Automatic Noise Modeling for Ghost-free HDR Reconstruction: Supplementary Material

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This supplementary material contains an extended illustration of the image-based calibration process (Sec. 1, see section 2.1 of the main paper) and additional experimental results (Sec. 2).

1 Camera gain estimation

Figures 1 and 2 illustrate our image-based calibration process used to estimate the camera gain parameter; Figure 3 shows the impact of different error levels in the gain estimation on the deghosted results. These figures extend the contents presented in Figs. 3 and 5 of the main paper.

Our image-based calibration algorithm can accurately estimate the gain from the input images whenever the scene contains flat regions at several intensity levels (as shown in the first to third row of Fig. 1). When such regions are not available in the scene (e.g. in highly texture scenes, or scenes with narrow range of illumination), the gain may be over-estimated (Fig. 1–bottom row), which results in images with lower signal-to-noise ratio (SNR). Even in this case, the results of our algorithm degrade gracefully with increasing calibration error, i.e. the final results are still free of ghosting artifacts (Fig. 3).

2 Additional experiments

Figure 4 show the deghosting result of an additional sequence named *Christmas market*. This sequence contains three exposures of a scene that shows dynamic objects undergoing local motion. This sequence is acquired using a Canon EOS 550D set at ISO400. Regardless of the low light in the scene, the gain estimate obtained with our image-based calibration ($g = 1.67$) is very close to the one obtained using flat-field calibration ($g = 1.87$). The successful calibration and the corresponding final deghosted image (Fig. 4) demonstrate how our algorithm generalizes well to different cameras and lighting conditions.

Figure 5a shows the selection of consistent image subsets produced by our deghosting method on the *Busy square* sequence. Our method produces labelings that adapt well to the change of content in the scene between images. Despite the high complexity of the composite, the resulting deghosted image does not show any visual discontinuities (Fig. 6).

Additional observations are: (1) Since in general averaging reduces the noise, the pixels whose irradiances are reconstructed from larger numbers of images tend to have lower noise than those reconstructed from fewer images; in the Fig. 6a, the color code corresponds to noise of the image set. In particular, the deghosted image has always lower noise level than any single image. (2) An interesting byproduct of our image-based calibration is that when it is combined with the HDR reconstruction procedure that we adopt [1], it provides estimates of the noise distribution of the final image as shown in Fig. 5b. This can be used for subsequent applications e.g., denoising and image matching which might benefit from knowing noise level.

To better appreciate the results of our experimental validation, the remainder of this section contains higher resolution versions of the results presented in the main paper: Figures 6–11 correspond to the *flower shop*, *cafe terrace*, *square at night*, *acrobat*, and *street traffic* sequences shown in the main paper. For Figs. 6 and 7, we present the corresponding labelings estimated by our algorithm.

