

# Does Image Anonymization Impact Computer Vision Training?

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## A. Additional Results

### A.1. Cityscapes All Metrics

Table 1, Table 2, and Table 3 includes all quantitative metrics for Cityscapes, COCO, and BDD100k.

### A.2. COCO Instance Segmentation

Table 4 includes experimental results training a Mask R-CNN for general instance segmentation on the COCO datasets. Specifically, we train a Mask R-50 FPN R-CNN. Note that we follow the experimental details from the Key-point R-CNN experiment in the main paper.

### A.3. Cityscapes - Ignoring Person Annotations

Table 5 show experimental results for Mask R-CNN [2] R-50 FPN on the Cityscapes dataset [1] without the person class. It is important to note that we measure the performance drop to the original dataset with person annotations removed.

## B. Qualitative Anonymization Examples

The following figures include qualitative examples from Cityscapes [1] and BDD100k [4].

- Cityscapes body: Figure 1, 2, 3.
- Cityscapes Body Histogram matching: Figure 7, 8, 9.
- Cityscapes face: Figure 4, 5, 6.
- BDD100k face: Figure 10, 11, 12, 13.
- BDD100k body: Figure 14, 15, 16, 17.

## References

[1] 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 *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3213–3223. IEEE, jun 2016. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11

[2] Kaiming He, Georgia Gkioxari, Piotr Dollar, and Ross Girshick. Mask R-CNN. In *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 2980–2988. IEEE, oct 2017. 1, 2

[3] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick. Microsoft COCO: Common Objects in Context. In *European conference on computer vision*, volume 8693 LNCS, pages 740–755. Springer, Cham, 2014. 2

[4] Fisher Yu, Haofeng Chen, Xin Wang, Wenqi Xian, Yingying Chen, Fangchen Liu, Vashisht Madhavan, and Trevor Darrell. BDD100K: A Diverse Driving Dataset for Heterogeneous Multitask Learning. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2633–2642. IEEE, jun 2020. 1, 2, 12, 13, 14, 15, 16, 17, 18, 19

Table 1. Instance segmentation AP on the Cityscapes [1] validation set with a Mask R-CNN [2] **R-50 FPN**. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization.

