Image Matting with KL-Divergence Based Sparse Sampling
Supplementary Material

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1. Additional Results

In this supplementary material, we provide more comparisons between the proposed approach and other image matting methods. Figure 1-4 present the results of our method along with the best performing matting models in the benchmark dataset [9] for the test images *doll*, *troll*, *net*, and *elephant*, respectively. Moreover, in Figure 5-8, we show additional matting results obtained with our approach and the state-of-the-art CWCT sampling [12] and Comprehensive sampling [10] methods on the training set in the benchmark. For these results, we also report the corresponding mean square error (MSE) values for quantitative comparison. Similarly, in Figure 9-10, we compare the performances with scribble based sparse inputs. As can be seen, our approach produces better results than competing Knn Matting [1] and Nonlocal Matting [8] methods which both concentrate on sparse user inputs to compute alpha matte maps[1].

2. Runtime Performance

In our work, we used the ADMM-based serial implementation of the DS3 method, but it is indeed highly parallelizable (See pg.7 of [3]). Overall, the runtime performance of our current implementation is better than Comprehensive sampling (CS) as our algorithm selects much less and more representative samples from the known regions, which significantly reduces runtime costs of the subsequent steps. For example, for doll, donkey and elephant images, the average running times over all trimaps are 341 secs for our method, and 414 secs for CS, on a PC with an Intel Xeon 2GHz CPU.

References

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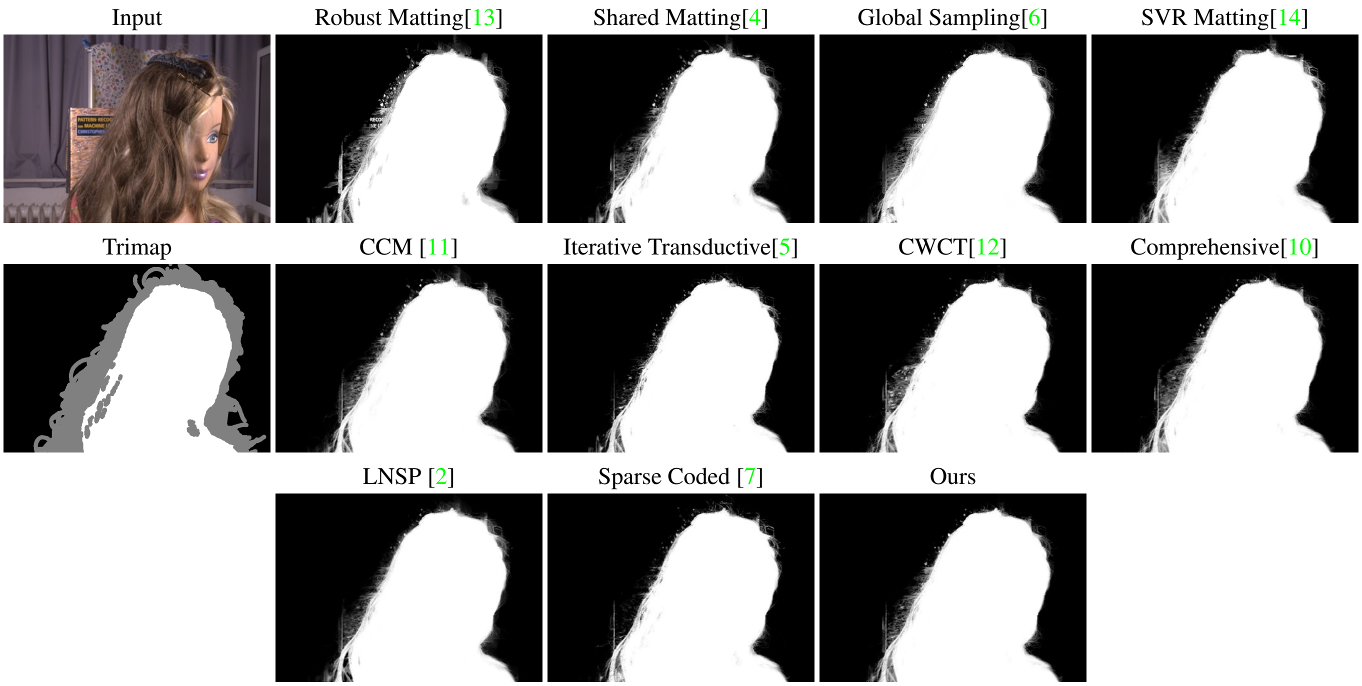

Figure 1. Alpha matting results for the test image *doll*.

