

A. Experiment: Variance of Brightness

As an additional experiment, we apply an artificial variation of brightness to the input and training images. By using extreme values, i.e., values that would generally even lie outside the valid range for images, we explore limitations of our approach.

Type of Variation. For brightness variation, we change the background color as well as the object brightness by random draws from a Gaussian distribution. Given standard deviation σ and image Img as well as silhouette Sil , we draw the varied image Img' as follows:

$$\text{Img}' \sim \text{Img} \cdot (1 + \text{Sil} \cdot \mathcal{N}(0, \sigma^2)) + |(1 - \text{Sil}) \cdot \mathcal{N}(0, \sigma^2)| \quad (7)$$

Note that, especially for larger σ , in most images the values actually exceed the range of values in the image ($[0, 1]$). We do *not* clip the values to $[0, 1]$.

Hyperparameters. In this experiment, we use 400 iterations for each style-transfer training to avoid instability due to the extreme variations and values in the data.

As shown in the plot in Fig. 8, for increasing variance of brightness, the accuracy drops, however, even for an extreme standard deviation of 4, the model still learns and does not break down entirely.

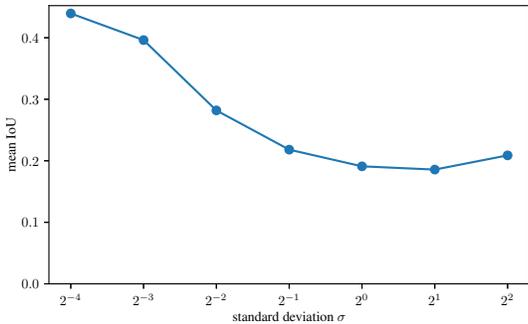


Figure 8: Mean IoU on the ShapeNet data set for varying degrees of variance applied to brightness.

B. Implementation Details

B.1. Image-to-Image Networks and Discriminator

Our basic building block performs convolution with filter size 4×4 and stride 2, followed by batch normalization and Leaky-ReLU with a slope parameter of $\alpha = 0.2$. We abbreviate this standard layer by $\text{C}k$, where k is the number of filters. The networks $F_{i \rightarrow r}$ and $F_{r \rightarrow i}$ are both symmetric residual networks, where the first half is defined by the chain of blocks $\text{C}64\text{-C}128\text{-C}256\text{-C}512\text{-C}512$. As final activation, we add a \tanh . The discriminator D consists of

the residual blocks $\text{C}64\text{-C}128\text{-C}256\text{-C}1$ followed by a logistic sigmoid activation.

B.2. 3D-Geometry Reconstruction Network

The architecture is based on convolutional layers ($\text{C}k$) with k filters of size 5×5 , a stride of 2, a padding of 2, and batch normalization. Further, it uses fully connected layers ($\text{F}k$), where k denotes the output dimension. The activation function for all layers except the last one is ReLU. With these definitions, the architecture can be written as $\text{C}64\text{-C}128\text{-C}256\text{-F}1024\text{-F}1024\text{-F}512\text{-F}1024\text{-F}2048\text{-F}1929$.

B.3. Ratio between Style and Content Loss

Table 4: Comparing ratios between the cycle-consistency content loss and the adversarial style loss.

Style loss	Cycle-consistency loss	IoU Acc.
1	100	0.2525
1	200	0.3458
1	400	0.3816
1	800	0.2925
1	1 600	0.2844

C. 3D Reconstruction Examples

In Fig. 9–10, we present further 3D mesh reconstruction examples.

D. Training of the Style-Transfer Examples

As in Fig. 6 of our work, we will show here the training process for 12 input images. Note that the first five rows display the first five training cycles while the *sixth row displays the tenth training cycle*. All other parameters are as in Fig. 6 of our work. Note that this covers only half of the entire training as we used 20 training cycles in our experiments.

