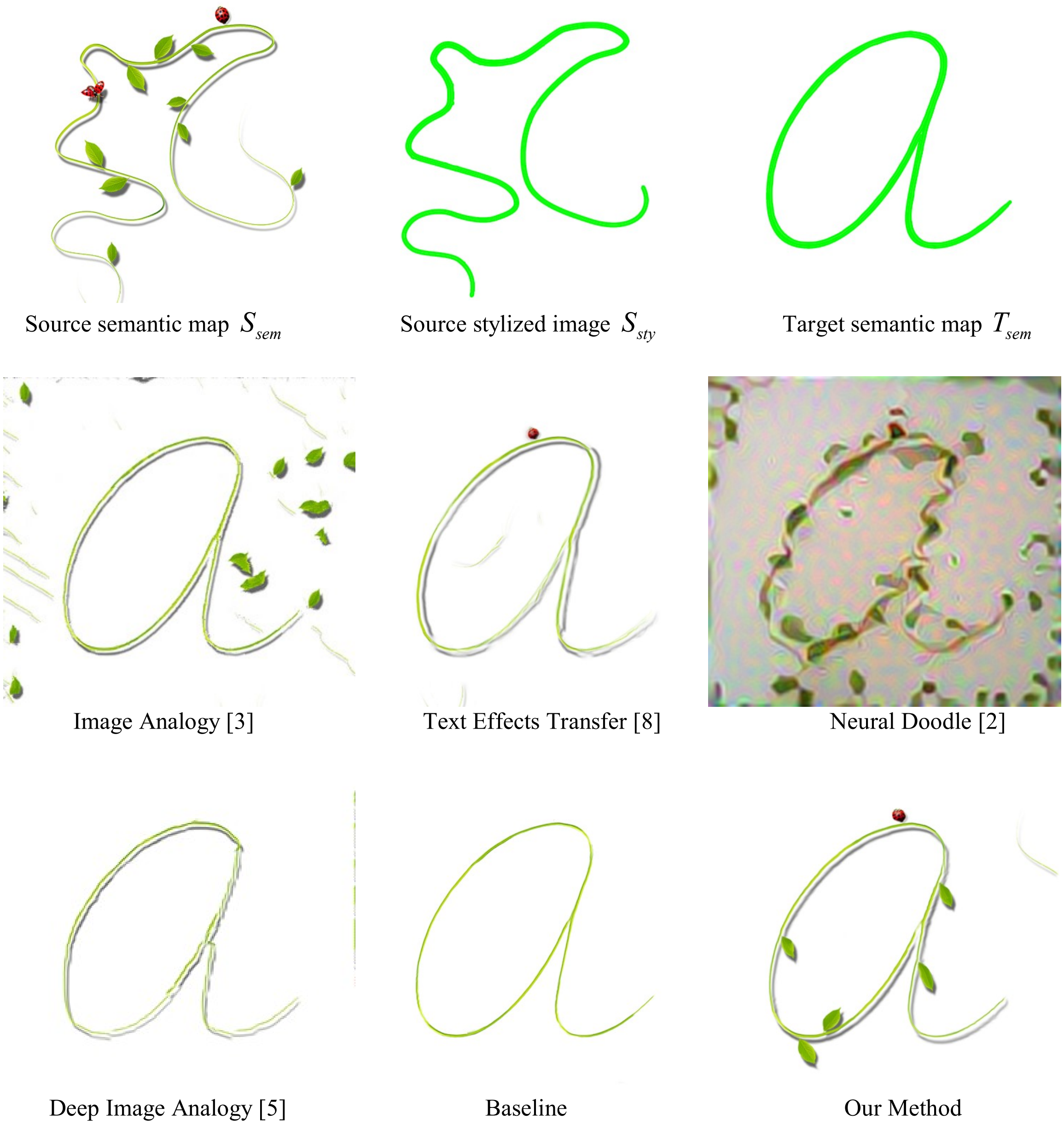


Figure 13. Comparison with state-of-the-art methods on the decorative pattern edit task.

