# Supplementary Materials for CVPR-2021 paper
# "Navigating the GAN Parameter Space for Semantic Image Editing"

## 1. Discovered visual effects

Figure 4, Figure 5, Figure 6, Figure 7 present more examples of visual effects achievable by navigating the StyleGAN2 parameter space. Additional examples for four datasets are provided in the GitHub repository[1] along with the PyTorch implementation of our method.

## 2. Dependence on the layer depth

Different generator layers were shown to capture different image properties [1]. Accordingly, navigating the parameter space of layers from different depths also discovers the effects of different types. For the LSUN-Horse dataset, Figure 7 visualizes the interpretable manipulations discovered at different depths, one manipulation per each StyleGAN2 layer. Notably, the earlier layers are generally responsible for global geometric transformations (size, leg length). Then, the intermediate layers typically result in more localized geometric manipulations (head size, thickness). They are followed by localized color manipulations (greens, white legs, background removal, shadows). The last layers correspond to global lighting effects (global lighting, horse reddening). Here we do not consider several final layers since they capture only trivial color-editing transformations. On other datasets, the distribution of typical effects over different layers is mostly the same.

## 3. Comparison of approaches

For a more quantitative comparison of the four approaches, we apply all of them to the fourth layer of the LSUN-Horse StyleGAN2 and manually annotate the controls discovered by each approach. For a fair comparison, each approach was set to discover $K$=64 directions. The result of the comparison is presented in Table 1. If different approaches reveal directions with the same semantic meaning, we underline the best of them, which corresponds to the most clear and disentangled effect. Overall, the hybrid scheme performs best, both in terms of the number of discovered effects and their visual quality.

## 4. Further experiments

Figure 1 demonstrates the FID values for different weights shift amplitudes. We also plot the FID values for one of the directions discovered with the GANSpace [4] approach in the latent space. The comparison of transformations induced by this latent shift and the weights shift is presented on Figure 2. Figure 3 demonstrates transformations induced by the weights shifts that are not reachable by $\mathcal{W}+$ shifts. As described in Section 4.3, we optimize these latent shifts to reproduce the weights shifts.

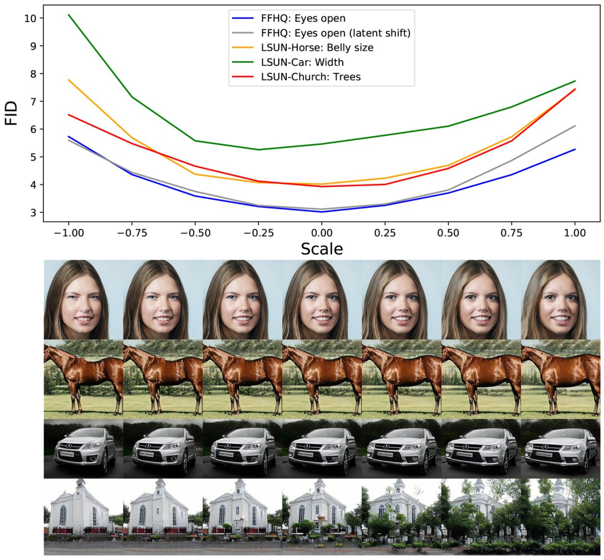



Figure 1. FID values for different weights shifts scales for some of the discovered directions. We also depict this plot for the "Opened eyes" direction discovered with the GANSpace in latent space.


Figure 2. Comparition of the "Opened eyes" direction discovered with our approach and the GANSpace method in $\mathcal{W}+$

## 5. Alternative GANs models

As the proposed approach is model-agnostic, here we present qualitative results for different generators. We always apply our technique to convolutional weights of a particular layer and use the same hyperparameters as for StyleGAN2. Here we present some of the discovered transformations for pix2pixHD [5] pretrained on

[1] https://github.com/yandex-research/navigan

| | |
|---|---|
| SVD | thickness |
| Optimization-based | thickness, rotation, legs distance |
| Spectrum-based | thickness, rotation, head size, body-head proportion, vertical shift |
| Hybrid | thickness, rotation, legs distance, body-head proportion, head rotation, belly size |

Table 1. Directions discovered by four methods by navigating the subspace of parameters for the fourth layer of LSUN-Horse StyleGAN2.