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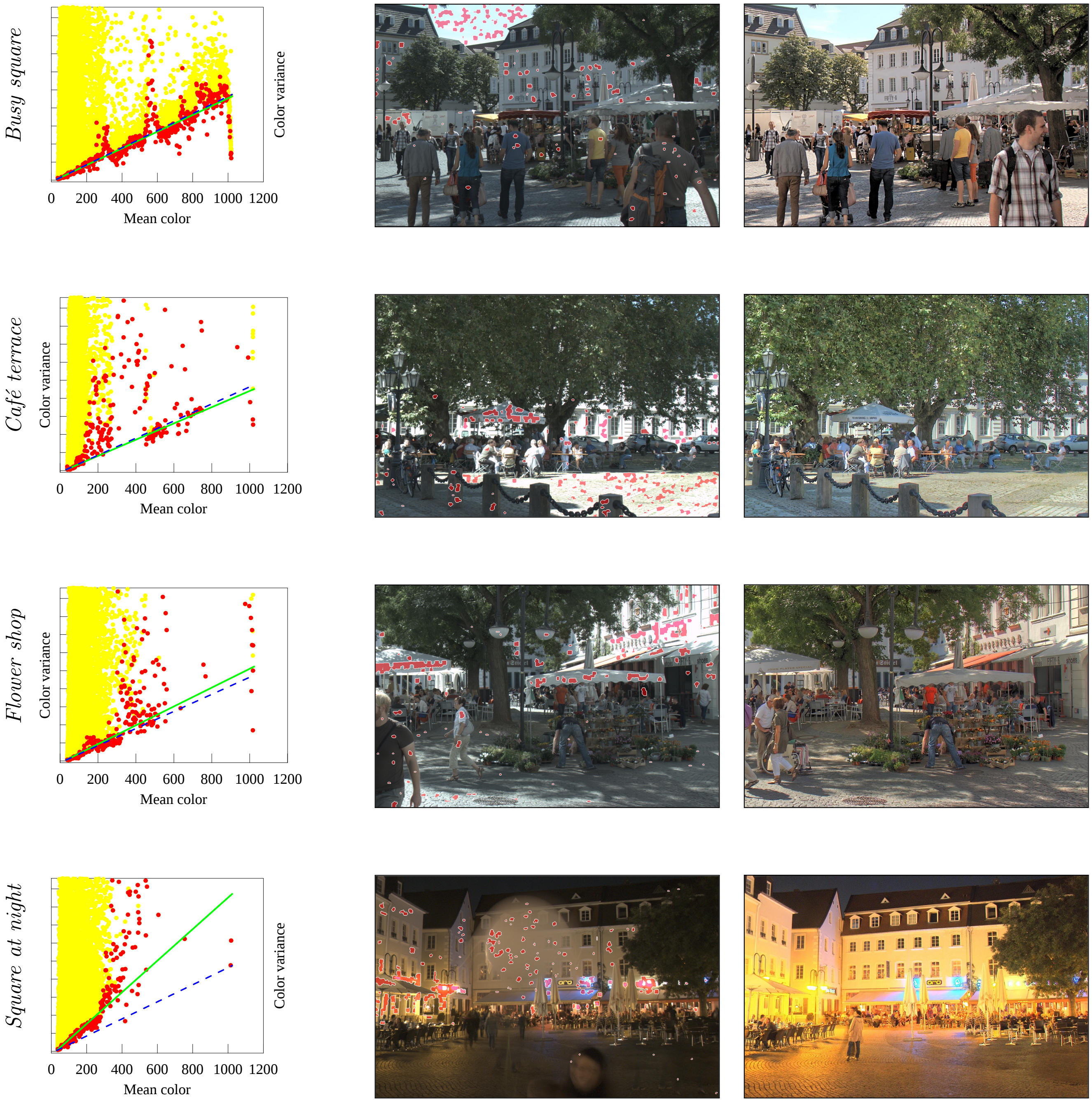
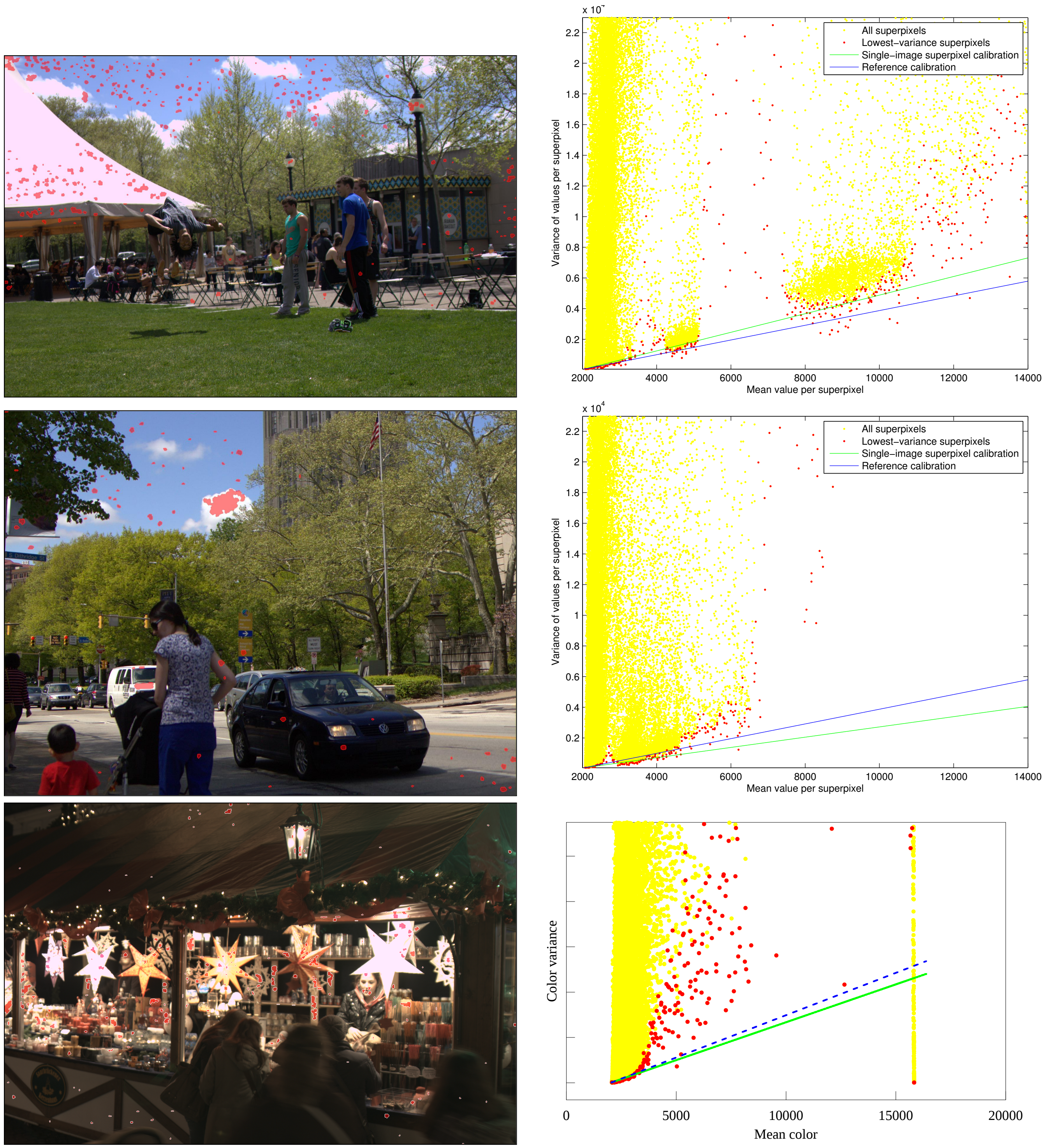