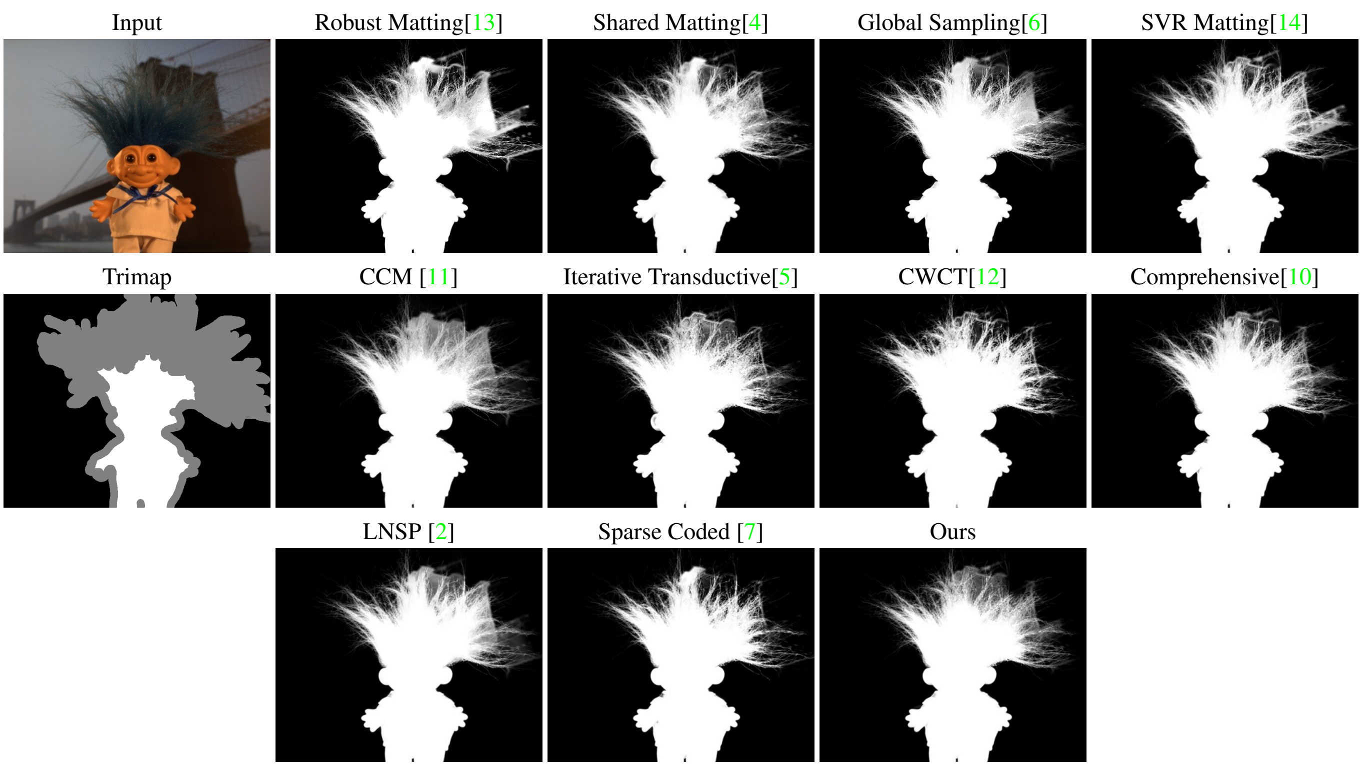

Figure 2. Alpha matting results for the test image *troll*.

