PieNet: Personalized Image Enhancement Network -Supplement Material-

Han-Ul Kim[1][0000−0001−7450−6600], Young Jun Koh[2][0000−0003−1805−2960], and Chang-Su Kim[1][0000−0002−4276−1831]

[1] Korea University, Seoul, Korea
hanulkim@mcl.korea.ac.kr, changsukim@korea.ac.kr
[2] Chungnam National University, Daejeon, Korea
yjkoh@cnu.ac.kr

§ User Study

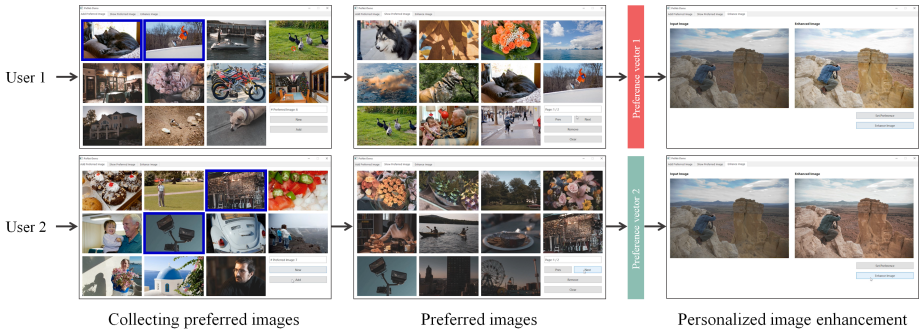


Fig. S-1: Illustration of the proposed personalization system.

– Fig. S-1 illustrates the user interface of the proposed personalization system for the user study in section 4.3. To collect preferred images, the system displays many types of pre-enhanced images. A user selects their preferred images among them. In this example, by employing 15 and 13 preferred images for users 1 and 2, PieNet produces personalized enhancement results effectively. Please see the supplementary video, which demonstrates this process.

§ Additional Experiments on MIT Adobe 5K dataset

– Table S-1 compares the PSNR scores of proposed algorithm with DUPE (2nd best performing method in Table 1). In Table S-1, we train DUPE for

Table S-1: Comparison of the proposed algorithm with DUPE [40] on MIT-Adobe 5K.

Method	A	B	C	D	E
DUPE [40]	23.05	23.75	23.61	23.18	23.20
Proposed	23.02	25.82	25.50	23.33	23.75

each photographer. Thus, DUPE needs five networks in total. In contrast, as a single network, the proposed PieNet enhances images for the five photographers adaptively using their preference vectors. Nevertheless, Table S-1 shows that PieNet provides better results for photographers B/C/D/E and is comparable for photographer A. On average, PieNet outperforms DUPE by 0.92 dB.

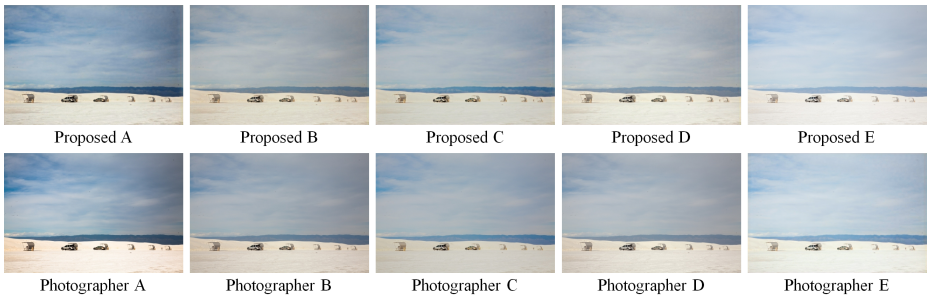
– Fig. S-2 compares qualitative enhancement results of the proposed algorithm with conventional algorithms: HDR [14], DPE [9], and DUPE [40]. The 'single user' setting in Table 1 in the main paper is adopted for all algorithms, which performs supervised learning using pairs of input and ground-truth (manually enhanced images by photographer C). We observe that the proposed PieNet yields much similar images to ground-truths than the convention algorithms do.
– Fig. S-3 and Fig. S-4 provide more personalized results of the proposed algorithm for photographers A/B/C/D/E on the MIT-Adobe5K dataset (the 'multiple users' test in Table 1). We see that the proposed algorithm adaptively produces output images in photographers A/B/C/D/E's styles, respectively.