Cityscapes [3] and for BigGAN [2] pretrained on Imagenet. During training for pix2pixHD, we use the same input segmentation masks for the original image $G_\theta(\mathrm{mask})$ and the shifted one $G_{\theta+t\cdot\xi_k}(\mathrm{mask})$. For BigGAN, we pass samples pairs $G_\theta(z,c)$ and $G_{\theta+t\cdot\xi_k}(z,c)$ with the same class label $c$ picked uniformly from $\{1,\dots,1000\}$.

## References


[1] David Bau, Jun-Yan Zhu, Hendrik Strobelt, Bolei Zhou, Joshua B Tenenbaum, William T Freeman, and Antonio Torralba. Gan dissection: Visualizing and understanding generative adversarial networks. In *International Conference on Learning Representations*, 2019. 1

[2] Andrew Brock, Jeff Donahue, and Karen Simonyan. Large scale GAN training for high fidelity natural image synthesis. In *International Conference on Learning Representations*, 2019. 2

[3] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In *Proc. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. 2

[4] Erik Härkönen, Aaron Hertzmann, Jaakko Lehtinen, and Sylvain Paris. Ganspace: Discovering interpretable gan controls. *NeurIPS*, 2020. 1

[5] Ting-Chun Wang, Ming-Yu Liu, Jun-Yan Zhu, Andrew Tao, Jan Kautz, and Bryan Catanzaro. High-resolution image synthesis and semantic manipulation with conditional gans. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018. 1

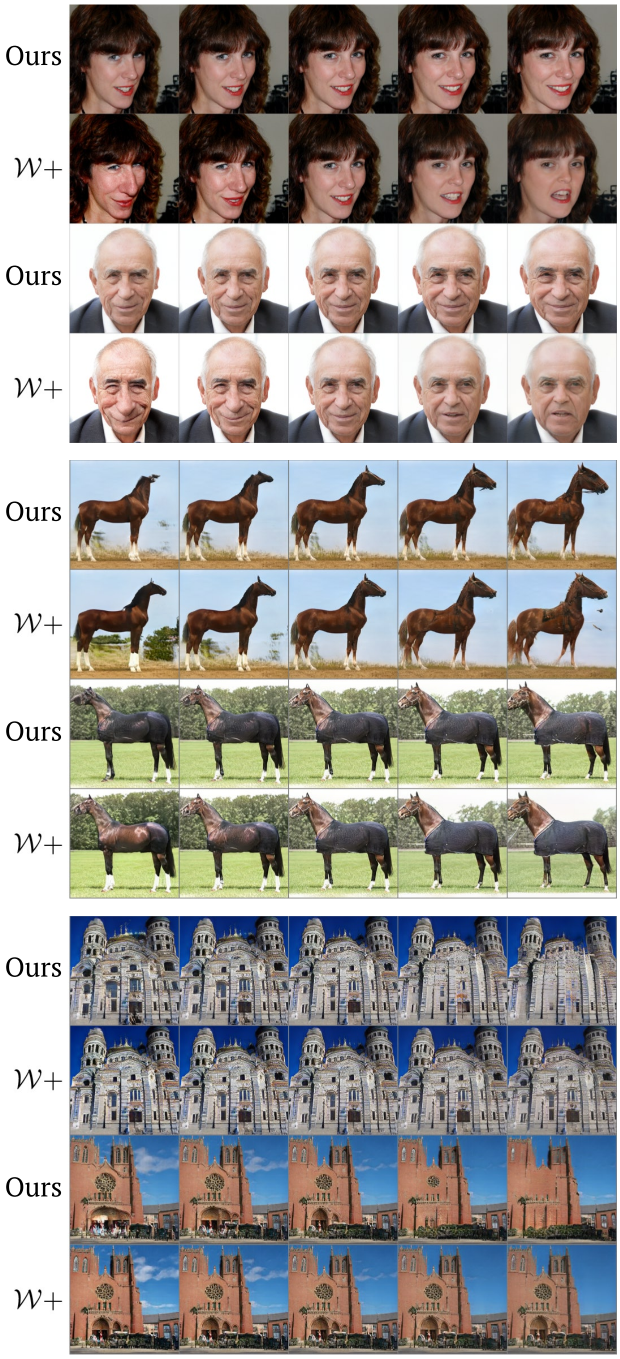




Figure 3. Unsatisfactory reproduction of “Face width”, “Horse head size” and “Plane walls” manipulations by the shifts in $\mathcal{W}+$.

