Supplementary Material: A Joint Intrinsic-Extrinsic Prior Model for Retinex

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The illumination contains the lightness information, so removing or adjusting the illumination can generate visually pleasing results for dark/backlit images. Among the competitors, SSR [7], MSRCR [9], SRIE [2] and WVM [4] are Retinex-based methods; NPE [12], GOLW [10], MF [3], LIME [6] are recent state-of-the-art image enhancement methods; HE [1] and BPDFHE [11] are two classical histogram equalization methods used as comparison baselines.

We focus on 35 identified challenging images with different illumination conditions collected from [12, 10, 3, 6, 2, 4], which are identified can be enhanced effectively by those methods. Fig. 1, Fig. 2 and Fig. 3 show the results of illumination adjustment comparing with six state-of-art methods [12, 10, 3, 6, 2, 4]. Since all of the illumination adjustment algorithms can obtain effective brightness enhancement on general outdoor images, and the ground truth of the enhanced image is unknown. Following [2, 4], a blind image quality assessment called natural image quality evaluator (NIQE) [8] is used to evaluate the enhanced results. In addition, Since NIQE is just for gray image assessment, we add a color image assessment called autoregressive-based image sharpness metric (ARISM) [5] for supplement. In Table 1 and Table 2, the proposed model has a lower average on NIQE/ARISM than the other state-of-art methods, which indicates that our model has a consistent good performance on different kinds of images.

References

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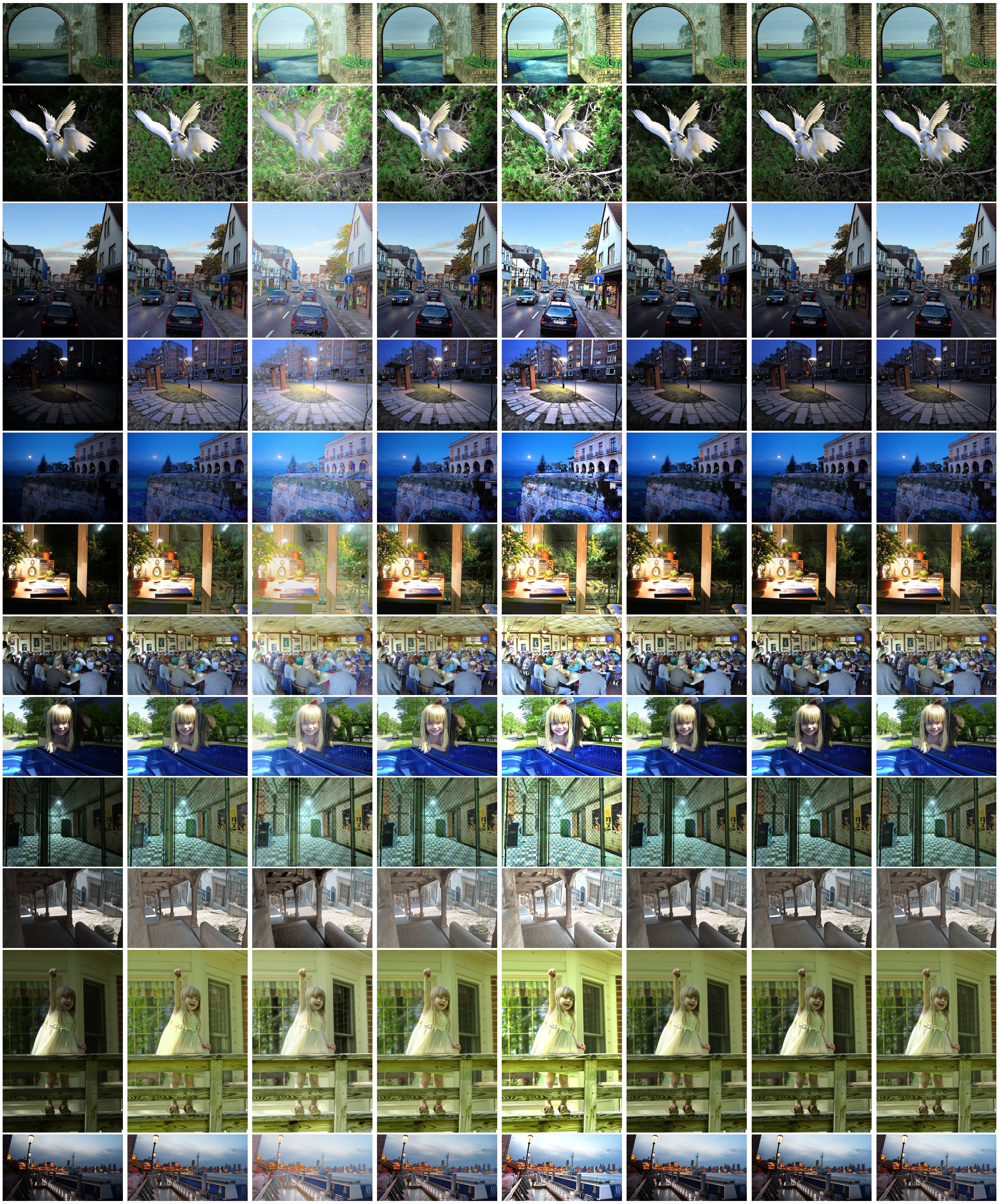
Table 1: Quantitative performance comparison on 35 images with NIQE. The Top-1 scores are shown in **red** for each row; a score is shown in blue if it is the Top-3 excluding the highest.