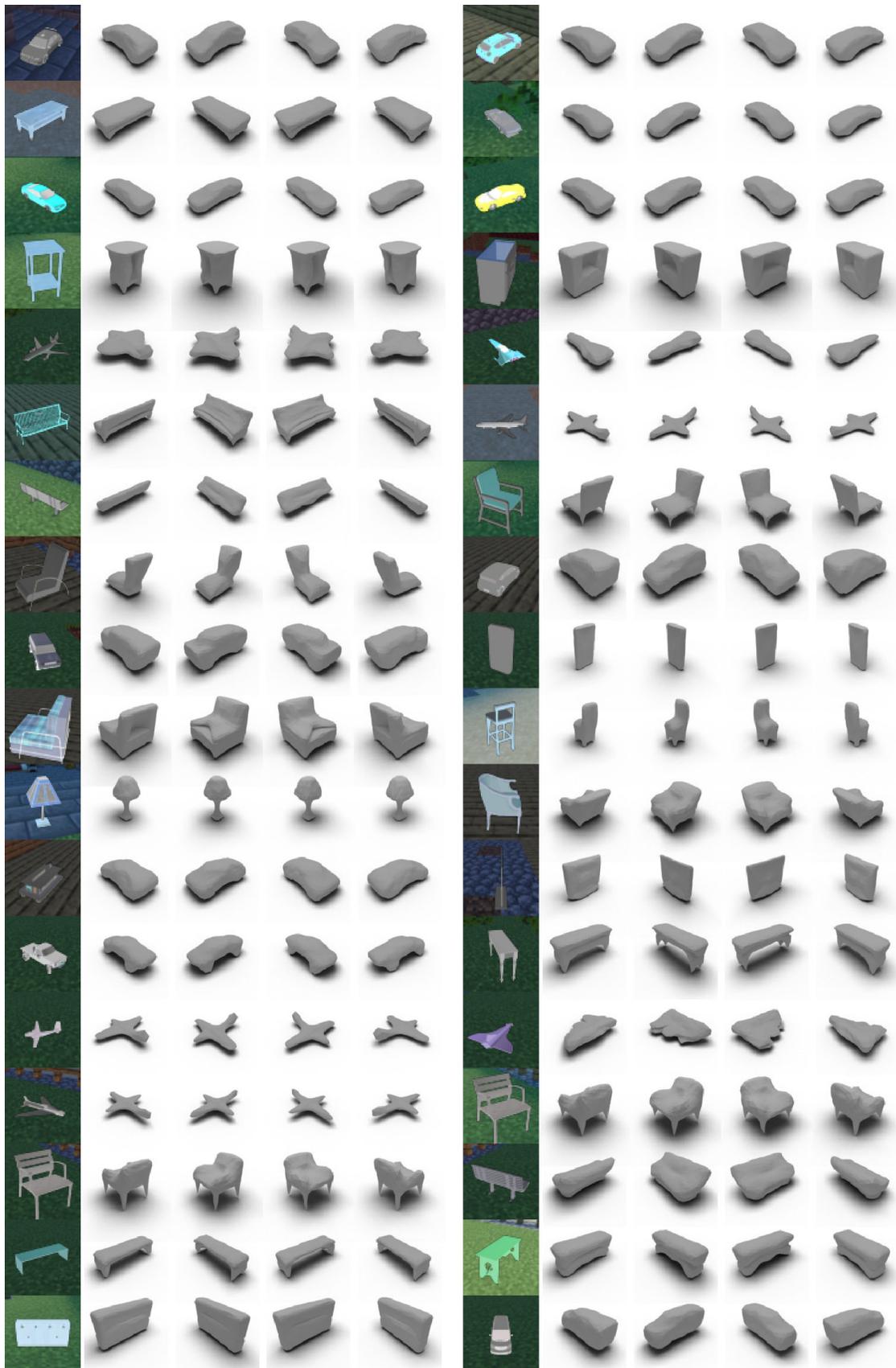


Figure 9: 3D Reconstruction Examples 1

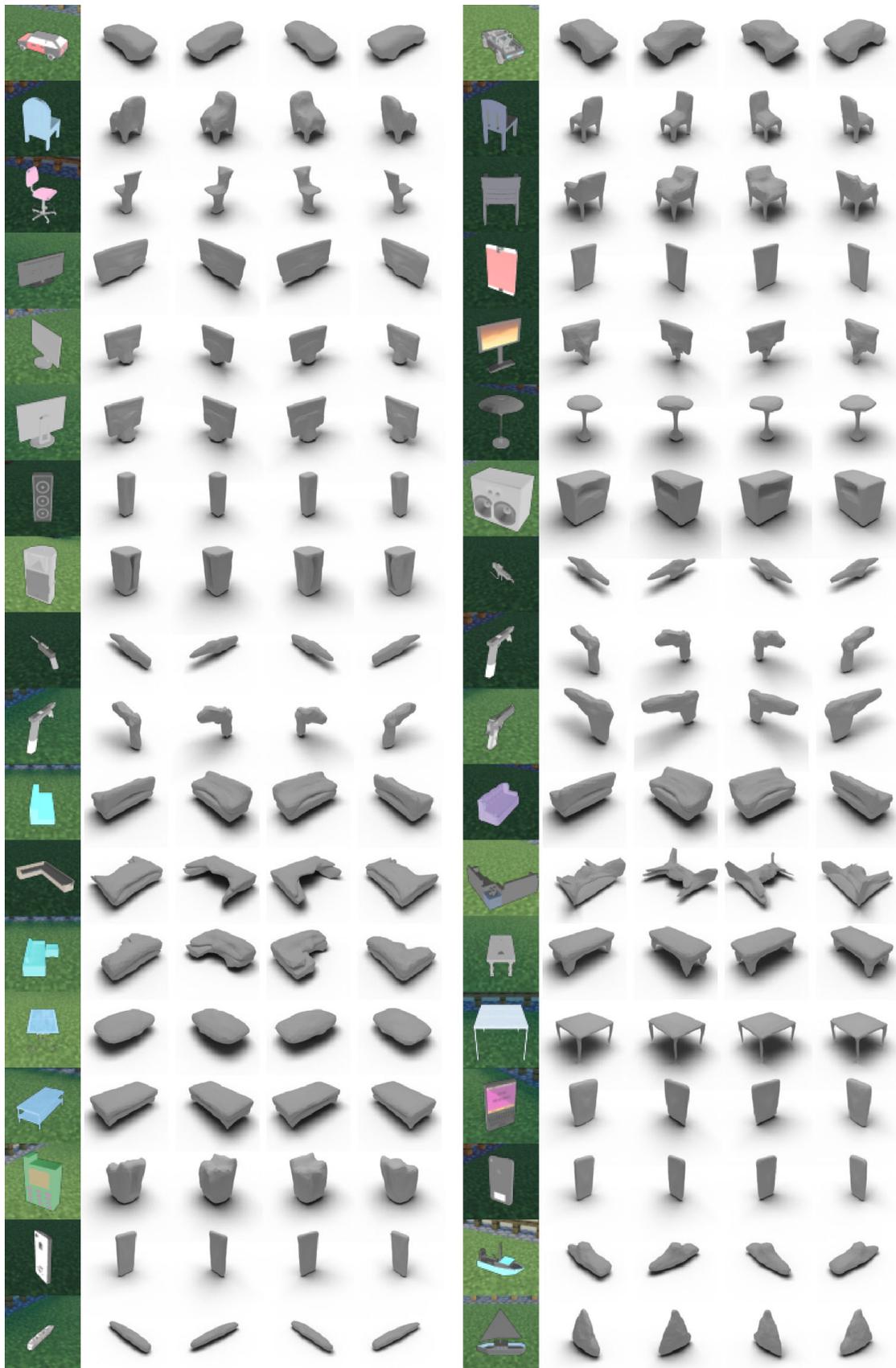


Figure 10: 3D Reconstruction Examples 2