Anonymization Method		AP ↑	AP@50 ↑	AP <sub>person</sub>	AP <sub>bus</sub>	AP <sub>bicycle</sub>	AP <sub>car</sub>	AP <sub>motorcycle</sub>	AP <sub>rider</sub>	AP <sub>train</sub>	AP <sub>truck</sub>
Face	Original	36.7 ± 0.1 (Δ)	62.8 ± 0.2 (Δ)	35.0 ± 0.2 (Δ)	57.6 ± 0.6 (Δ)	23.6 ± 0.2 (Δ)	53.6 ± 0.0 (Δ)	21.9 ± 0.1 (Δ)	28.8 ± 0.2 (Δ)	37.2 ± 0.4 (Δ)	36.1 ± 0.4 (Δ)
	Blur	36.4 ± 0.2 (-0.3)	62.5 ± 0.2 (-0.3)	34.9 ± 0.1 (-0.1)	<b>58.0 ± 0.5 (0.4)</b>	<b>23.3 ± 0.1 (-0.3)</b>	53.1 ± 0.1 (-0.5)	20.8 ± 0.5 (-1.1)	28.6 ± 0.1 (-0.2)	37.0 ± 1.3 (-0.2)	35.5 ± 0.5 (-0.6)
	Mask-out	<b>36.7 ± 0.2 (0.0)</b>	<b>63.1 ± 0.2 (0.3)</b>	34.9 ± 0.1 (-0.1)	57.5 ± 0.5 (-0.1)	23.2 ± 0.2 (-0.4)	53.2 ± 0.0 (-0.4)	21.4 ± 0.1 (-0.5)	28.7 ± 0.1 (-0.1)	<b>39.5 ± 0.2 (2.3)</b>	35.5 ± 0.3 (-0.6)
Body	Realistic	36.6 ± 0.1 (-0.1)	62.8 ± 0.3 (0.0)	<b>35.0 ± 0.1 (0.0)</b>	57.2 ± 0.3 (-0.4)	23.2 ± 0.2 (-0.4)	<b>53.4 ± 0.1 (-0.2)</b>	<b>21.7 ± 0.3 (-0.2)</b>	<b>28.8 ± 0.0 (0.0)</b>	36.6 ± 1.2 (-0.6)	<b>36.7 ± 0.5 (0.6)</b>
	Blur	31.4 ± 0.2 (-5.3)	54.5 ± 0.4 (-8.3)	2.1 ± 0.1 (-32.9)	56.7 ± 0.6 (-0.9)	22.7 ± 0.1 (-0.9)	52.9 ± 0.1 (-0.7)	20.9 ± 0.2 (-1.0)	25.9 ± 0.2 (-2.9)	34.4 ± 0.5 (-2.8)	36.0 ± 0.7 (-0.1)
	Mask-out	31.2 ± 0.1 (-5.5)	53.2 ± 0.1 (-9.6)	0.7 ± 0.1 (-34.3)	55.6 ± 0.4 (-2.0)	22.9 ± 0.2 (-0.7)	52.9 ± 0.1 (-0.7)	21.7 ± 0.7 (-0.2)	25.3 ± 0.2 (-3.5)	35.5 ± 0.5 (-1.7)	35.1 ± 0.3 (-1.0)
Body	Realistic	34.6 ± 0.1 (-2.1)	59.0 ± 0.3 (-3.8)	20.3 ± 0.2 (-14.7)	<b>58.5 ± 0.2 (0.9)</b>	<b>23.2 ± 0.1 (-0.4)</b>	<b>53.4 ± 0.1 (-0.2)</b>	21.2 ± 0.2 (-0.7)	27.9 ± 0.5 (-0.9)	<b>36.1 ± 1.5 (-1.1)</b>	35.8 ± 0.6 (-0.3)
	Realistic + HM	34.3 ± 0.2 (-2.4)	58.9 ± 0.2 (-3.9)	21.3 ± 0.3 (-13.7)	57.9 ± 0.2 (0.3)	22.8 ± 0.1 (-0.8)	<b>53.4 ± 0.1 (-0.2)</b>	22.0 ± 0.2 (0.1)	27.6 ± 0.1 (-1.2)	34.0 ± 1.1 (-3.2)	35.7 ± 0.2 (-0.4)
	Realistic + HM-LO	<b>34.8 ± 0.2 (-1.9)</b>	<b>60.0 ± 0.3 (-2.8)</b>	<b>21.5 ± 0.1 (-13.5)</b>	57.7 ± 0.8 (0.1)	<b>23.2 ± 0.2 (-0.4)</b>	53.2 ± 0.0 (-0.4)	<b>22.2 ± 0.3 (0.3)</b>	<b>28.1 ± 0.1 (-0.7)</b>	34.9 ± 1.4 (-2.3)	<b>37.3 ± 0.7 (1.2)</b>

Table 2. Keypoint (Kp.) AP on the COCO [3] validation set with a Keypoint **R-50 FPN** R-CNN [2].