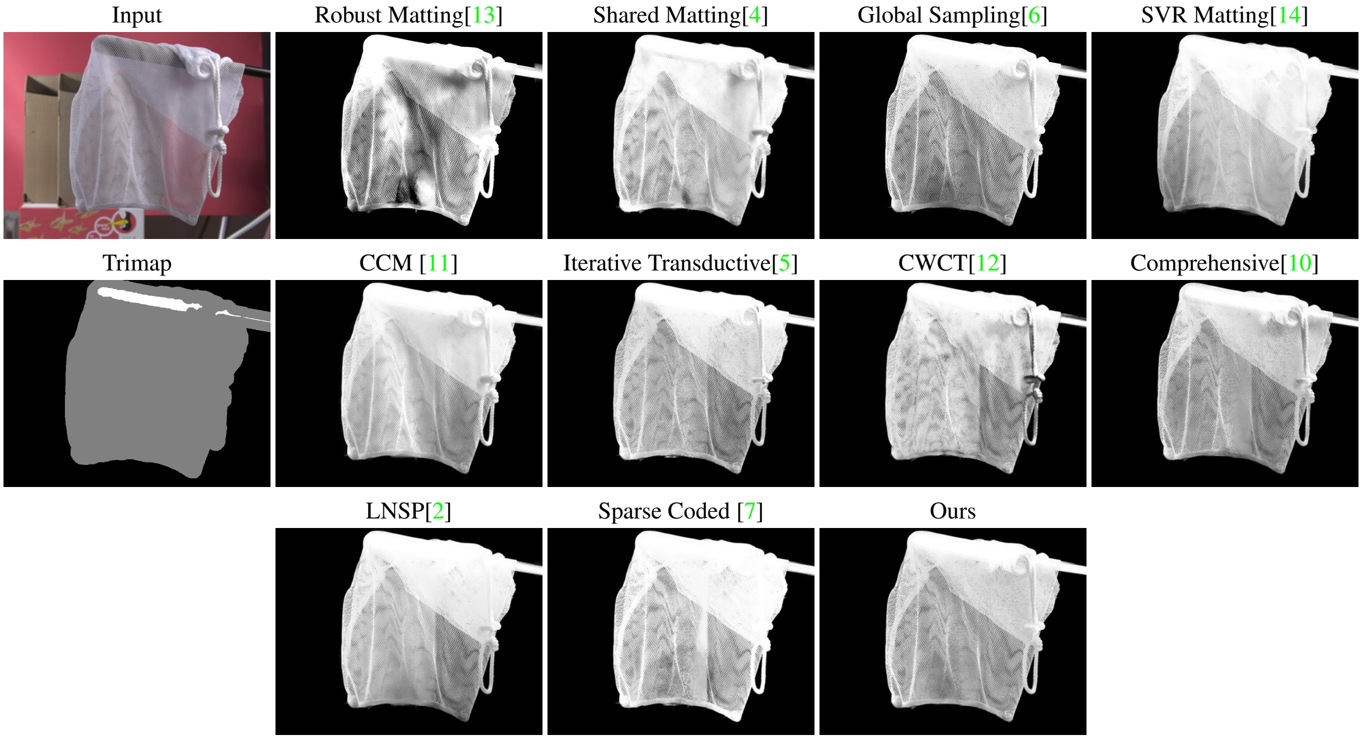

Figure 3. Alpha matting results for the test image *net*.