§ Additional Experiments on the expanded MIT Adobe 5K dataset

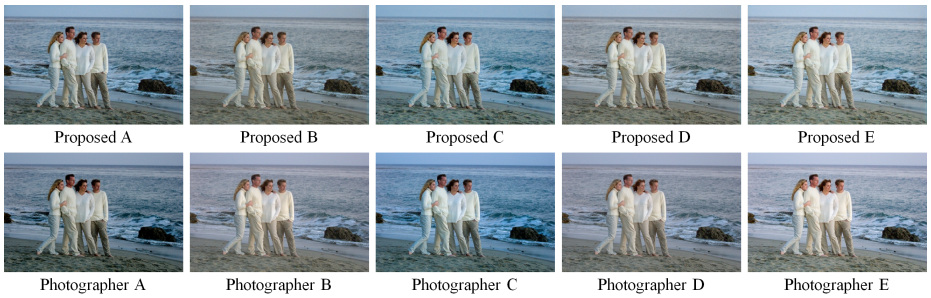
– Fig. S-5 shows an example of the expanded MIT Adobe 5k dataset. The first fifteen images are obtained using predefined settings in Adobe Lightroom. And we generate 8 enhanced results by conventional algorithms [2, 3, 6, 12, 13, 16, 29, 41]. Also, the expanded dataset includes five photographer's results in the MIT Adobe 5k dataset[5]. Note that these methods provide differently enhanced images and represent various preference styles of users.
– Fig. S-6 provides additional personalized results for five users (LDR, WVM, Lightroom Natural, Lightroom RedLiftMatte, and photographer E) in the test set of the expanded MIT-Adobe5K dataset. These personalized results demonstrate the excellent scalability of the proposed algorithm to accommodate new users.

(a) HDR [14] (b) DPE [9] (c) DUPE [40] (d) Proposed (e) Photographer C

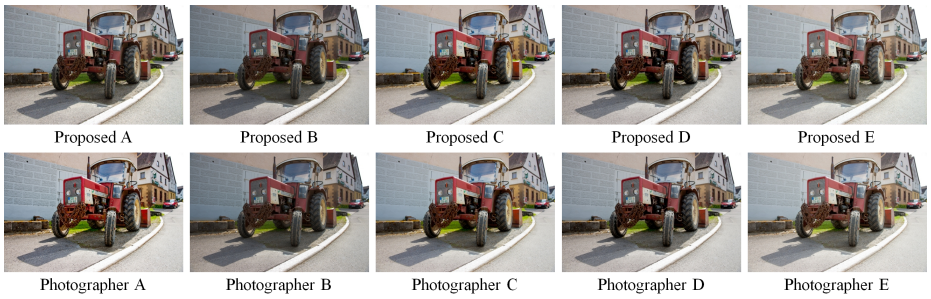
Fig. S-2: Qualitative comparison of the proposed algorithm with the conventional algorithms [9,14,40] on MIT-Adobe 5K. As ground-truth images, we use the enhanced images by photographer C.



(a)

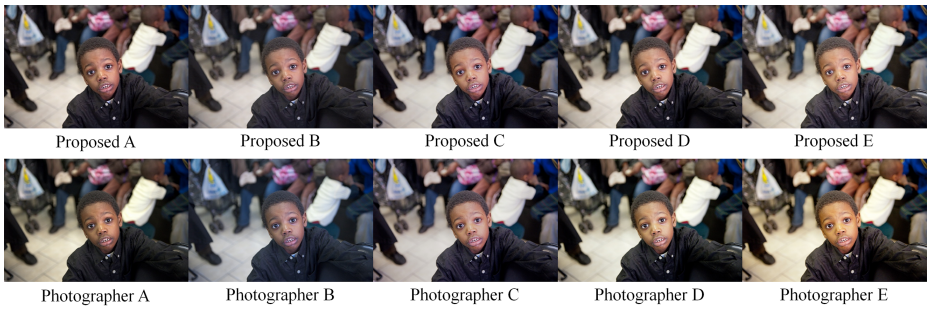


(b)