Figure 11: Training of the Style-Transfer Example 1

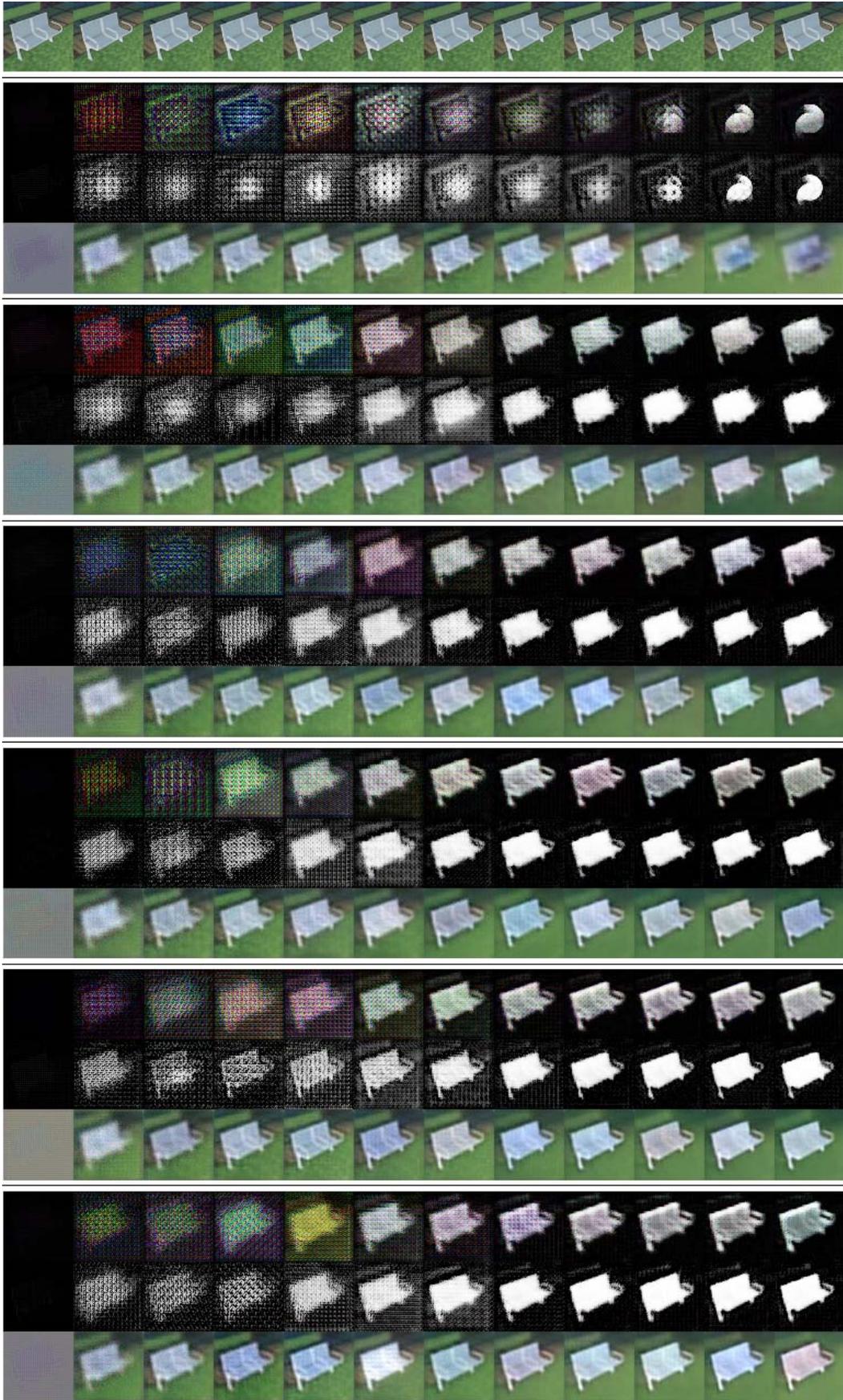


Figure 12: Training of the Style-Transfer Example 2