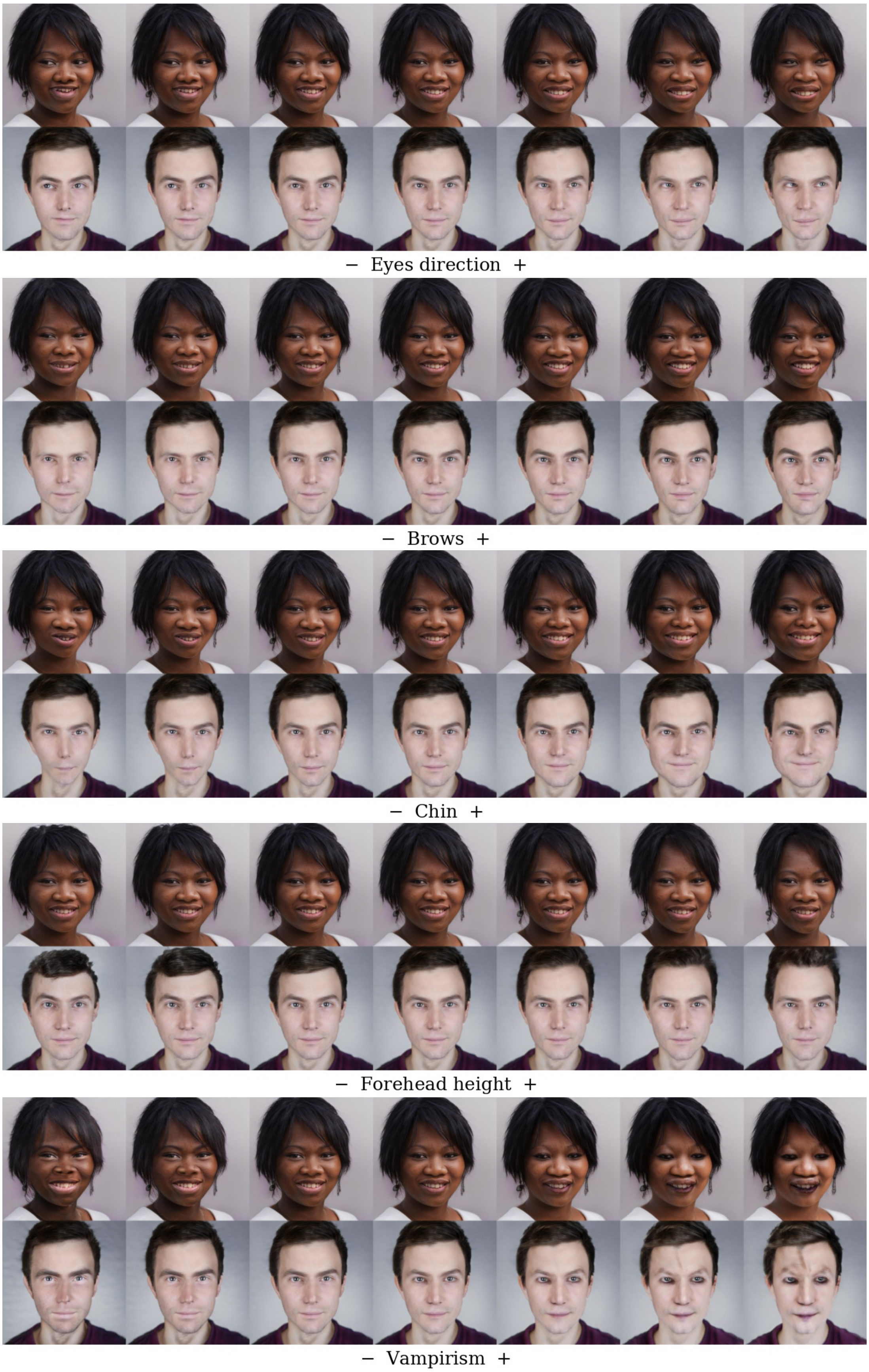



Figure 4. Examples of effects discovered for FFHQ StyleGAN2.

Figure 5. Examples of effects discovered for LSUN-Church StyleGAN2.