(a) Gain estimate **(b)** Super pixels **(c)** Deghosted HDR

Figure 1: Image-based gain calibration for the Canon Powershot S5. **(a)** The mean and variance of each super pixel are shown in a scatter plot, where low-variance super pixels are shown in red, and the remaining (high-variance) super pixels are shown in yellow. In these plots, the green lines show the predicted color variance using image-based calibration, whereas blue dashed lines show the results using flat-field calibration. **(b)** The red regions correspond to super pixels with low-color variance found in one of the input images. **(c)** The final deghosting results.

References

[1] Miguel Granados, Boris Ajdin, Michael Wand, Christian Theobalt, Hans-Peter Seidel, and Hendrik P. A. Lensch. Optimal HDR reconstruction with linear digital cameras. In *Proc. CVPR*, pages 215–222, 2010.

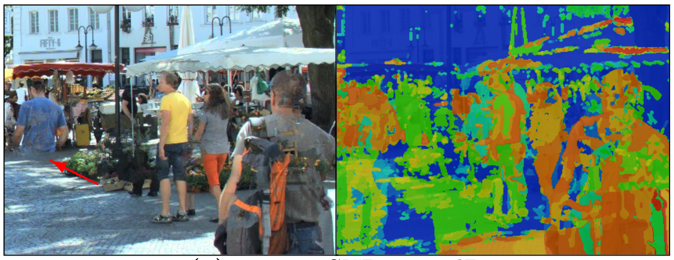


(a) Super pixels selected for calibration

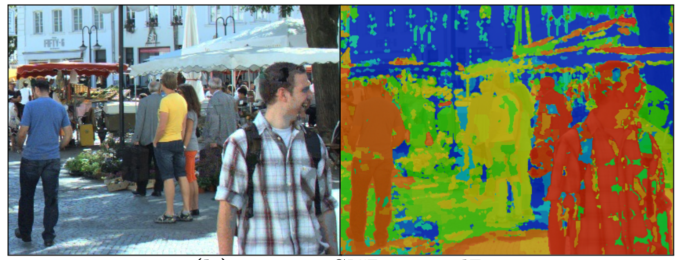
(b) Super-pixel mean and variance scatter plot

Figure 2: Image-based calibration with the Canon EOS 550D: (top) *acrobat* sequence, (middle) *street traffic*, and (bottom) *Christmas market*. In the latter sequence, despite the scarcity of low-variance super pixels in this low light scene, the camera gain was accurately calibrated when compared with the ground-truth.

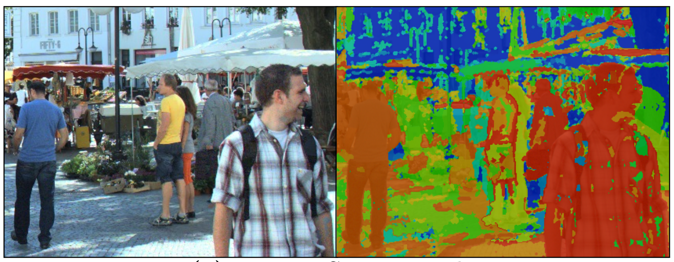
[2] Pradeep Sen, Nima Khademi Kalantari, Maziar Yaesoubi, Soheil Darabi, Dan Goldman, and Eli Shechtman. Robust patch-based hdr reconstruction of dynamic scenes. *ACM TOG*, 31(6), 2012.