Method	HE [1]	BPDFHE [11]	SSR [7]	MSRCR [9]	NPE [12]	GOLW [10]	MF [3]	LIME [6]	SRIE [2]	WVM [4]	Ours
archway	3.5259	3.2506	3.5092	3.3500	3.2147	3.0956	3.6133	4.0170	2.9565	**2.6499**	2.9867
birds	3.4078	3.6936	2.9803	3.9062	3.0969	3.3926	3.2341	3.4994	**2.7740**	2.9655	2.9051
block	5.2713	5.5138	5.1009	5.7648	5.1825	5.7673	5.0512	5.5159	5.5670	5.4183	**4.8868**
campus	2.1570	3.0507	2.2460	2.2130	2.4755	2.5515	2.5623	2.4464	2.4251	2.2191	**2.1355**
castle	2.3023	2.8224	2.2692	2.4356	2.1736	2.4925	2.4210	2.3805	2.2164	**2.0869**	2.2086
desktop	2.4829	2.7201	2.4381	2.9715	**2.3694**	2.8961	2.3964	2.9322	2.4703	2.5762	2.4524
dinner	2.3883	2.4409	2.1848	2.1798	2.3273	**1.8191**	2.4637	2.1362	2.4026	2.3838	2.1829
driving	1.8145	2.4351	1.9116	1.9300	2.0754	**1.6975**	2.1382	2.1919	2.0113	2.0502	1.8663
factory	4.1352	3.9798	4.0430	4.9218	4.1547	**3.9541**	4.2249	4.4692	4.1941	4.0139	4.0835
gallery	3.2317	3.1086	3.1017	3.2816	3.1097	3.0101	3.1284	3.5870	3.1992	3.4733	**2.8617**
girl	2.7473	3.1113	2.9017	3.0204	2.5497	**2.4755**	2.6880	2.5922	2.9976	3.1475	2.7564
harbor	3.4850	3.6095	3.1677	3.6205	**2.9221**	3.5232	3.2637	3.5438	3.2708	3.2986	3.2608
laser	8.2207	9.2963	8.3620	6.9841	8.0624	**5.5172**	8.9346	9.4776	6.5198	6.4236	6.5851
light	**3.8335**	5.7080	4.7559	4.6477	5.0186	4.2875	5.1677	5.0745	5.6849	4.8644	4.9199
nightfall	**2.5712**	2.6630	2.6113	3.1551	2.7028	3.0069	2.6281	2.8275	2.7457	2.7231	2.8203
nighttime	2.7257	2.7044	**2.4318**	2.7081	2.7220	2.7145	3.4148	2.8332	2.6160	2.5330	2.5872
parking	3.6226	4.2029	3.3628	3.6729	3.3749	3.6313	3.3024	**3.1945**	3.6914	3.9150	3.6424