Anonymization Method		Box AP ↑	Box AP@50 ↑	Box AP@75 ↑	Box AP <sub>r</sub> ↑	Box AP <sub>m</sub> ↑	Box AP <sub>s</sub> ↑	Kp. AP ↑	Kp. AP@50 ↑	Kp. AP@75 ↑	Kp. AP <sub>r</sub> ↑	Kp. AP <sub>m</sub> ↑
Face	Original	55.7 ± 0.0 (Δ)	83.3 ± 0.0 (Δ)	60.7 ± 0.1 (Δ)	73.0 ± 0.1 (Δ)	62.9 ± 0.1 (Δ)	37.8 ± 0.1 (Δ)	65.2 ± 0.0 (Δ)	86.3 ± 0.2 (Δ)	71.1 ± 0.2 (Δ)	73.0 ± 0.0 (Δ)	61.2 ± 0.1 (Δ)
	Blur	50.3 ± 0.2 (-5.4)	77.0 ± 0.2 (-6.3)	54.6 ± 0.1 (-6.1)	67.8 ± 0.4 (-5.2)	52.3 ± 0.2 (-10.6)	37.1 ± 0.0 (-0.7)	53.5 ± 0.2 (-11.7)	74.5 ± 0.4 (-11.8)	57.6 ± 0.2 (-13.5)	63.5 ± 0.3 (-9.5)	48.6 ± 0.1 (-12.6)
	Mask-out	49.9 ± 0.2 (-5.8)	76.6 ± 0.2 (-6.7)	54.1 ± 0.3 (-6.6)	66.9 ± 0.6 (-6.1)	52.3 ± 0.1 (-10.6)	36.8 ± 0.1 (-1.0)	52.0 ± 0.3 (-13.2)	73.5 ± 0.3 (-12.8)	56.2 ± 0.4 (-14.9)	61.4 ± 0.3 (-11.6)	47.7 ± 0.2 (-13.5)
Body	Realistic	54.3 ± 0.1 (-1.4)	81.7 ± 0.1 (-1.6)	59.0 ± 0.1 (-1.7)	<b>72.7 ± 0.1 (-0.3)</b>	60.0 ± 0.1 (-2.9)	37.3 ± 0.2 (-0.5)	60.6 ± 0.1 (-4.6)	<b>82.9 ± 0.3 (-3.4)</b>	65.9 ± 0.1 (-5.2)	69.9 ± 0.1 (-3.1)	<b>56.1 ± 0.2 (-5.1)</b>
	Realistic refined	54.4 ± 0.0 (-1.3)	<b>81.8 ± 0.1 (-1.5)</b>	<b>59.1 ± 0.1 (-1.6)</b>	<b>72.7 ± 0.1 (-0.3)</b>	<b>60.1 ± 0.2 (-2.8)</b>	<b>37.5 ± 0.1 (-0.3)</b>	<b>60.8 ± 0.2 (-4.4)</b>	<b>82.9 ± 0.2 (-3.4)</b>	<b>66.2 ± 0.4 (-4.9)</b>	<b>70.2 ± 0.1 (-2.8)</b>	<b>56.1 ± 0.3 (-5.1)</b>
	Blur	17.8 ± 0.0 (-37.9)	35.1 ± 0.1 (-48.2)	16.3 ± 0.1 (-44.4)	2.6 ± 0.1 (-70.4)	10.5 ± 0.1 (-52.4)	33.3 ± 0.1 (-4.5)	4.4 ± 0.1 (-60.8)	9.1 ± 0.2 (-77.2)	3.7 ± 0.1 (-67.4)	0.4 ± 0.1 (-72.6)	10.4 ± 0.1 (-50.8)
Body	Mask-out	17.4 ± 0.1 (-38.3)	34.5 ± 0.1 (-48.8)	15.5 ± 0.2 (-45.2)	2.1 ± 0.1 (-70.9)	10.6 ± 0.2 (-52.3)	32.5 ± 0.1 (-5.3)	2.0 ± 0.1 (-63.2)	4.9 ± 0.2 (-81.4)	1.4 ± 0.1 (-69.7)	0.1 ± 0.1 (-72.9)	4.1 ± 0.1 (-57.1)
	Realistic	<b>24.0 ± 0.1 (-31.7)</b>	<b>46.1 ± 0.2 (-37.2)</b>	<b>22.4 ± 0.1 (-38.3)</b>	<b>8.2 ± 0.3 (-64.8)</b>	<b>26.4 ± 0.3 (-36.5)</b>	<b>34.1 ± 0.1 (-3.7)</b>	<b>15.6 ± 0.1 (-49.6)</b>	<b>29.4 ± 0.2 (-56.9)</b>	<b>14.2 ± 0.1 (-56.9)</b>	<b>13.0 ± 0.1 (-60.0)</b>	<b>22.5 ± 0.1 (-38.7)</b>

Table 3. Instance segmentation AP on the BDD100K [4] validation set with a Mask R-CNN [2] **R-50 FPN**.