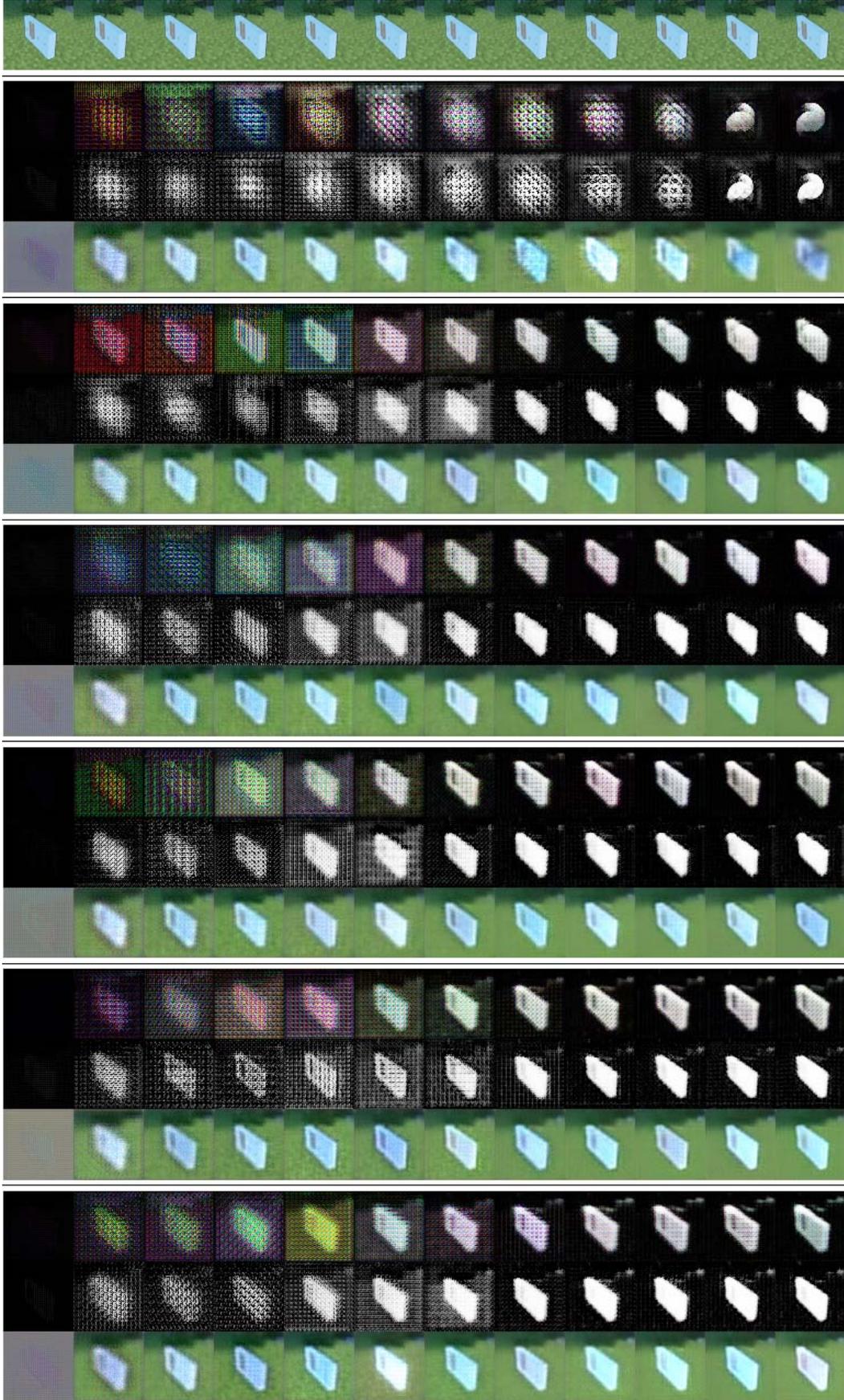


Figure 13: Training of the Style-Transfer Example 3



Figure 14: Training of the Style-Transfer Example 4

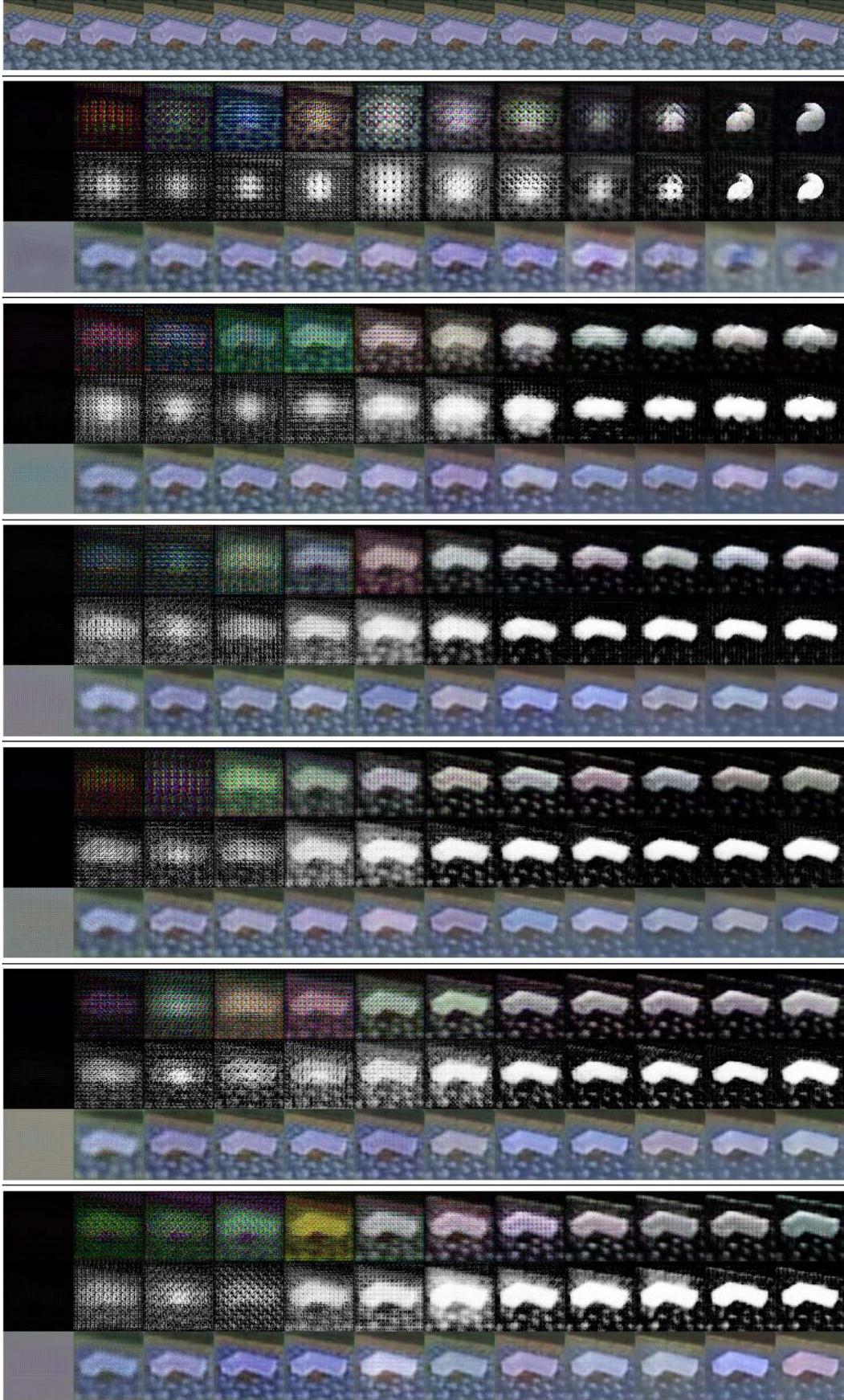