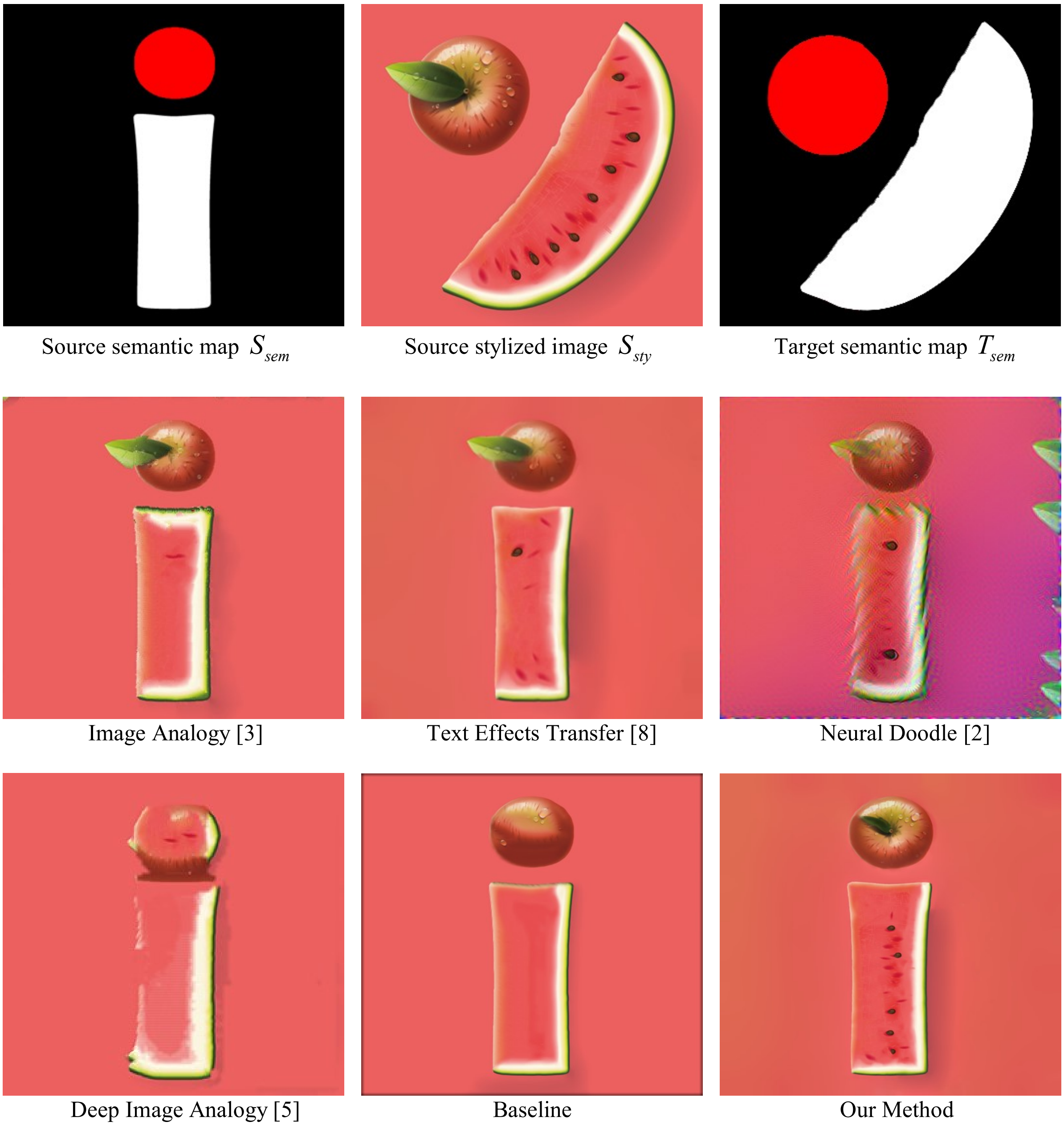


Figure 14. Comparison with state-of-the-art methods on the special effect text generation task.