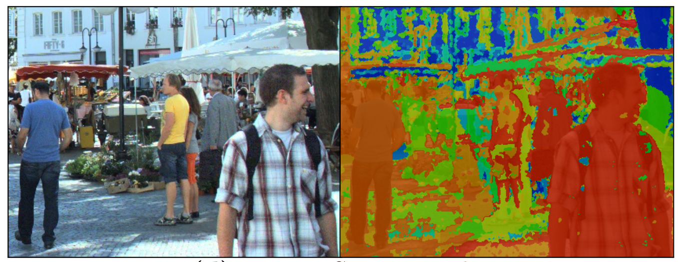
(a) $g - 6\sigma$, SNR=28.5dB



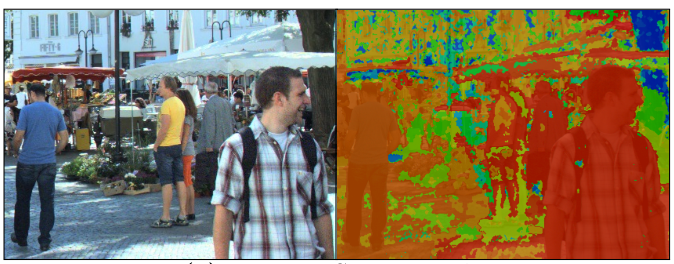
(b) $g - 3\sigma$, SNR=27.2dB



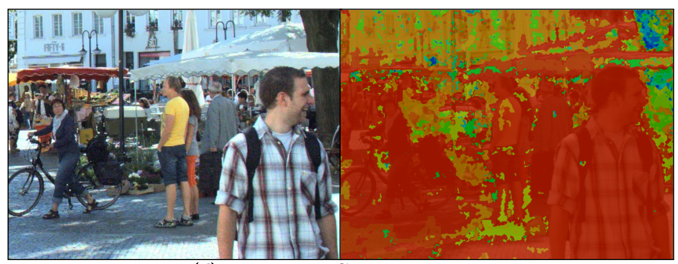
(c) $g + 0\sigma$, SNR=26.5dB



(d) $g + 6\sigma$, SNR=24.8dB



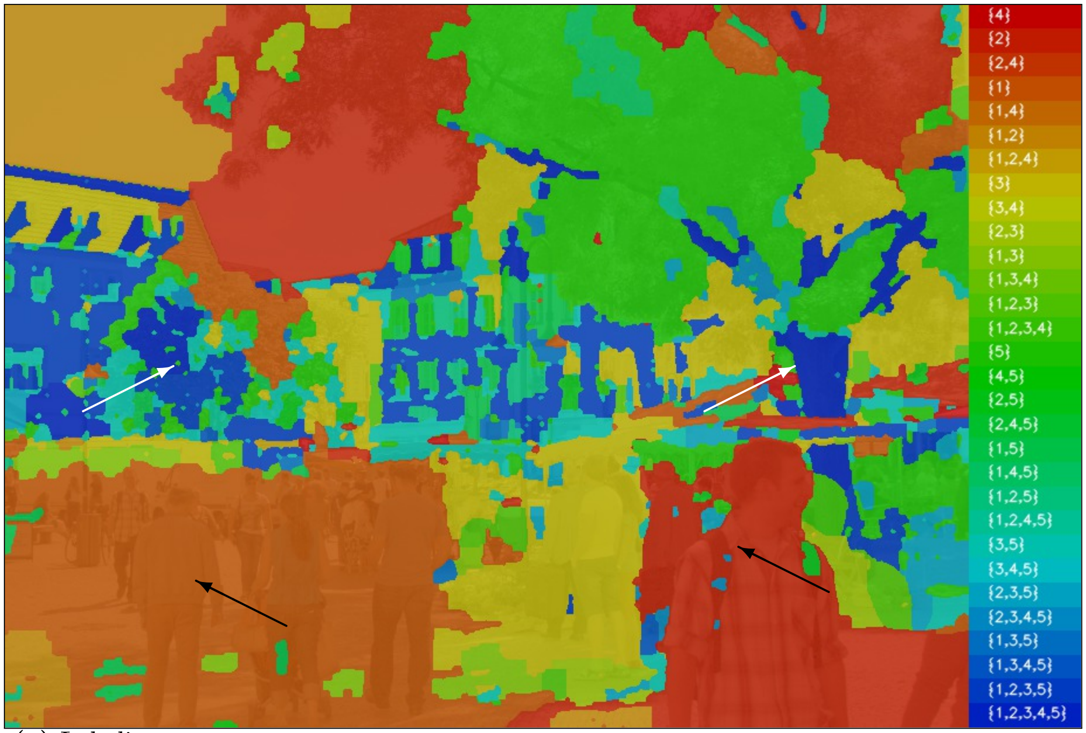
(e) $g + 12\sigma$, SNR=23.6dB



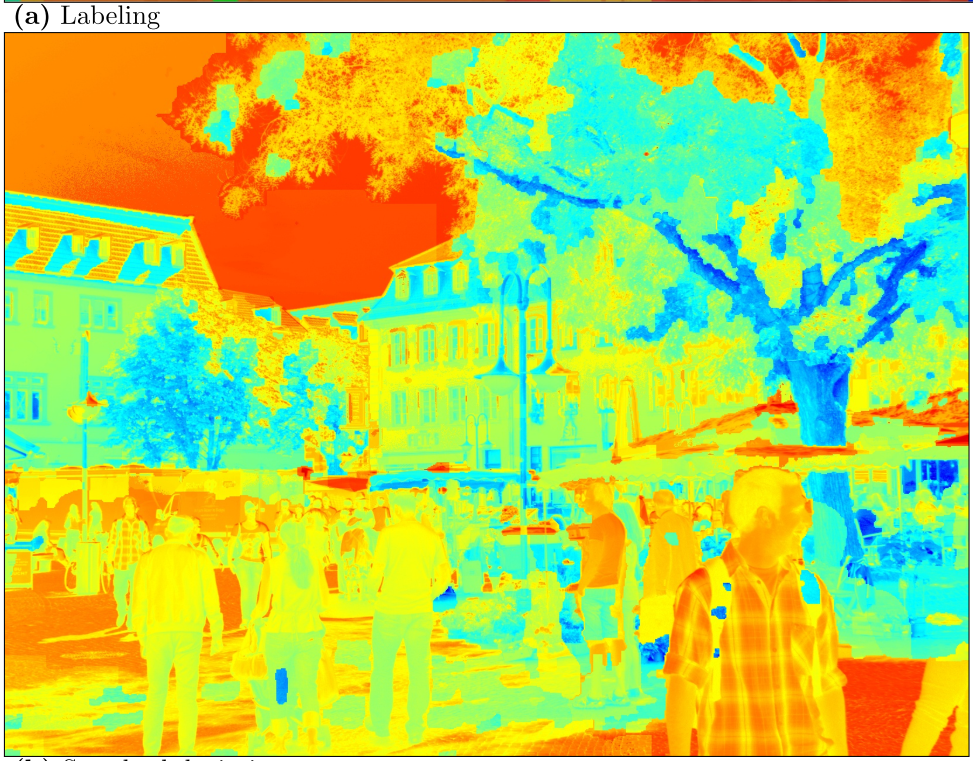
(f) $g + 24\sigma$, SNR=21.1dB

Figure 3: Robustness of the deghosting algorithm to the inaccuracy of the camera gain calibration. Each pair of images corresponds to the tone-mapped HDR reconstruction (left) and its corresponding labeling (right) for a specific level of calibration error. The SNR values are computed as the average ratio of the estimated irradiance and the standard deviation, i.e. $20\,\mathbb{A}\mathrm{vg}[\log_{10}\hat{\mu}_{x(p)}/\hat{\sigma}_{x(p)}]$. The results indicate that our algorithm is robust against slight under-estimation and large over-estimation of the camera gain parameter. When the gain is under-estimated, the predicted image noise becomes over-estimated. This can make the irradiance equality test more lenient, and therefore, can lead to ghosting artifacts (a, red arrow). However, this case was never observed in our experiments since the color variance (on which it depends) is never under-estimated. On the other hand, when the gain is over-estimated, the image variance is under-estimated, which leads to more strict consistency tests. This lowered the signal-to-ratio (SNR) of the result (as the algorithm finds smaller consistent subsets of images), but it did not cause ghosting artifacts (c-e). Even when over-estimation of the gain parameter occurs in practice, our algorithm still creates plausible HDR images.

Figure 4: Deghosting result on the *Christmas market* sequence.



(a) Labeling



(b) Standard deviation

Figure 5: Visualization of the of HDR deghosting process for the *busy square* sequence: **(a)** Labeling corresponding to the subset per pixel selected by the algorithm (out of 31 possible subsets); the subset labels on the right hand side are sorted from top to bottom in order of decreasing variance of the irradiance estimates. **(b)** Standard deviation of the deghosted HDR image, where larger subsets generally produce irradiance estimates with lower noise; blue denotes low noise, red high noise.