Figure 15: Training of the Style-Transfer Example 5

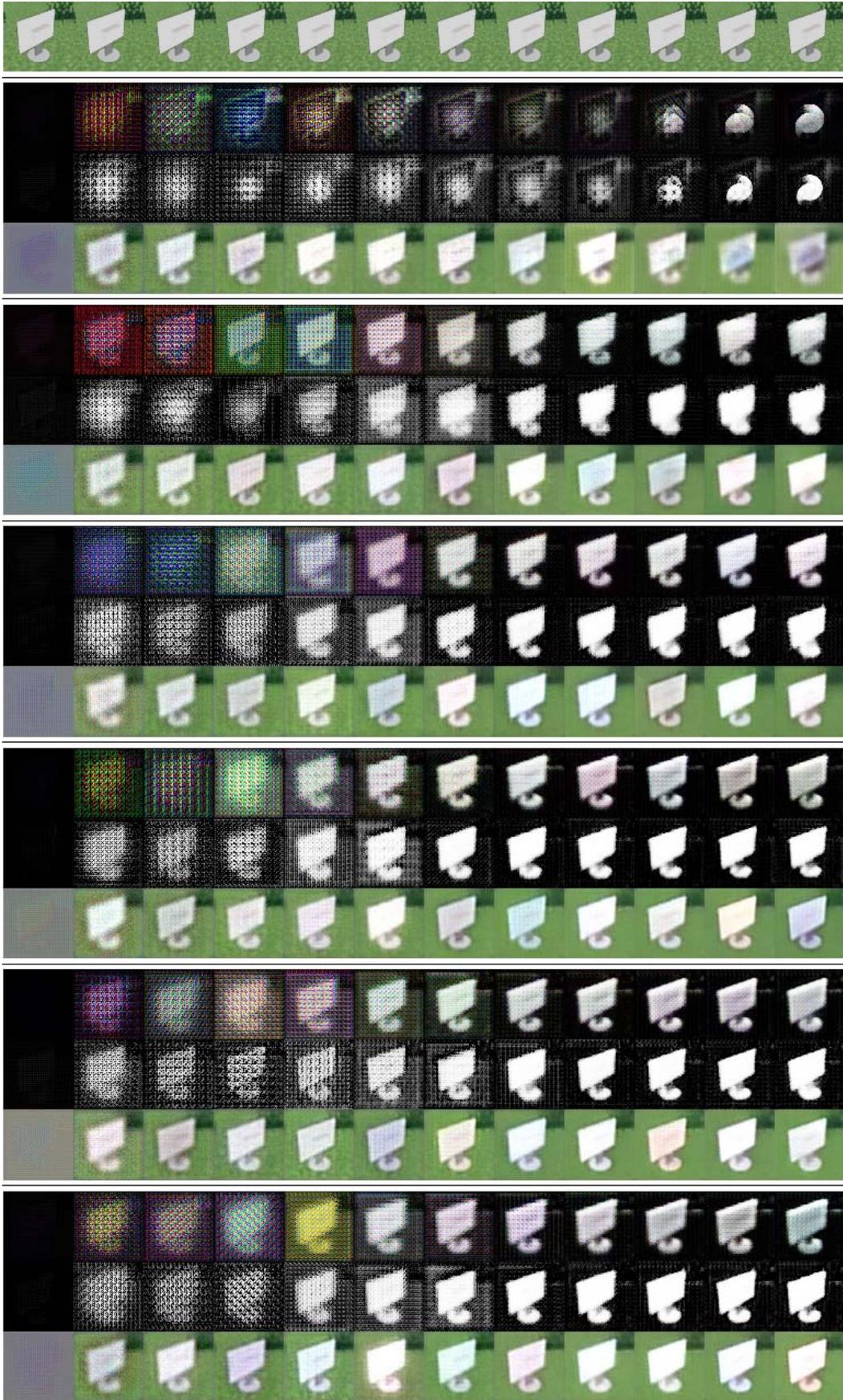


Figure 16: Training of the Style-Transfer Example 6