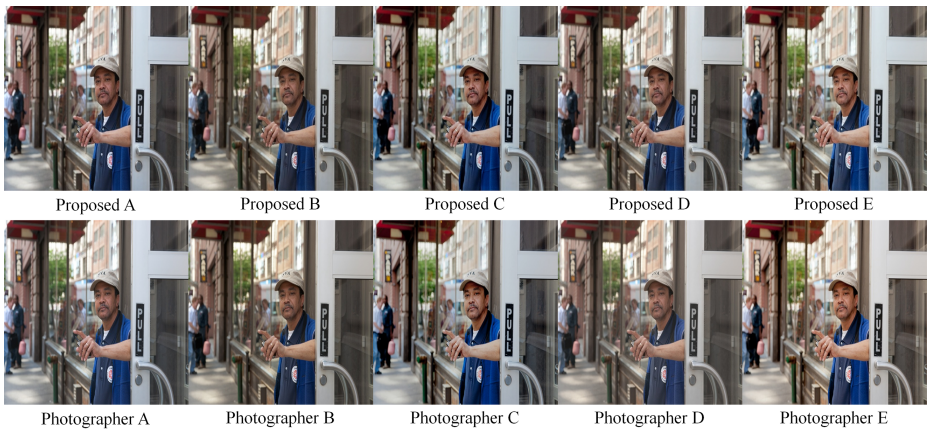


(c)

Fig. S-3: Personalized image enhancement results of the proposed algorithm for photographers A/B/C/D/E.



(a)



(b)

(c)

Fig. S-4: Personalized image enhancement results of the proposed algorithm for photographers A/B/C/D/E.