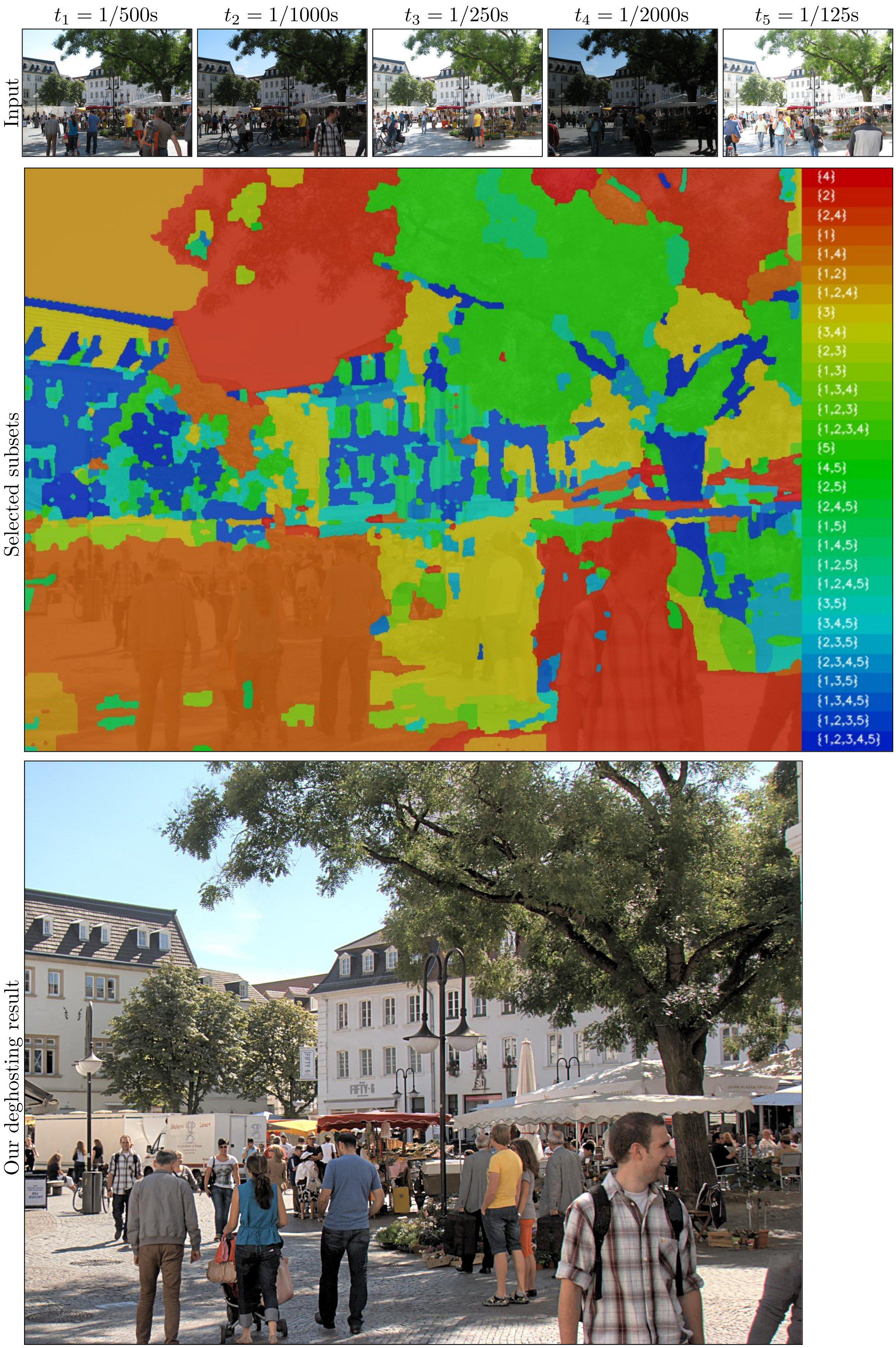


Figure 6: Deghosting result for the *busy square* sequence.