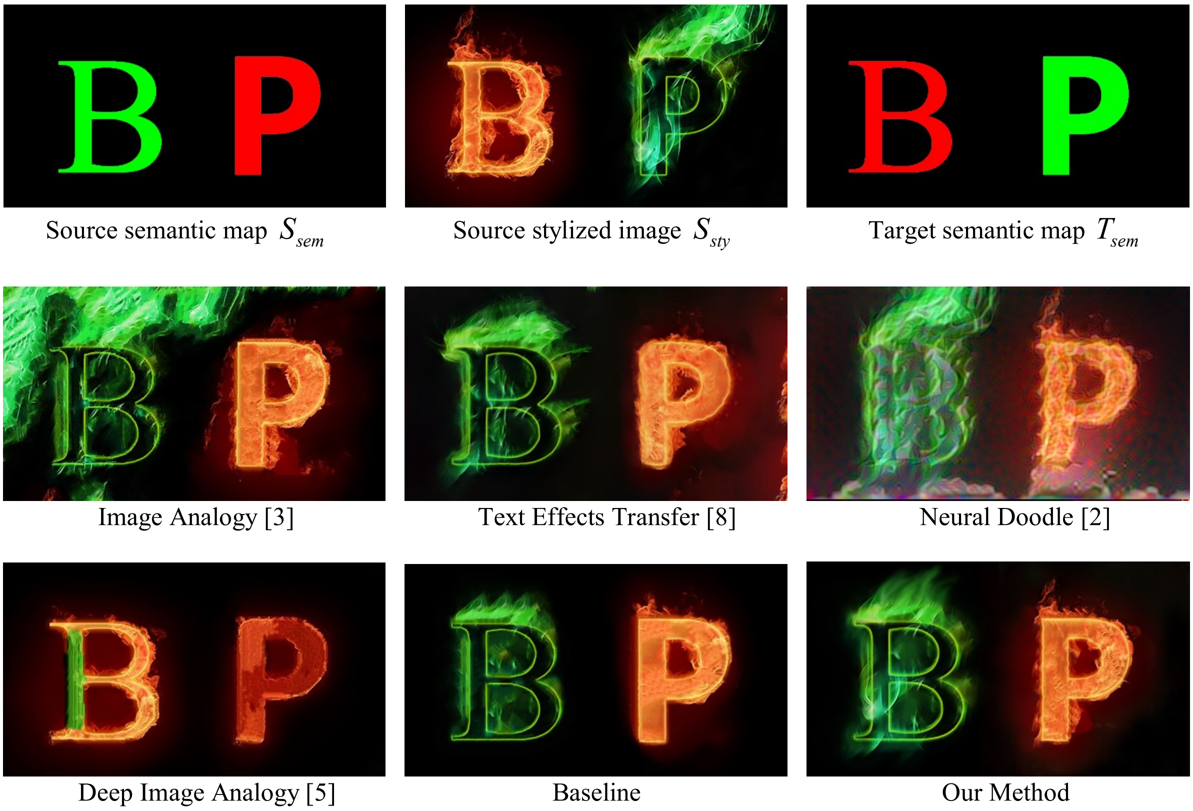
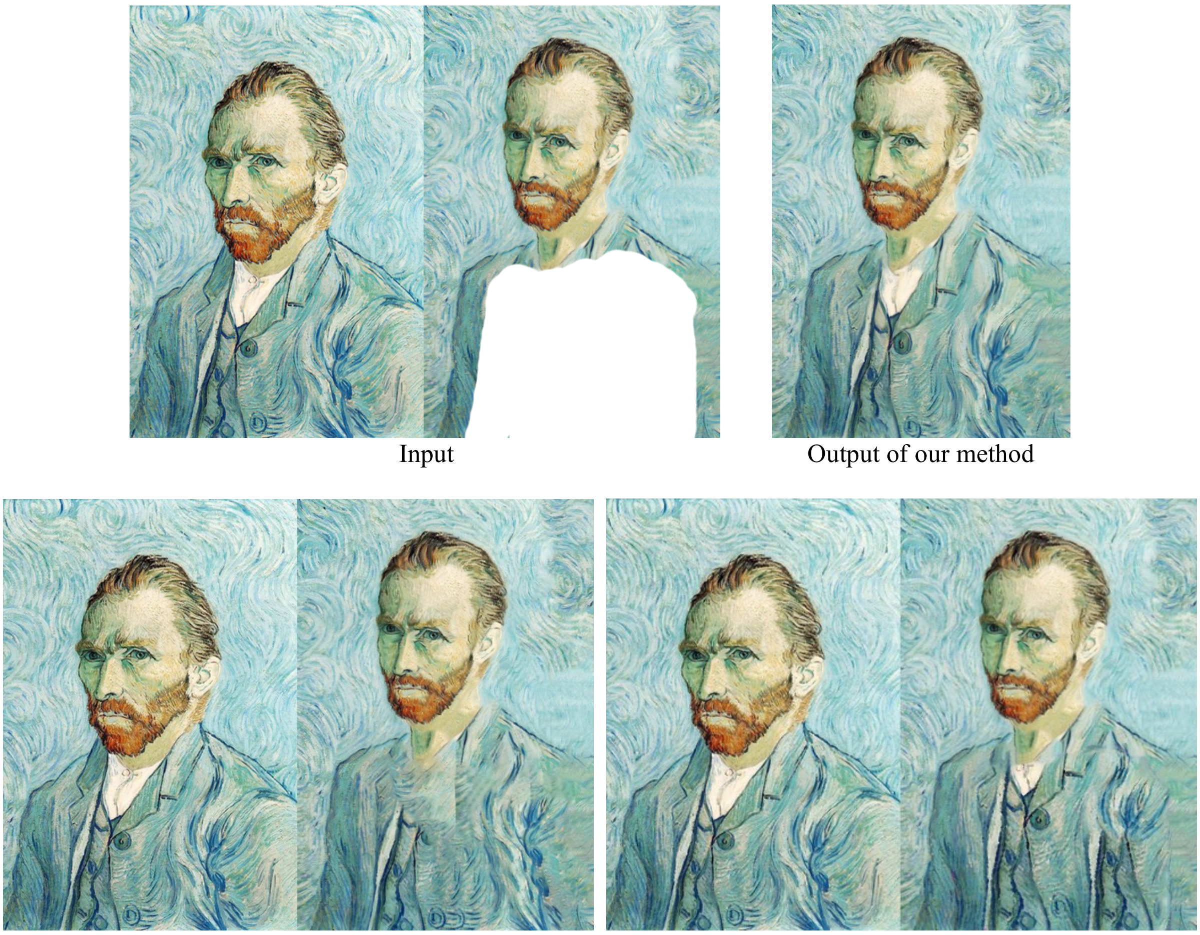