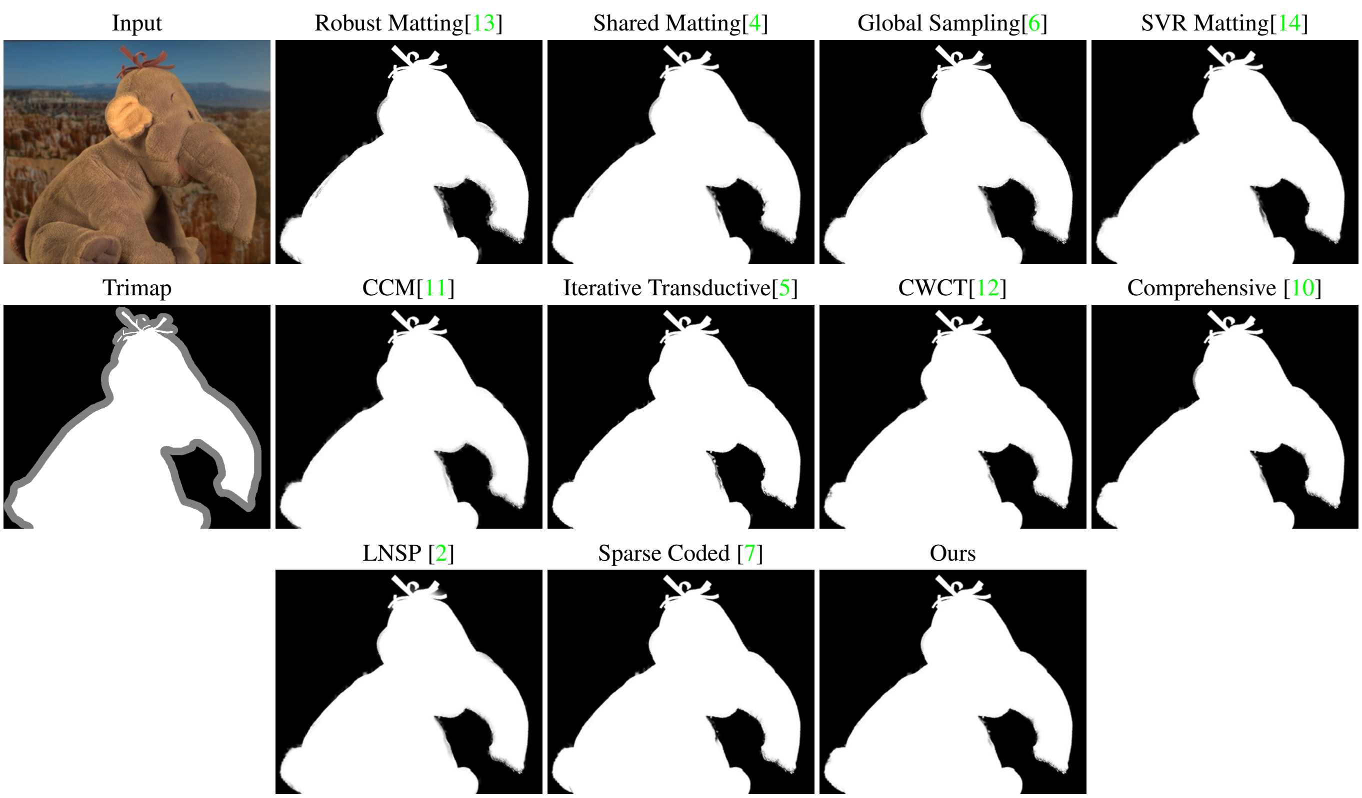

Figure 4. Alpha matting results for the test image *elephant*.