Figure 17: Training of the Style-Transfer Example 7

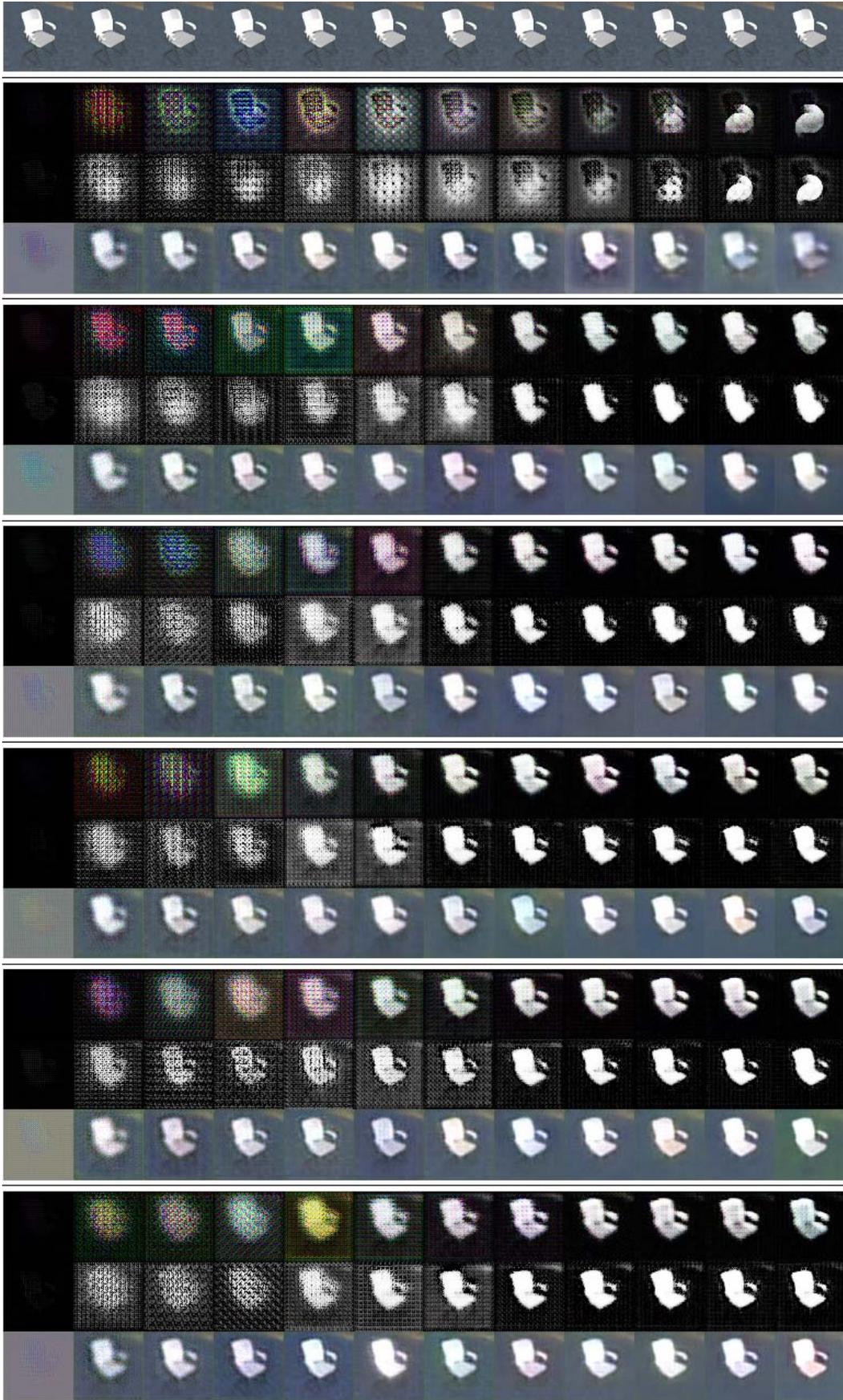


Figure 18: Training of the Style-Transfer Example 8