plantain	2.4703	2.5717	2.3614	2.7291	2.4731	2.3990	2.5193	2.6941	2.3304	**2.3011**	2.3231
potting	2.8606	2.9355	2.8137	**2.7201**	2.7658	2.7458	2.8601	2.9527	2.8039	3.0083	2.8011
river	3.3322	3.3581	3.2574	3.4849	**3.1282**	3.4796	3.1973	3.3503	3.2775	3.2726	3.4708
road	5.5588	5.8406	6.0144	29.2447	5.9589	6.0574	6.5722	6.2638	5.7811	**5.1925**	5.8085
robot	5.5183	5.4092	**5.1677**	6.1134	5.4340	5.8069	5.4845	6.2280	6.2593	5.6421	5.6163
room	2.7515	3.5751	2.5836	2.3139	2.5116	**2.2392**	2.9568	2.6759	3.0209	2.8960	2.9263
sailing	2.7180	2.5673	2.3882	2.2067	2.5338	2.2277	2.8018	2.9529	2.3732	**2.1352**	2.2746
sculpture	5.1381	5.3039	4.8856	**4.6423**	4.7890	4.7527	4.9542	5.2143	5.1663	5.0275	5.0320
shoe	4.0735	4.2381	4.1592	4.5426	4.1270	4.4098	**3.8254**	4.0520	4.0637	3.9467	3.8715
skyscraper	**4.8120**	5.3514	5.4804	5.6777	5.5037	5.5512	5.4049	5.4637	5.3133	5.1650	5.5277
snacks	3.1579	4.1443	3.0209	3.2247	3.0677	3.1665	3.1048	**2.8400**	3.3564	3.3666	3.2514
stadium	2.7181	2.8878	2.3150	2.5532	2.5116	2.3654	2.3774	2.3508	2.4106	**2.2747**	2.3889
statue	3.1747	3.2586	3.1535	3.2172	3.1569	3.1009	3.2691	3.1107	2.9723	**2.7604**	3.0200
street	2.1299	2.4327	2.0080	2.3936	2.1396	2.2099	2.0601	**1.9361**	2.2594	2.0716	2.0256
sunset	3.2032	3.3427	3.4294	3.3107	3.3091	**2.9946**	3.4189	3.1804	3.6008	3.6488	3.4234
swan	3.7151	3.1566	2.3702	3.0316	2.7968	2.7488	2.8479	2.9336	2.4280	**2.2716**	2.3618
venice	3.1076	2.8926	2.9868	3.3558	3.2090	3.4362	3.1833	**2.7610**	3.3999	3.1332	3.1342
woman	2.2987	2.8571	2.4510	2.4730	2.3709	2.2402	**2.2016**	2.8628	2.5051	2.7239	2.5328
Mean	3.4475	3.7267	3.3778	4.2285	3.4091	3.3647	3.5335	3.6155	3.4590	3.3594	**3.3409**