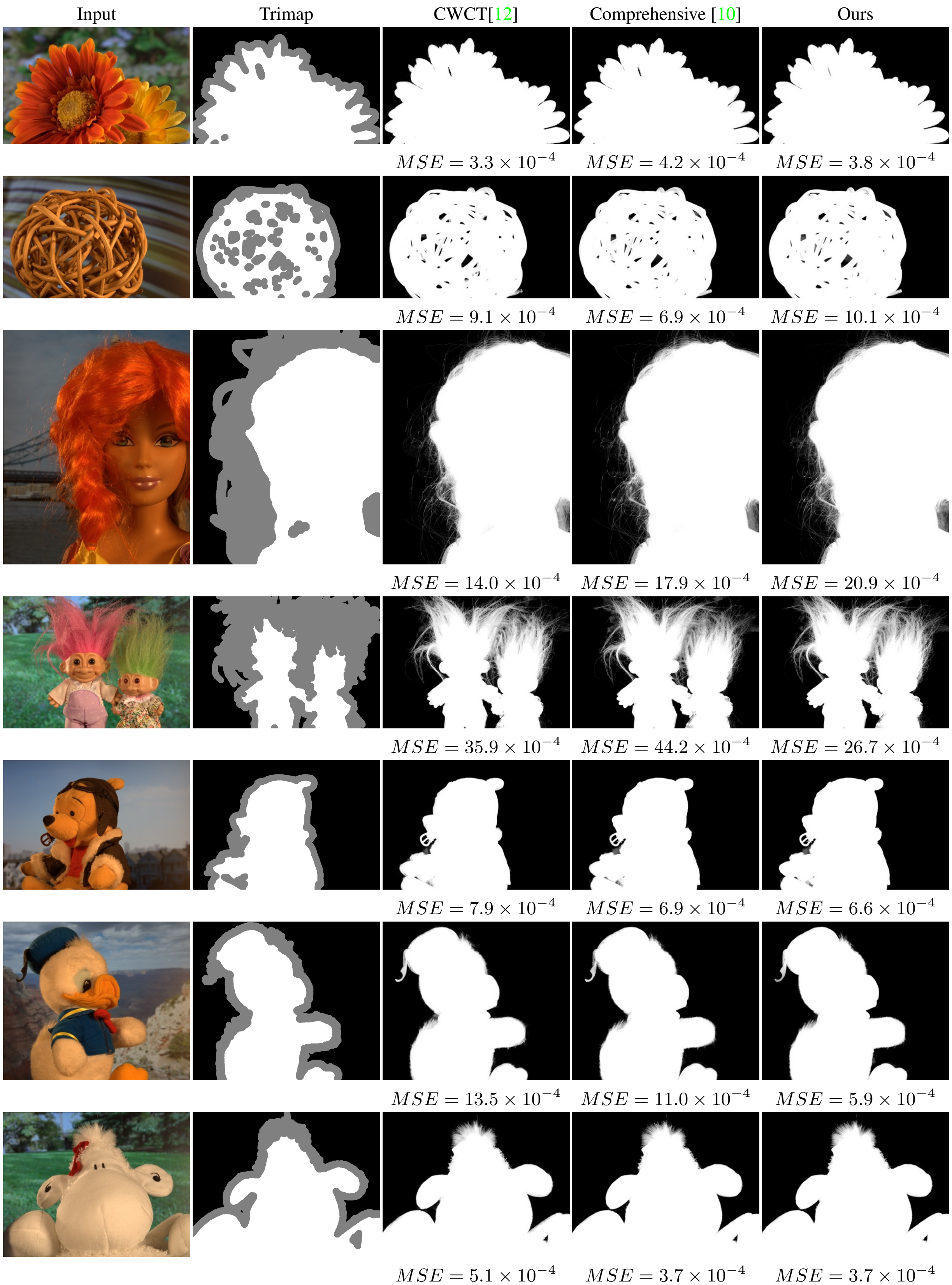

Figure 5. Alpha matting results for the training images(1-7).