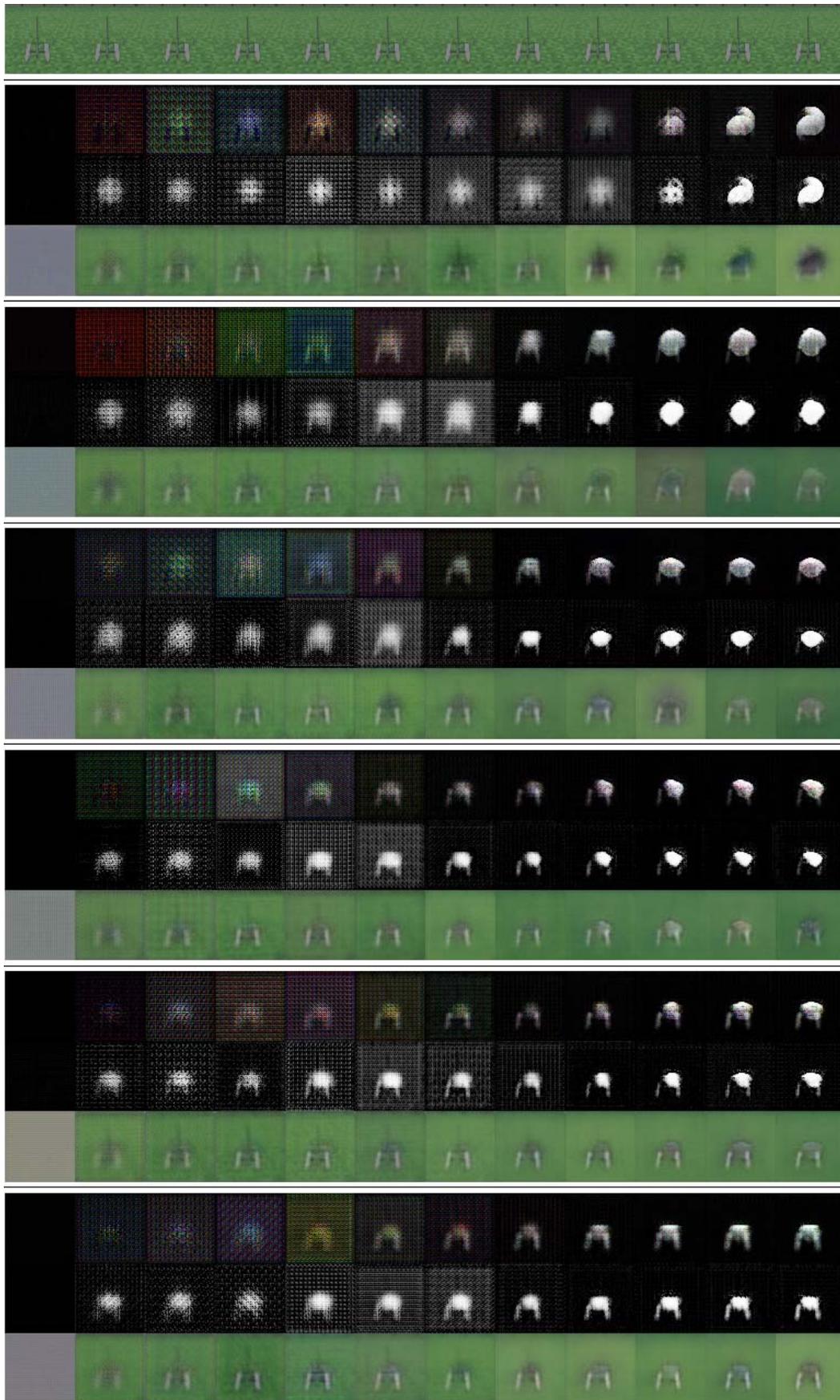


Figure 19: Training of the Style-Transfer Example 9

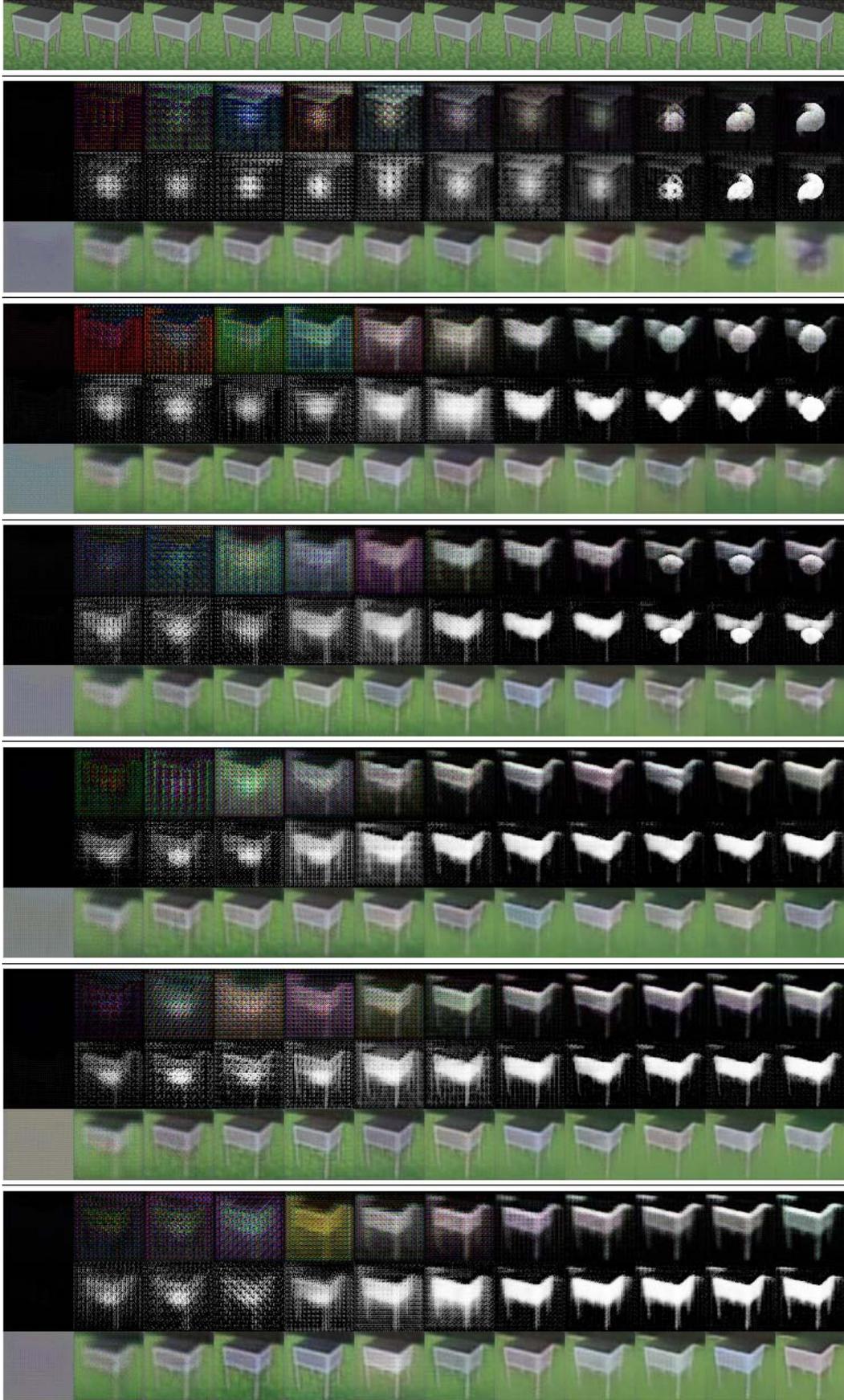


Figure 20: Training of the Style-Transfer Example 10