Method		AP ↑	AP@50 ↑	AP <sub>pedestrian</sub>	AP <sub>bus</sub>	AP <sub>bicycle</sub>	AP <sub>car</sub>	AP <sub>motorcycle</sub>	AP <sub>rider</sub>	AP <sub>train</sub>	AP <sub>truck</sub>
Face	Original	20.2 ± 0.2	34.9 ± 0.4	32.0 ± 0.0	30.2 ± 0.2	6.0 ± 0.3	45.4 ± 0.1	11.0 ± 0.9	9.7 ± 0.3	0.0 ± 0.0	26.9 ± 0.4
	Blur	20.5 ± 0.1 (0.3)	<b>35.9 ± 0.1 (1.0)</b>	<b>31.7 ± 0.1 (-0.3)</b>	30.1 ± 0.3 (-0.1)	<b>6.9 ± 0.2 (0.9)</b>	45.4 ± 0.1 (0.0)	13.8 ± 1.0 (2.8)	<b>9.4 ± 0.3 (-0.3)</b>	0.0 ± 0.0 (0.0)	26.5 ± 0.2 (-0.4)
	Mask-out	20.3 ± 0.1 (0.1)	35.3 ± 0.3 (0.4)	31.4 ± 0.1 (-0.6)	29.9 ± 0.5 (-0.3)	5.8 ± 0.3 (-0.2)	45.5 ± 0.1 (0.1)	14.4 ± 0.6 (3.4)	8.8 ± 0.4 (-0.9)	0.0 ± 0.0 (0.0)	26.3 ± 0.2 (-0.6)
Body	Realistic	<b>20.6 ± 0.1 (0.4)</b>	35.8 ± 0.3 (0.9)	31.6 ± 0.2 (-0.4)	<b>30.7 ± 0.6 (0.5)</b>	6.7 ± 0.4 (0.7)	<b>45.6 ± 0.1 (0.2)</b>	<b>14.7 ± 0.7 (3.7)</b>	8.7 ± 0.2 (-1.0)	0.0 ± 0.0 (0.0)	<b>26.7 ± 0.0 (-0.2)</b>
	Blur	15.4 ± 0.1 (-4.8)	26.3 ± 0.2 (-8.6)	0.5 ± 0.0 (-31.5)	29.5 ± 0.6 (-0.7)	5.4 ± 0.2 (-0.6)	<b>45.6 ± 0.0 (0.2)</b>	12.1 ± 0.9 (1.1)	4.2 ± 0.3 (-5.5)	0.0 ± 0.0 (0.0)	25.9 ± 0.6 (-1.0)
	Mask-out	15.3 ± 0.0 (-4.9)	25.5 ± 0.1 (-9.4)	0.0 ± 0.0 (-32.0)	<b>30.8 ± 0.2 (0.6)</b>	5.5 ± 0.2 (-0.5)	45.5 ± 0.1 (0.1)	10.9 ± 0.2 (-0.1)	3.9 ± 0.5 (-5.8)	0.0 ± 0.0 (0.0)	<b>26.0 ± 0.4 (-0.9)</b>
Body	Realistic	<b>17.0 ± 0.1 (-3.2)</b>	<b>28.9 ± 0.4 (-6.0)</b>	<b>12.8 ± 0.1 (-19.2)</b>	29.7 ± 0.4 (-0.5)	<b>6.7 ± 0.3 (0.7)</b>	45.2 ± 0.2 (-0.2)	10.3 ± 0.6 (-0.7)	<b>5.8 ± 0.4 (-3.9)</b>	0.0 ± 0.0 (0.0)	25.9 ± 0.4 (-1.0)

Table 4. Instance segmentation AP on the COCO [3] validation set with a Mask **R-50 FPN** R-CNN [2].

Anonymization Method		Box AP ↑	Segm. AP ↑	Bbox. AP <sub>person</sub> ↑
Face	Original	40.9 ± 0.0 (Δ)	37.0 ± 0.0 (Δ)	55.3 ± 0.1 (Δ)
	Blur	40.7 ± 0.0 (-0.2)	36.9 ± 0.1 (-0.1)	51.9 ± 0.1 (-3.4)
	Mask-out	40.6 ± 0.1 (-0.3)	36.9 ± 0.0 (-0.1)	51.6 ± 0.1 (-3.7)
	Realistic	<b>40.8 ± 0.1 (-0.1)</b>	<b>37.0 ± 0.0 (0.0)</b>	<b>54.6 ± 0.1 (-0.7)</b>

Table 5. Instance segmentation AP on the Cityscapes [1] validation set with a Mask R-CNN [2] **R-50 FPN**. Note that the "person" class is removed from all experiments in this table, including the original dataset.