Figure 15. Comparison with state-of-the-art methods on the texture swap task.

3. Results with Image Completion Methods

Our idea is inspired by image completion problem. Semantic map provides more information for boundary patches, after those are correctly synthesized, this interactive texture transfer problem could almost be degenerated into an image completion task with a large hole to be filled via boundary propagation. We have tried two state-of-the-art inpainting methods [4, 9] but our experimental results show that both of them fail to synthesize structural textures with such a large hole. They are prone to texture dislocation or fail to preserve local high-frequency structures without enough structural guidance.



Input

Output of our method

Output of [4]

Output of [9]

Figure 16. Results with state-of-the-art image completion methods.

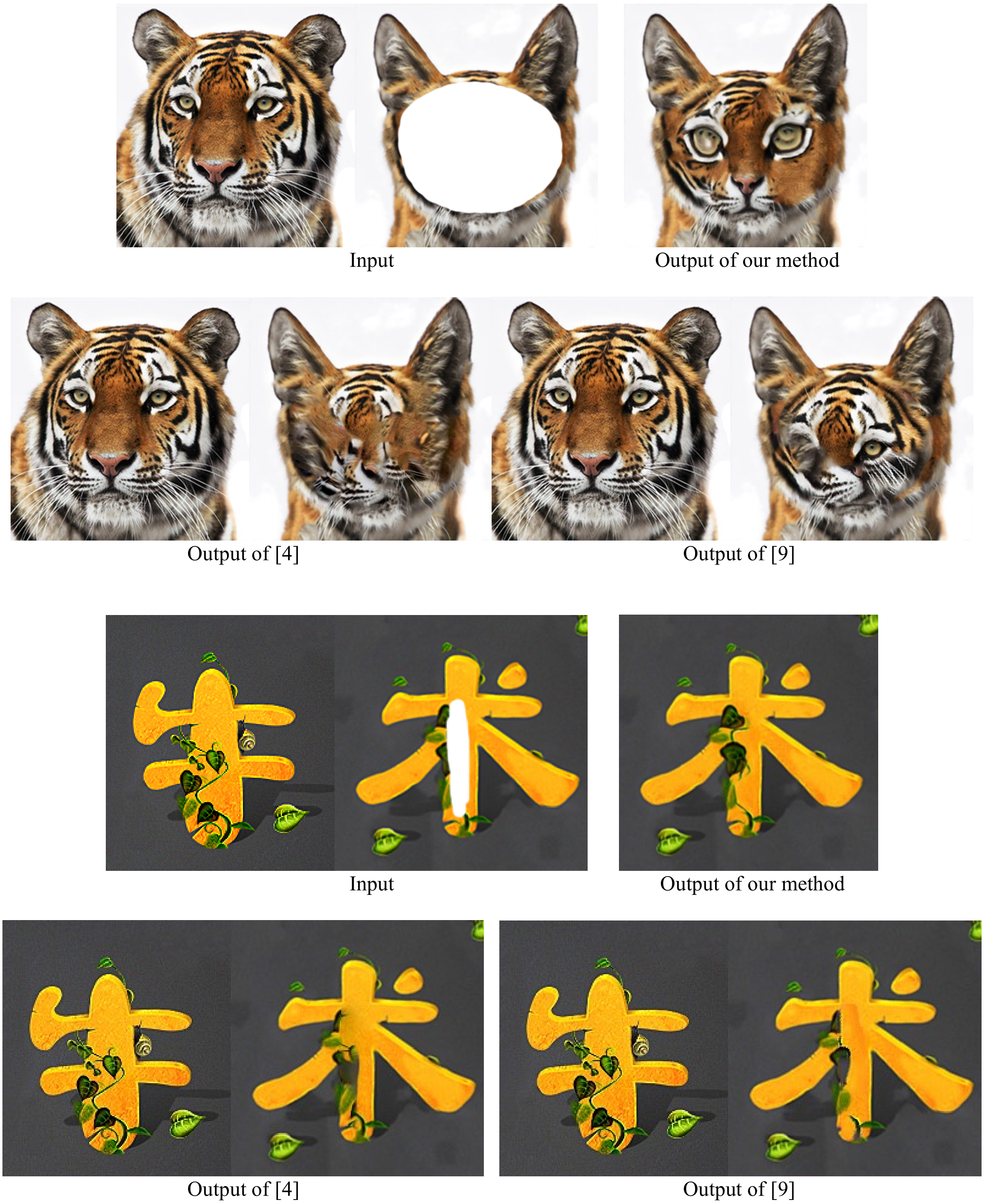
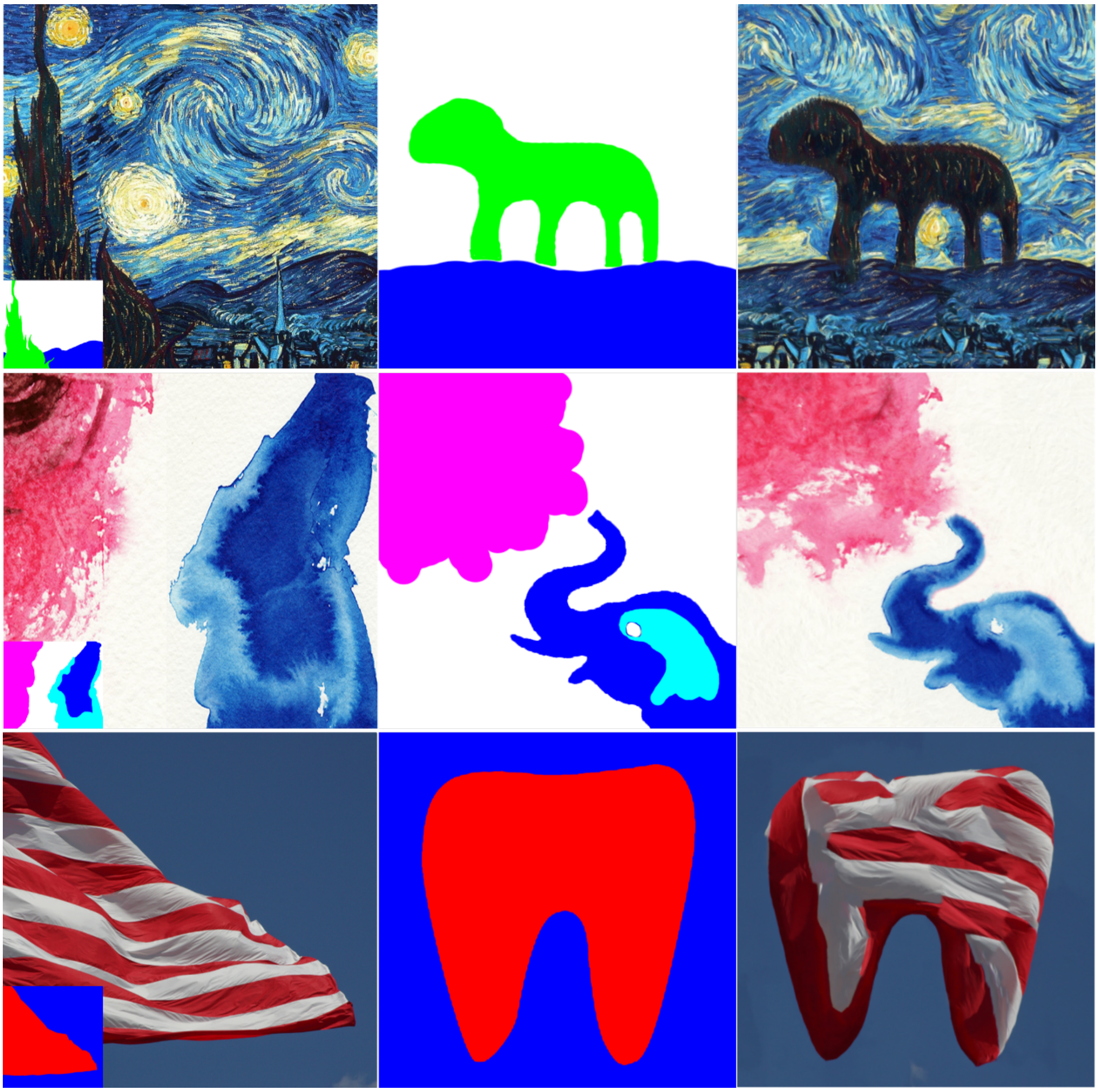