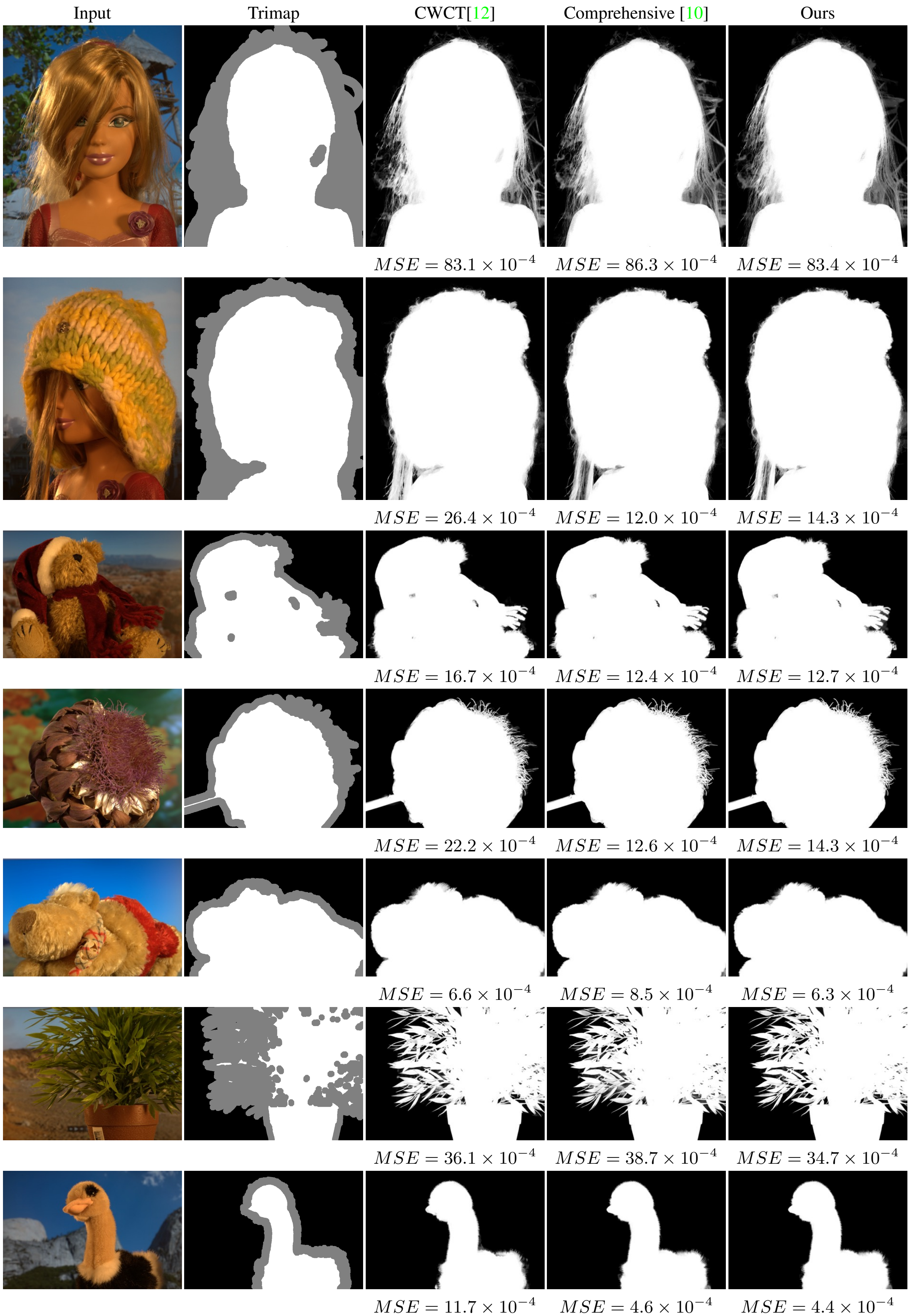

Figure 6. Alpha matting results for the training images(8-14).

Figure 7. Alpha matting results for the training images(15-21).