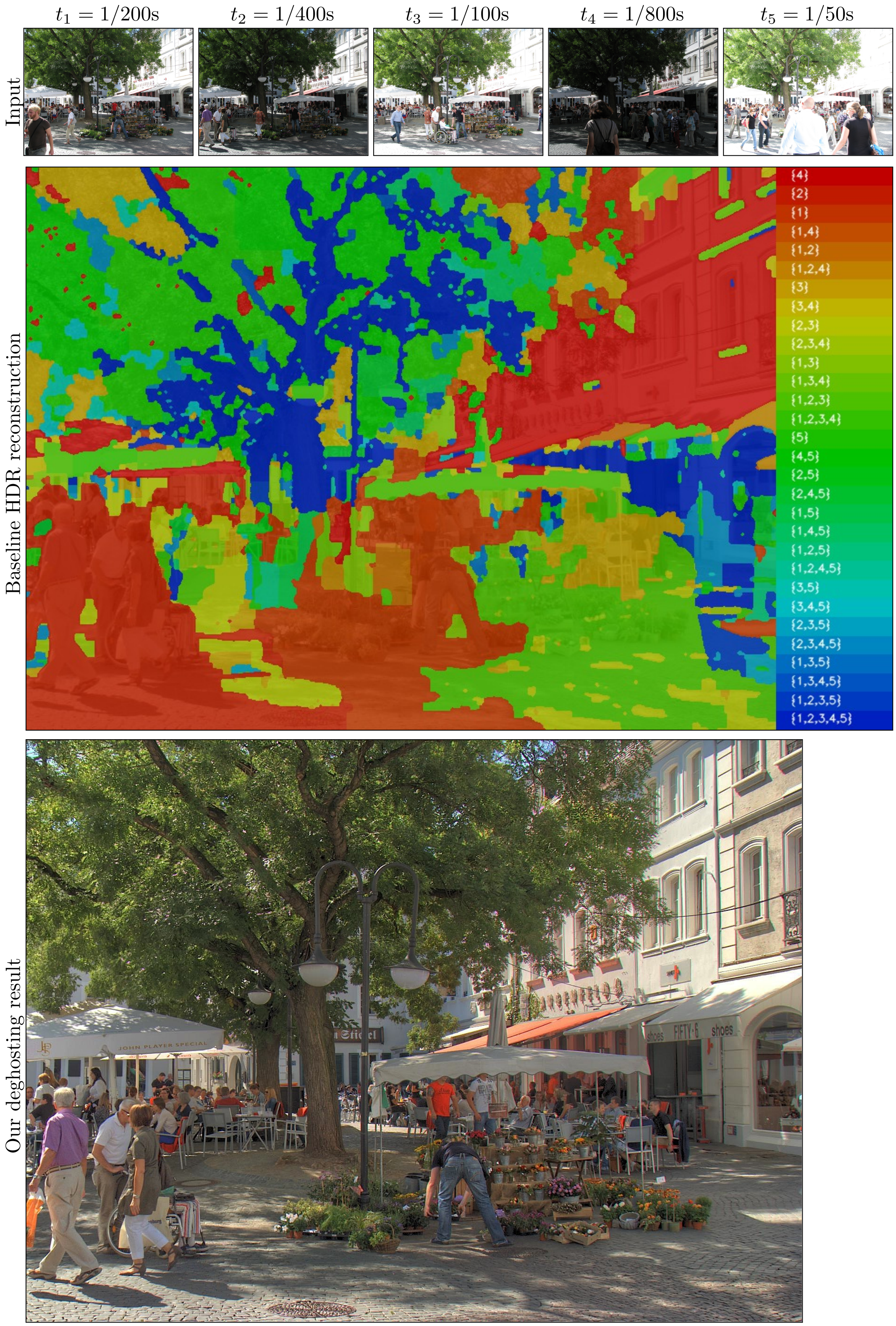


Figure 7: Deghosting result for the *flower shop* sequence.

Figure 8: Comparison with the method of Sen et al. [2] on the *café terrace* sequence. Magenta arrows point to regions whose dynamic range could not be extended.