Figure 17. Results with state-of-the-art image completion methods.

4. Results with drastically different semantic inputs.

Our method can also handle images with drastically different semantic inputs. But it is hard for people to tell where the internal structure to generate in target is reasonable, if salient structure in image and no similar with semantic inputs. The images with nearly-homogeneous textures can be better transferred of this part.



Input (source) Input (semantics) Output (target)

Figure 18. Results with drastically different semantic inputs. Image courtesy of Lukáč *et al.* [12].

5. Failure cases.

Input1 Output1 Input2 Output2

Figure 19. Failure cases due to the illumination in the background of real image. Image courtesy of Zcool [1].

Input1 Output1 Input2 Output2

Figure 20. Failure cases due to the fading color in the background of real image (example 1) and the disability to produce scale geometric transfer (example 2), like exaggerations of the face and the ears. Image courtesy of Zcool [1].

Bibliography

[1] Zcool. http://www.zcool.com.cn.

[2] A. J. Champandard. Semantic style transfer and turning two-bit doodles into fine artworks. arXiv preprint arX-iv:1603.01768, 201

[3] A. Hertzmann, C. E. Jacobs, N. Oliver, B. Curless, and D. H. Salesin. Image analogies. In Proceedings of the 28th annual conference on Computer graphics and interactive techniques, pages 327–340. ACM, 2001.

[4] J.-B. Huang, S. B. Kang, N. Ahuja, and J. Kopf. Image completion using planar structure guidance. ACM Transactions on Graphics (TOG), 33(4):129, 2014.

[5] J. Liao, Y. Yao, L. Yuan, G. Hua, and S. B. Kang. Visual attribute transfer through deep image analogy. arXiv preprint arXiv:1705.01088, 2017.

[6] Y. Wexler, E. Shechtman, and M. Irani. Space-time completion of video. IEEE Transactions on pattern analysis and machine intelligence, 29(3), 2007.

[7] C. Barnes, E. Shechtman, A. Finkelstein, and D. B. Goldman. Patchmatch: A randomized correspondence algorithm for structural image editing. ACM Trans. Graph., 28(3):241, 2009.

[8] S. Yang, J. Liu, Z. Lian, and Z. Guo. Awesome typography: Statistics-based text effects transfer. arXiv preprint arX-iv:1611.09026, 2016.

[9] S. Darabi, E. Shechtman, C. Barnes, D. B. Goldman, and P. Sen. Image melding: Combining inconsistent images using patch-based synthesis. ACM Trans. Graph., 31(4):82–1, 2012.

[10] J. Lu, C. Barnes, C. Wan, P. Asente, R. Mech, and A. Finkelstein. Decobrush: drawing structured decorative patterns by example. ACM Transactions on Graphics (TOG), 33(4):90, 2014.

[11] Envato. https://design.tutsplus.com/

[12] M. Lukáč, J. Fiser, J.-C. Bazin, O. Jamriska, A. Sorkine-Hornung, and D.Sykora. Painting by feature: texture boundaries for example-based image creation. ACM Transactions on Graphics (TOG), 32(4):116, 2013.