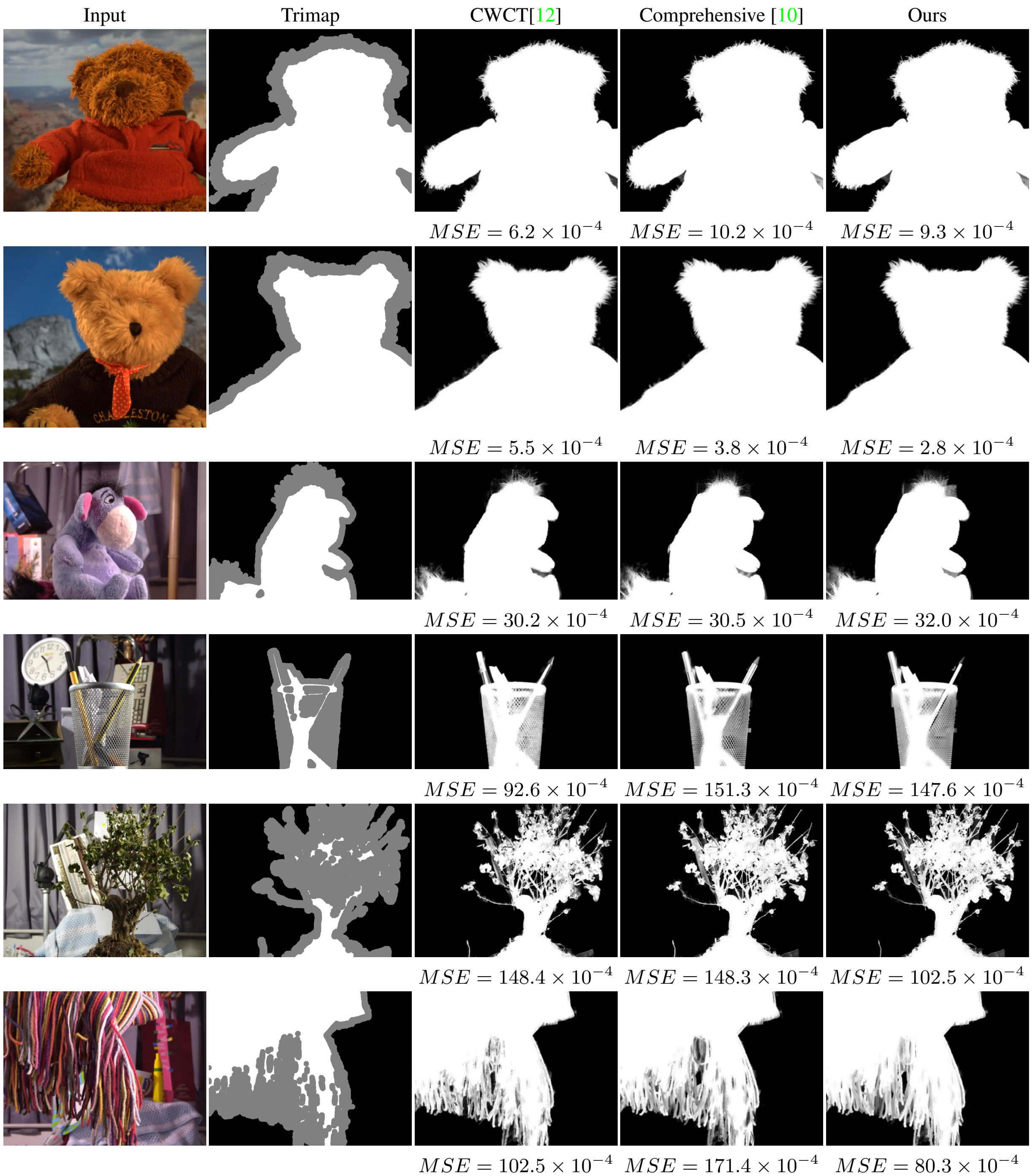

Figure 8. Alpha matting results for the training images(22-27).

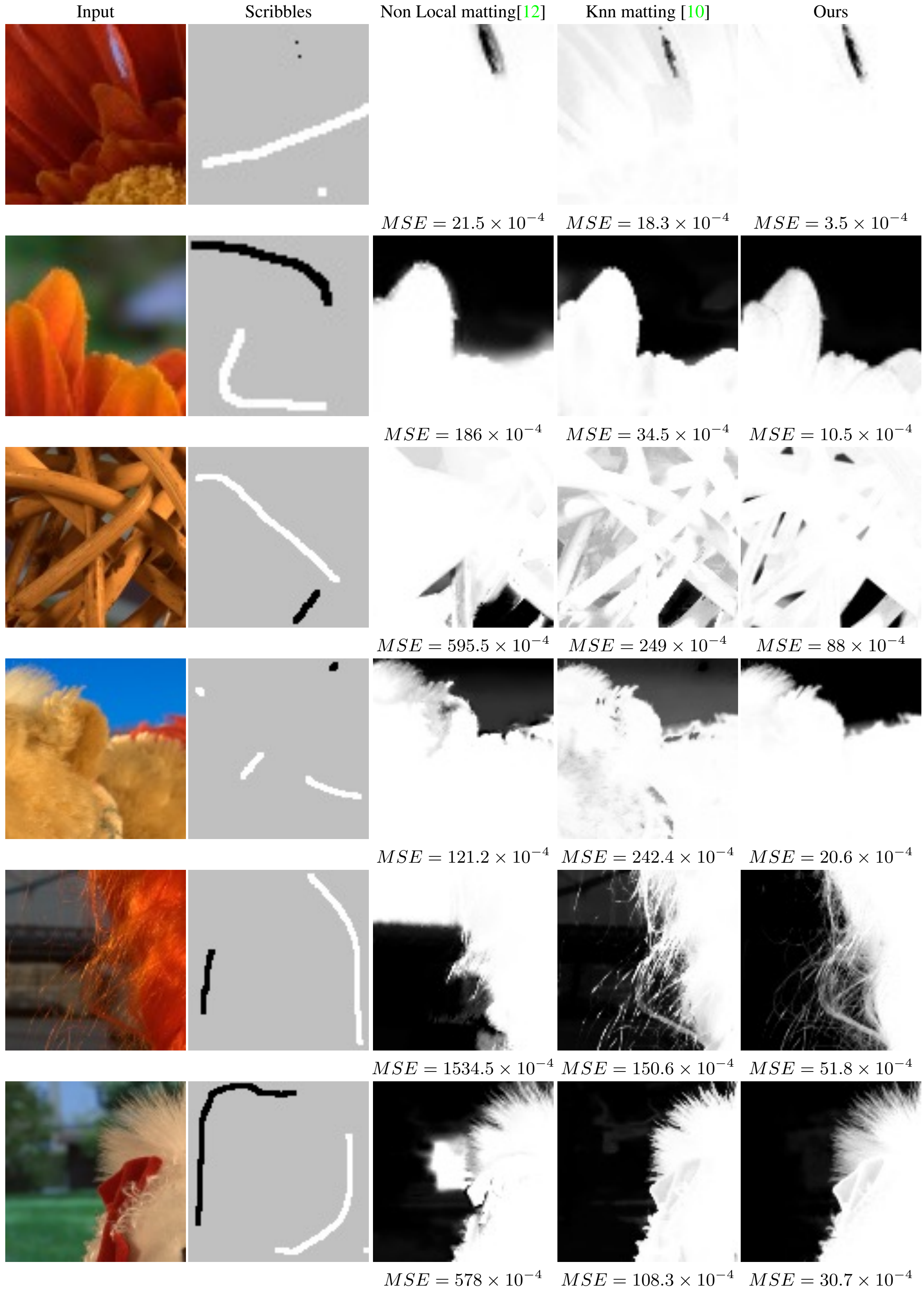

Figure 9. Alpha matting results for the training images with scribble based user inputs.