Anonymization Method		AP ↑	AP@50 ↑	AP <sub>bus</sub>	AP <sub>bicycle</sub>	AP <sub>car</sub>	AP <sub>motorcycle</sub>	AP <sub>rider</sub>	AP <sub>train</sub>	AP <sub>truck</sub>
Body	Original	30.9 ± 0.3 (Δ)	52.7 ± 0.7 (Δ)	56.1 ± 0.3 (Δ)	22.2 ± 0.1 (Δ)	51.3 ± 0.1 (Δ)	20.5 ± 0.3 (Δ)	25.9 ± 0.2 (Δ)	36.3 ± 1.4 (Δ)	34.7 ± 0.8 (Δ)
	Blur	30.4 ± 0.1 (-0.5)	51.6 ± 0.1 (-1.1)	56.3 ± 0.1 (0.2)	21.9 ± 0.1 (-0.3)	50.7 ± 0.1 (-0.6)	21.1 ± 0.2 (0.6)	24.4 ± 0.2 (-1.5)	35.8 ± 0.6 (-0.5)	33.3 ± 0.5 (-1.4)
Body	Mask-out	30.6 ± 0.2 (-0.3)	51.8 ± 0.3 (-0.9)	55.3 ± 0.8 (-0.8)	21.5 ± 0.0 (-0.7)	51.1 ± 0.1 (-0.2)	20.7 ± 0.3 (0.2)	23.7 ± 0.2 (-2.2)	38.3 ± 0.6 (2.0)	34.4 ± 0.6 (-0.3)



(a) Body - Gaussian

(b) Body - Mask Out

(c) Body - Realistic

Figure 1. Random anonymization examples from Cityscapes [1]. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization. Note that the images are compressed.



(a) Body - Gaussian

(b) Body - Mask Out

(c) Body - Realistic

Figure 2. Random anonymization examples from Cityscapes [1]. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization. Note that the images are compressed.





(a) Body - Gaussian

(b) Body - Mask Out

(c) Body - Realistic

Figure 3. Random anonymization examples from Cityscapes [1]. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization. Note that the images are compressed.



(a) Face - Gaussian

(b) Face - Mask Out

(c) Face - Realistic

Figure 4. Random anonymization examples from Cityscapes [1]. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization. Note that the images are compressed.



(a) Face - Gaussian

(b) Face - Mask Out

(c) Face - Realistic

Figure 5. Random anonymization examples from Cityscapes [1]. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization. Note that the images are compressed.





(a) Face - Gaussian

(b) Face - Mask Out

(c) Face - Realistic

Figure 6. Random anonymization examples from Cityscapes [1]. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization. Note that the images are compressed.



(a) Body - Realistic

(b) Body - Realistic (HM)

(c) Body - Realistic (HM-LO)

Figure 7. Random anonymization examples from Cityscapes [1]. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization. Note that the images are compressed.





(a) Body - Realistic

(b) Body - Realistic (HM)

(c) Body - Realistic (HM-LO)

Figure 8. Random anonymization examples from Cityscapes [1]. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization. Note that the images are compressed.



(a) Body - Realistic

(b) Body - Realistic (HM)

(c) Body - Realistic (HM-LO)

Figure 9. Random anonymization examples from Cityscapes [1]. **HM**=Histogram matching. **HM-LO**=Histogram matching via Latent Optimization. Note that the images are compressed.



(a) Face - Gaussian

(b) Face - Mask Out

(c) Face - Realistic

Figure 10. Random anonymization examples from BDD100K [4]. Note that the images are compressed.