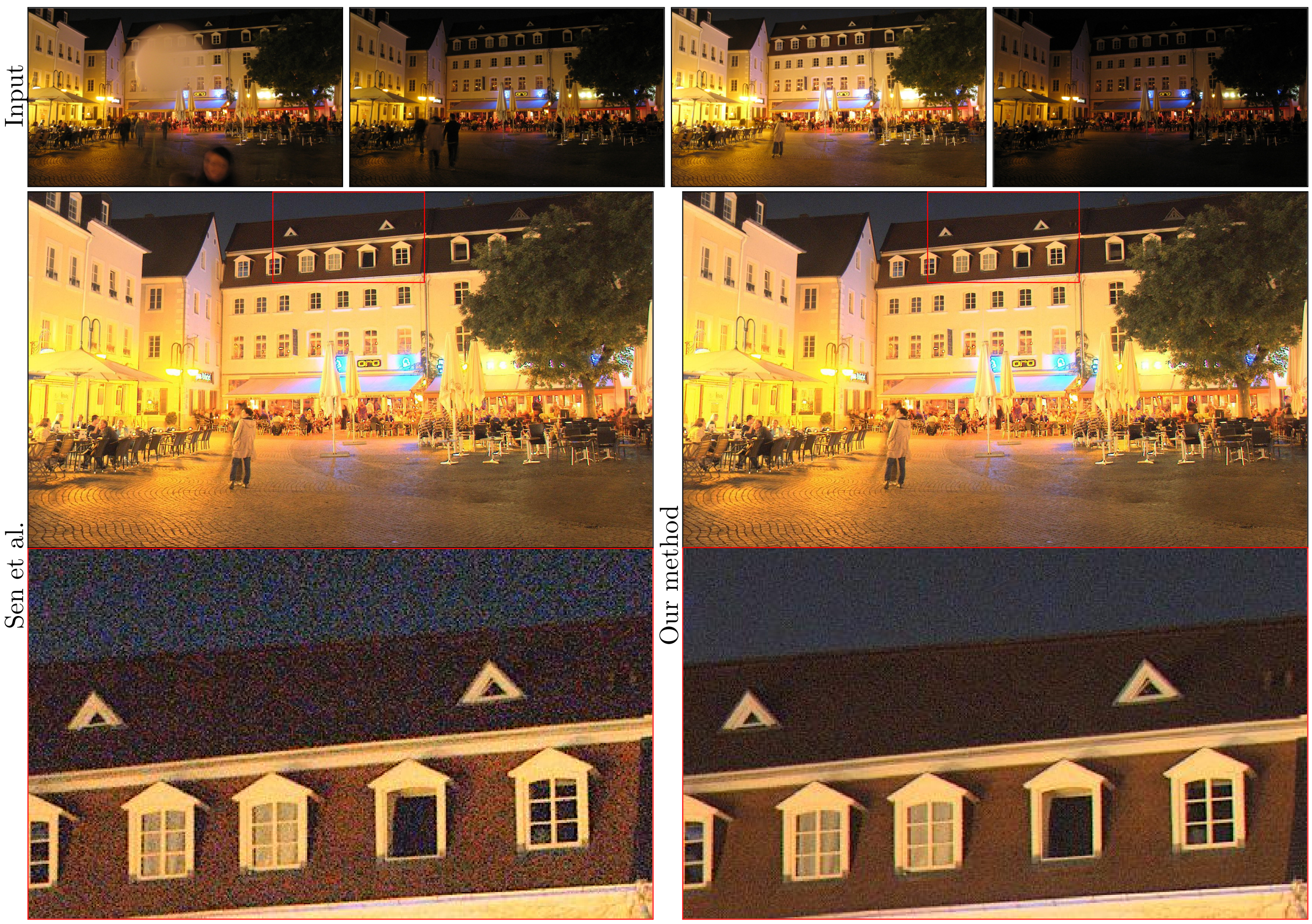


Figure 9: Comparison with method of Sen et al. [2] on the *square at night* sequence. The inlay shows a noise whose noise could not be removed by averaging additional images in the input.

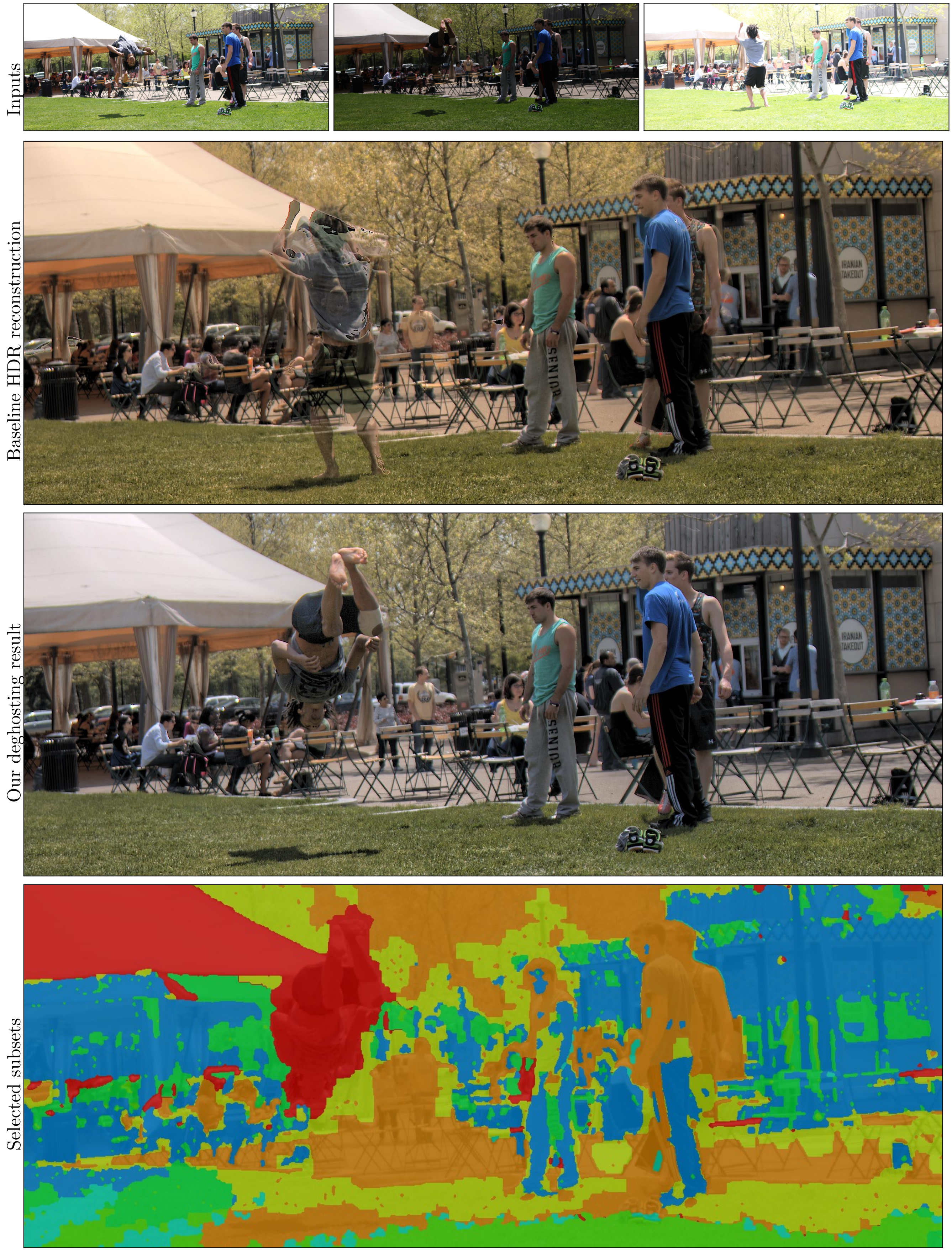


Figure 10: Deghosting result on the *Acrobat* sequence.

Figure 11: Deghosting result on the *Street traffic* sequence.