Figure 21: Training of the Style-Transfer Example 11

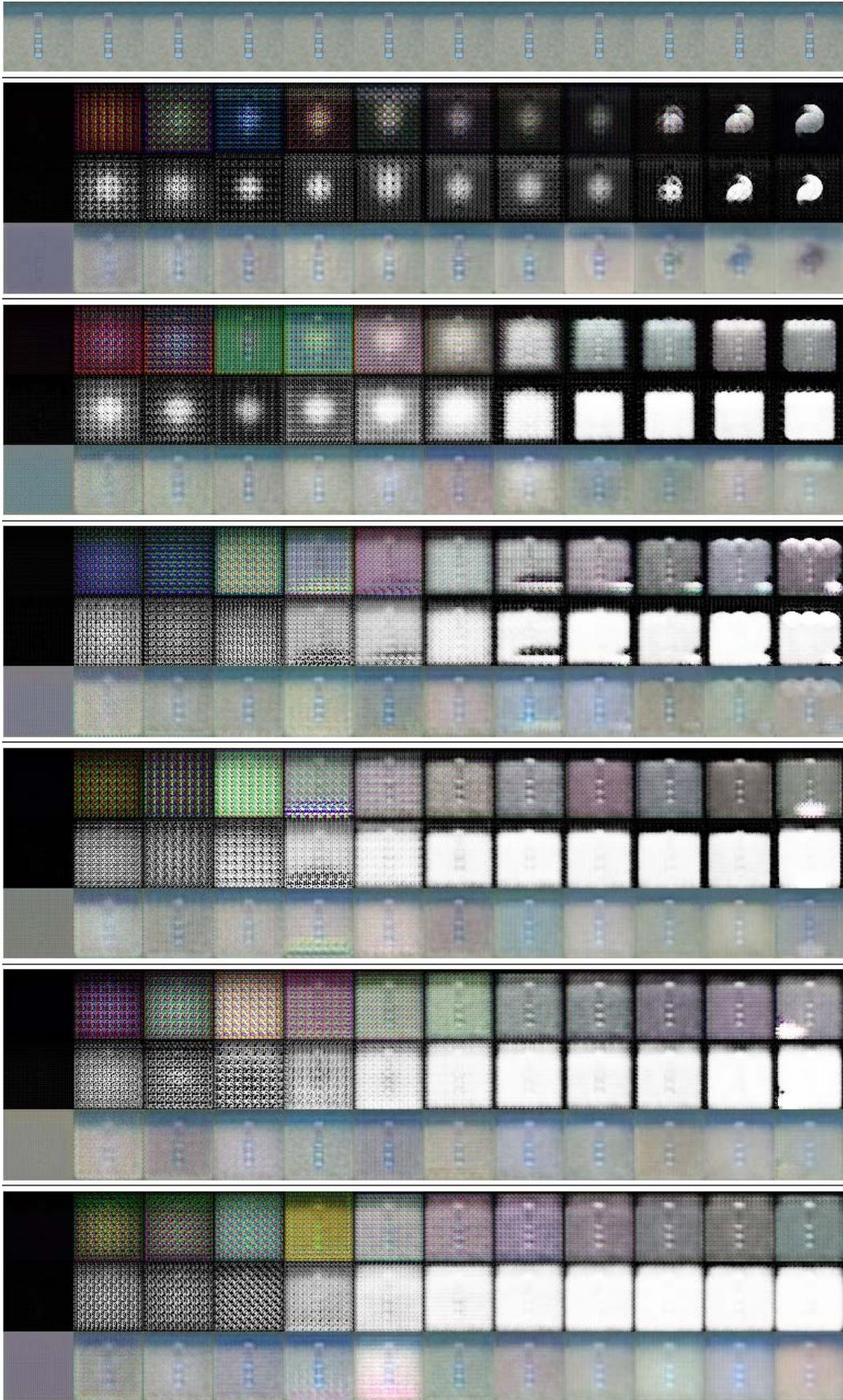


Figure 22: Training of the Style-Transfer Example 12