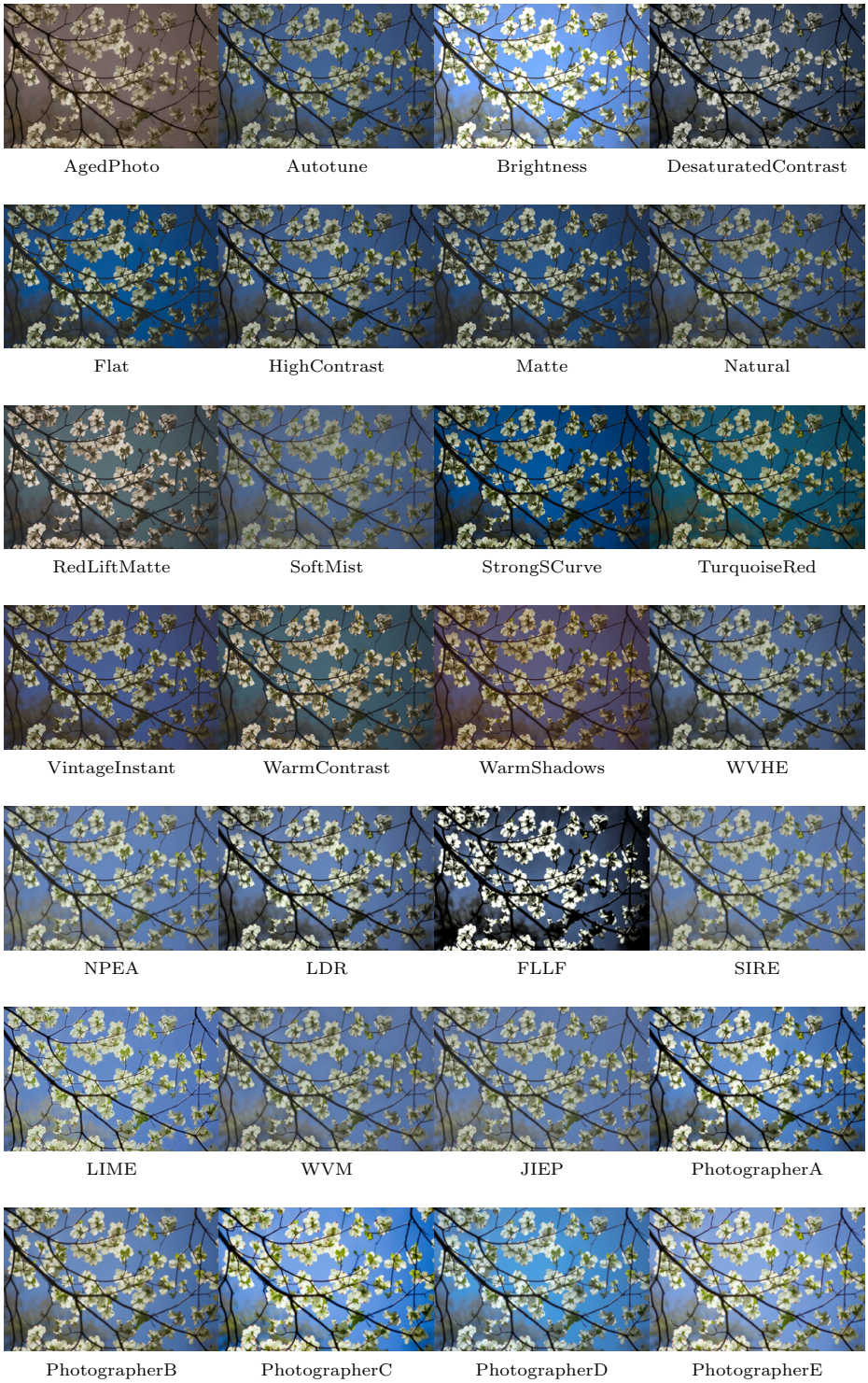


Fig. S-5: An example of the expanded MIT-Adobe 5k dataset

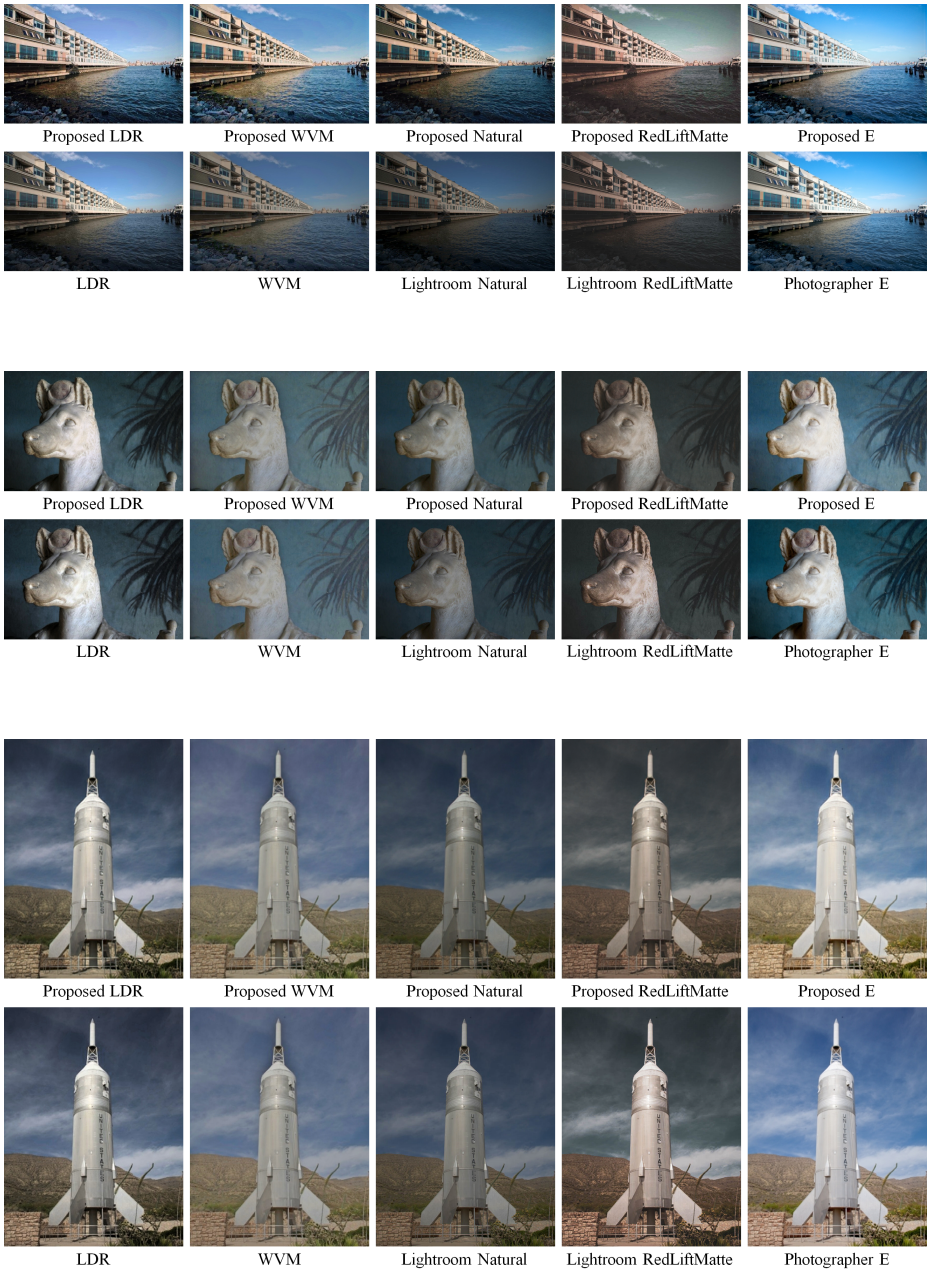


Fig. S-6: Personalized image enhancement results of the proposed algorithm for five users in the test set of the expanded MIT-Adobe5K dataset. In this test, we use 20 preferred images to generate each preference vector.