− Clouds +

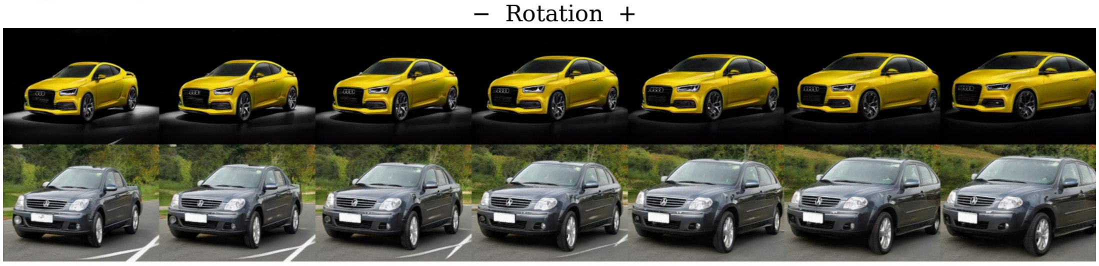
− Cones +

− Plane walls +

Figure 6. Examples of effects discovered for LSUN-Car StyleGAN2.

− Height +

− Rotation +



− Size +

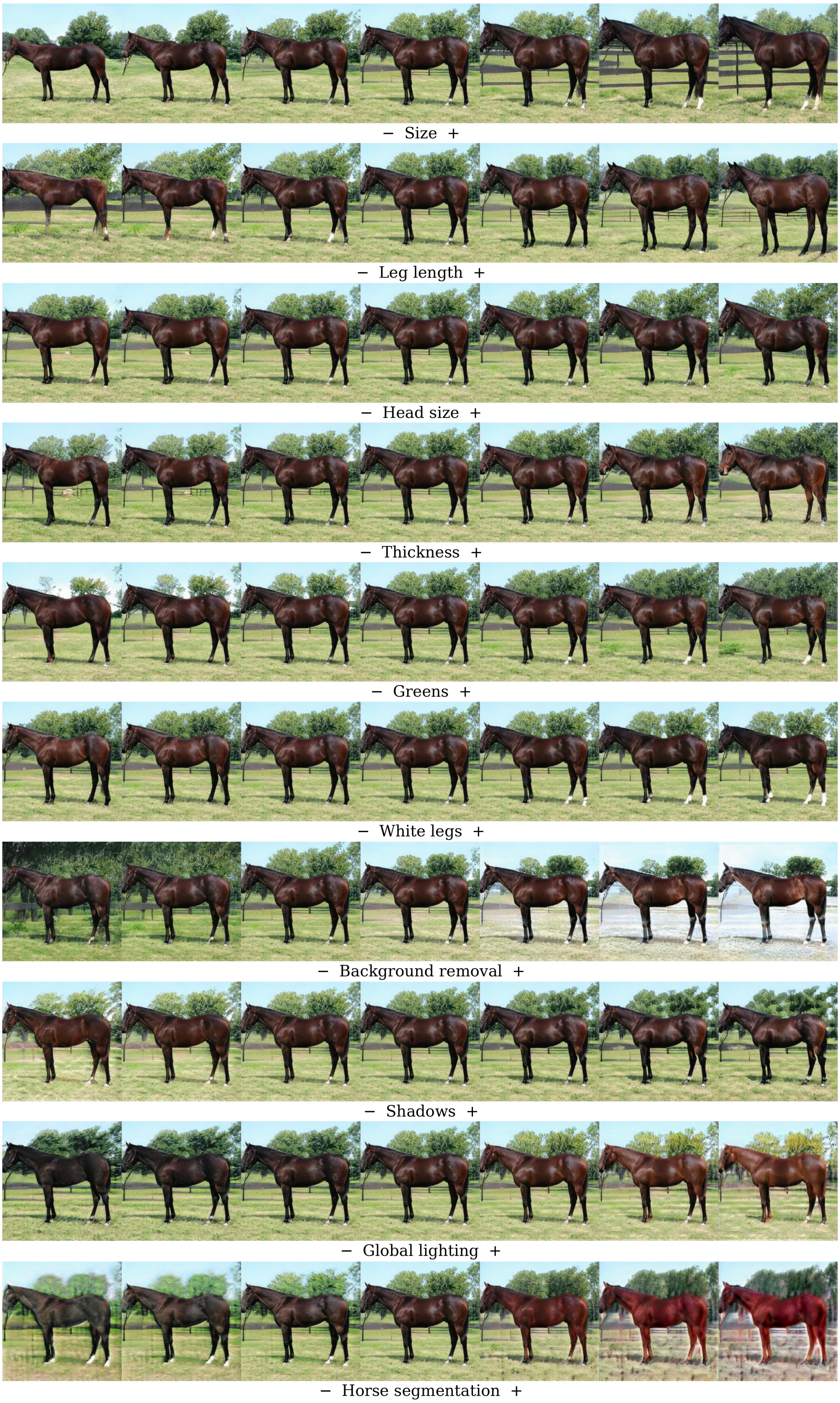



Figure 7. The effects discovered for the different layers of StyleGAN2 trained on the LSUN-Horse dataset. Each row corresponds to the particular StyleGAN2 generator layer.