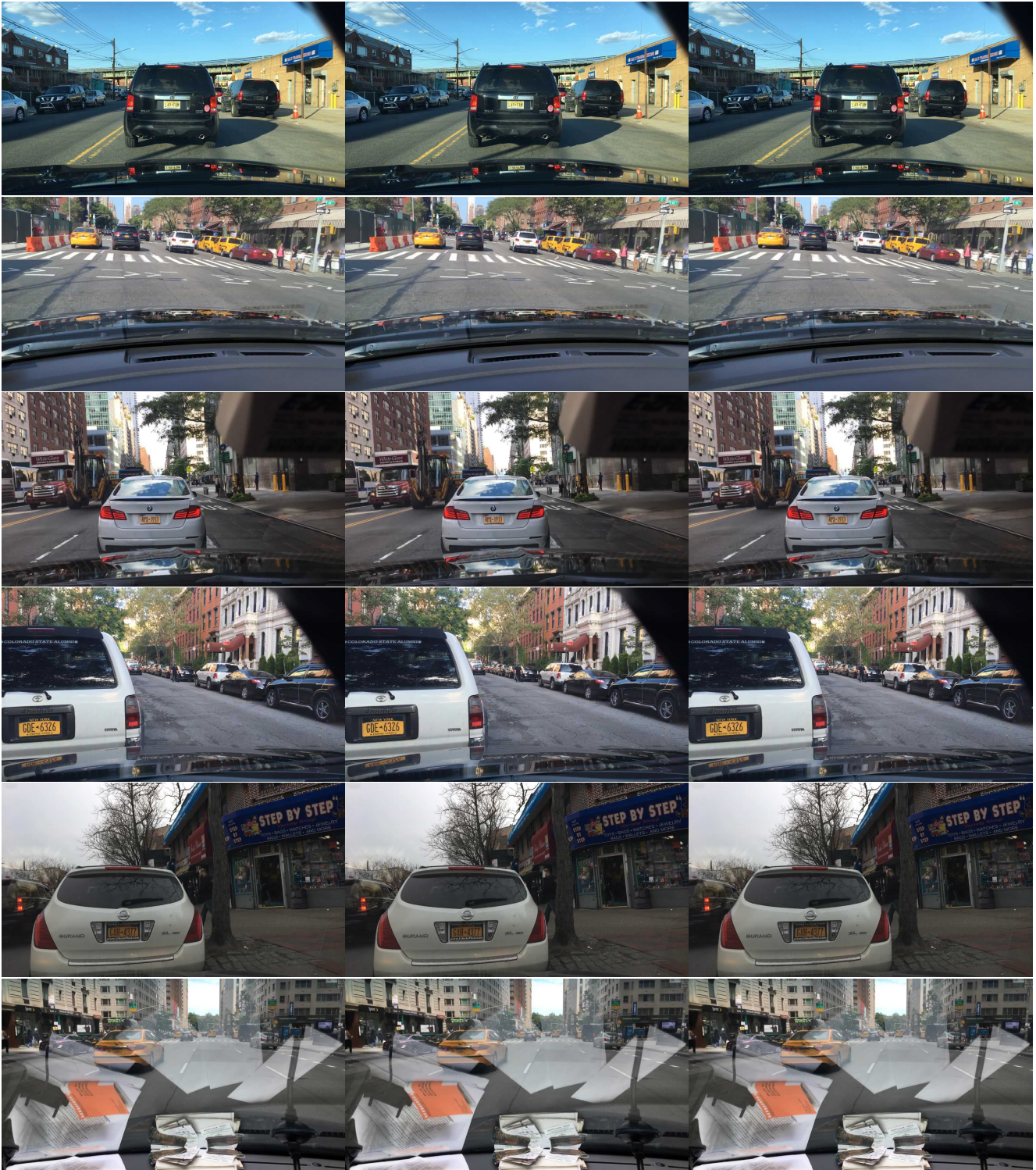


(a) Face - Gaussian

(b) Face - Mask Out

(c) Face - Realistic

Figure 11. Random anonymization examples from BDD100K [4]. Note that the images are compressed.



(a) Face - Gaussian

(b) Face - Mask Out

(c) Face - Realistic

Figure 12. Random anonymization examples from BDD100K [4]. Note that the images are compressed.





(a) Face - Gaussian

(b) Face - Mask Out

(c) Face - Realistic

Figure 13. Random anonymization examples from BDD100K [4]. Note that the images are compressed.



(a) Body - Gaussian

(b) Body - Mask Out

(c) Body - Realistic

Figure 14. Random anonymization examples from BDD100K [4]. Note that the images are compressed.