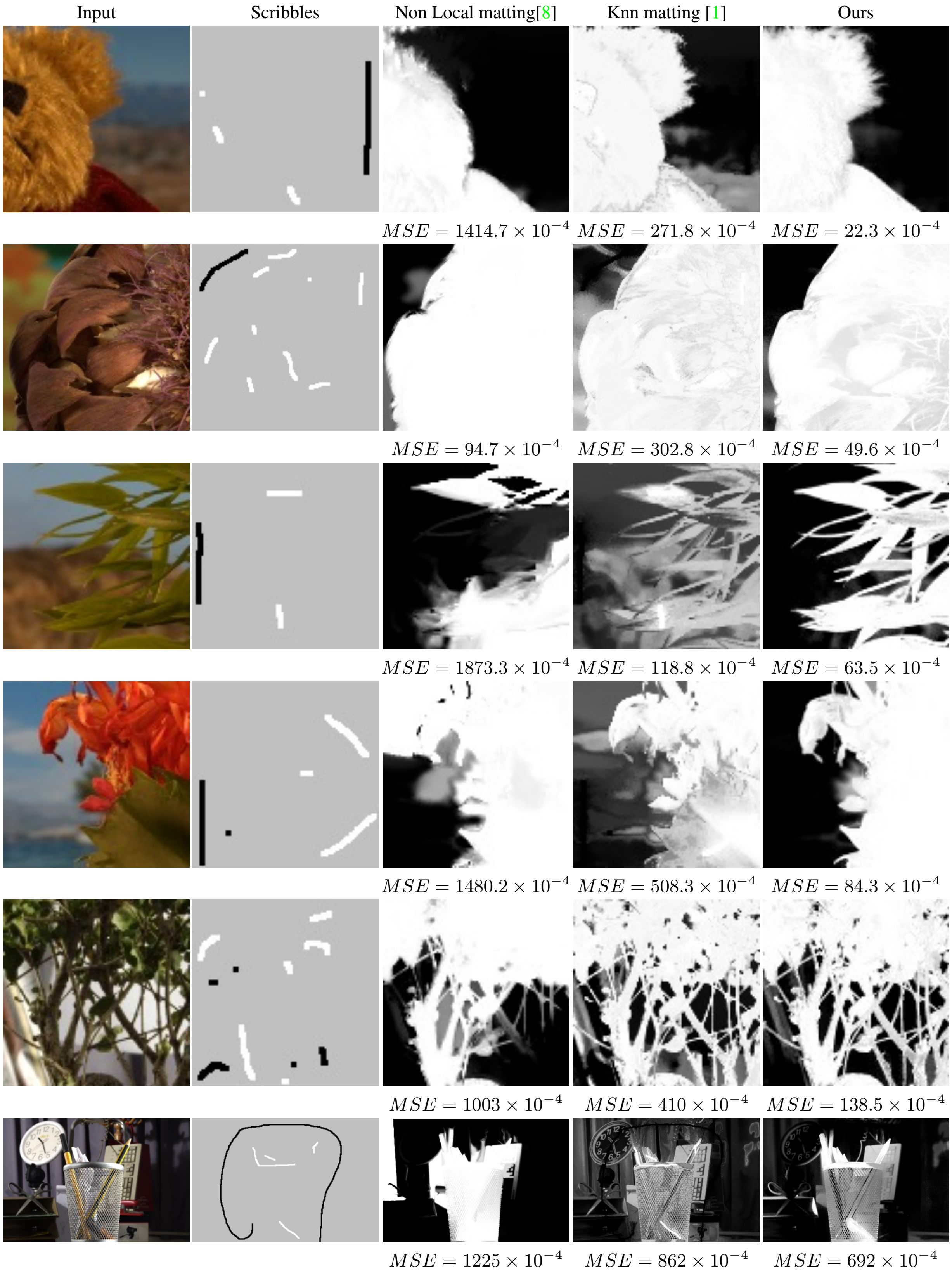

Figure 10. Alpha matting results for the training images with scribble based user inputs.