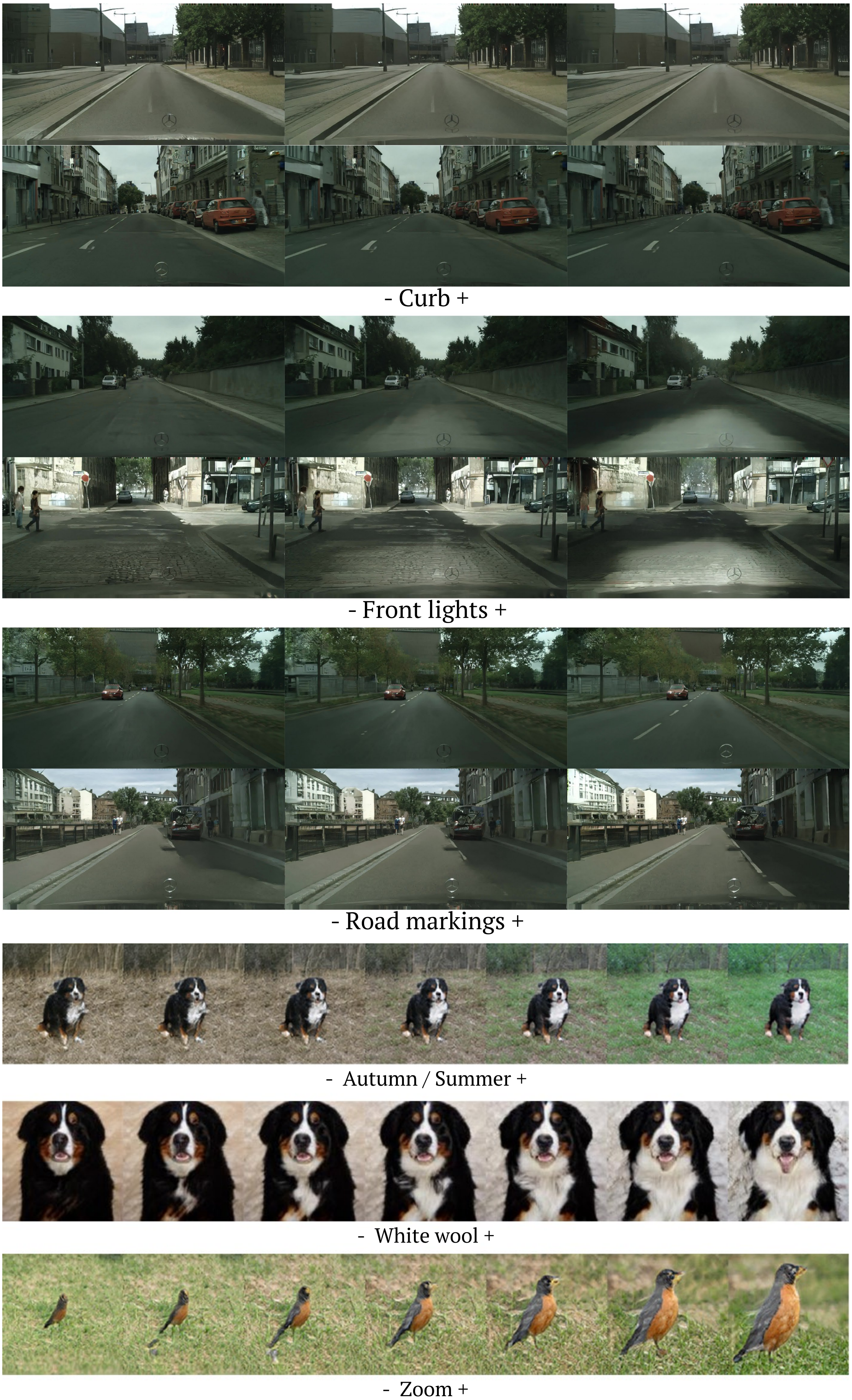



Figure 8. Some of the effects discovered for pix2pixHD model pretrained on Cityscapes (top 3) and BigGAN (bottom 3).