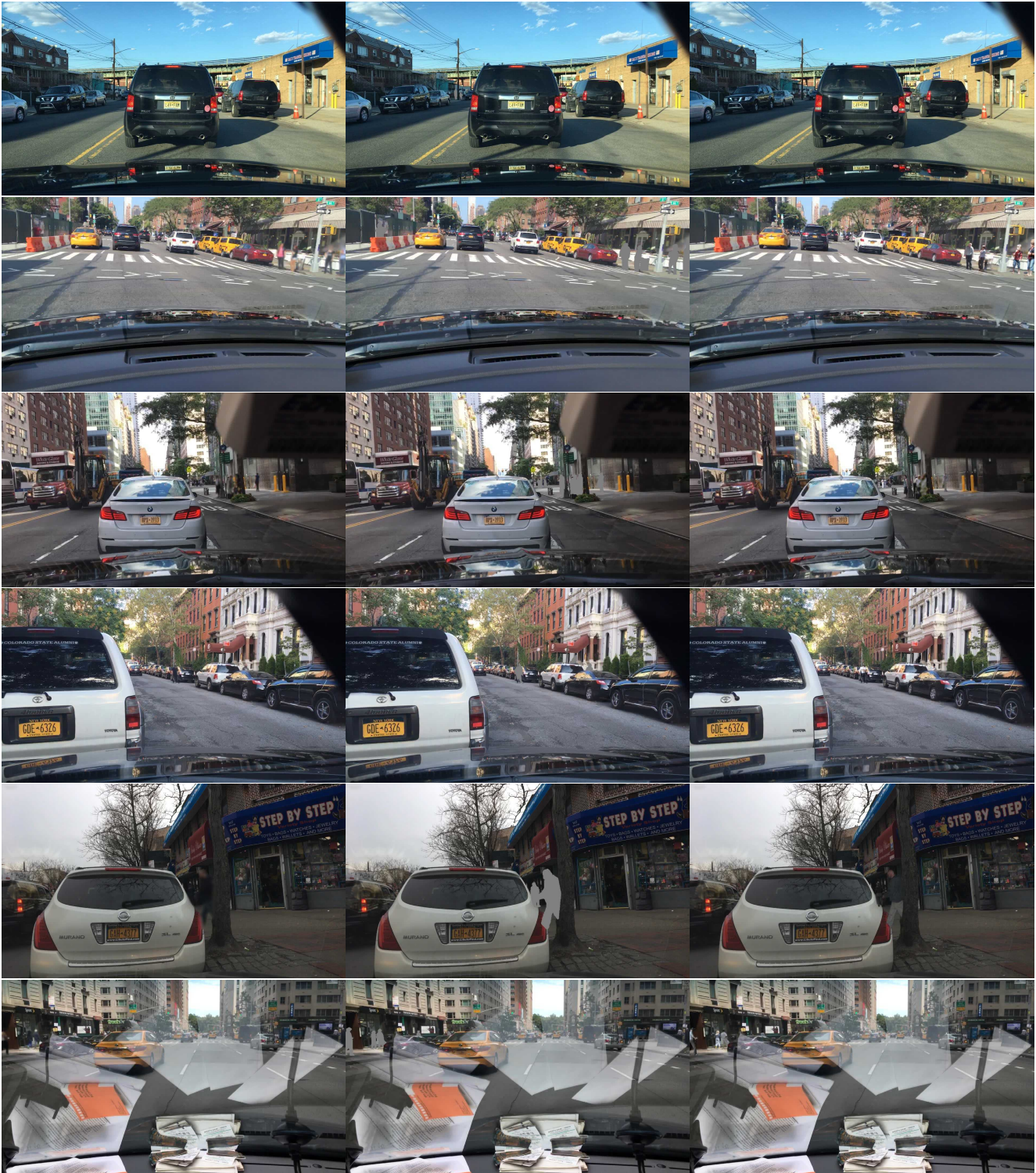


(a) Body - Gaussian

(b) Body - Mask Out

(c) Body - Realistic

Figure 15. Random anonymization examples from BDD100K [4]. Note that the images are compressed.



(a) Body - Gaussian

(b) Body - Mask Out

(c) Body - Realistic

Figure 16. Random anonymization examples from BDD100K [4]. Note that the images are compressed.





(a) Body - Gaussian

(b) Body - Mask Out

(c) Body - Realistic

Figure 17. Random anonymization examples from BDD100K [4]. Note that the images are compressed.