Table 2: Quantitative performance comparison on 35 images with ARISM. The Top-1 scores are shown in **red** for each row; a score is shown in blue if it is the Top-3 excluding the highest.

Method	HE [1]	BPDFHE [11]	SSR [7]	MSRCR [9]	NPE [12]	GOLW [10]	MF [3]	LIME [6]	SRIE [2]	WVM [4]	Ours
archway	3.2338	3.3987	3.0706	3.2691	**3.0324**	3.1156	3.0352	3.2832	3.1391	3.0718	3.0846
birds	2.9857	3.4226	2.8513	3.0308	2.9116	3.6474	2.8350	3.0585	**2.7982**	2.8064	2.8109
block	3.3768	3.6635	3.4324	3.5183	3.2146	3.7339	**3.1862**	3.4129	3.2579	3.2823	3.3203
campus	3.1575	4.0213	3.0761	3.2714	3.1028	4.3859	3.0712	3.1483	3.0693	**3.0596**	3.0926
castle	3.0227	3.4041	2.9970	3.1811	3.0430	3.2138	2.9510	3.0016	2.9670	**2.9369**	2.9484
desktop	3.3007	3.1341	2.8611	3.0464	2.9454	3.0905	2.9184	2.9842	**2.8381**	2.8445	2.9097
dinner	3.2120	3.0960	3.0211	2.9786	3.0420	3.0279	3.0028	3.1158	3.0008	**2.9370**	3.0076
driving	3.3850	3.1419	3.0358	3.0564	3.0207	3.0226	3.0200	3.0933	3.0105	**2.9792**	3.0444
factory	3.1350	3.3300	3.0843	3.2487	3.0695	3.0883	**2.9827**	3.4753	3.3283	3.0514	3.0228
gallery	2.9521	2.9937	3.0959	2.8681	3.0160	2.8741	2.8983	3.1335	2.8710	**2.8495**	2.8666
girl	3.3303	3.0154	2.9131	2.9598	3.0473	3.0112	2.9788	3.0060	2.8849	**2.8240**	2.9131
harbor	2.9584	3.0697	2.9460	3.2832	2.9519	3.5216	2.9153	3.1231	**2.8987**	2.9105	2.9245
laser	3.1202	5.0950	3.1062	3.1956	3.1226	3.1144	3.1078	3.1469	3.0737	3.0674	**3.0454**
light	6.2300	4.3653	3.8461	3.3951	3.5634	4.4134	3.4646	3.7555	**3.1917**	3.4749	3.2210
nightfall	2.9199	3.0235	2.8324	2.8821	2.8636	2.8336	**2.8077**	2.8706	2.8116	2.8096	2.8211
nighttime	3.0547	3.3977	2.9283	2.9443	3.1242	4.0070	3.0763	3.2071	2.9065	2.9930	**2.8556**
parking	3.0512	3.0275	2.9095	2.9431	2.9316	3.0790	2.8895	2.9859	2.8772	**2.8449**	2.8748
plantain	3.0500	3.0993	3.0072	3.0621	3.0422	3.0146	2.9668	3.2081	2.9875	2.9730	**2.9615**
potting	3.0425	3.0567	2.9063	2.9970	2.9411	3.0282	2.9192	2.9528	2.9288	**2.8976**	2.9070
river	2.9976	2.9381	2.8449	2.8938	2.8945	2.8130	2.8264	2.9484	2.8069	**2.7927**	2.8195
road	5.1045	4.0756	3.3576	**2.9373**	3.4225	3.2422	3.3452	3.3954	3.3947	3.3791	3.3979
robot	2.9121	2.7787	2.7730	2.8830	2.9240	2.8422	2.8778	2.9015	**2.7473**	2.7509	2.7684
room	3.1999	3.3162	3.0960	3.1561	3.2046	3.5388	3.0777	3.2112	2.9671	2.9592	**2.8992**
sailing	3.1903	3.2997	3.1917	3.1164	3.1474	3.1716	3.1114	3.4387	**3.1067**	3.1515	3.2078
sculpture	2.8485	2.8894	**2.7796**	2.8399	2.8506	2.8347	2.7859	2.8219	2.7864	2.7825	2.8172
shoe	3.1072	3.0460	3.0451	3.0541	3.2590	3.5222	3.1257	3.2820	3.0092	**2.9517**	2.9611
skyscraper	2.9130	3.1416	2.8321	3.0255	2.8469	4.9736	2.8304	2.8897	2.8003	**2.7875**	2.7984
snacks	3.1526	3.2228	2.9889	3.2237	3.0945	3.6077	3.0258	3.1074	2.9496	2.9827	**2.9165**
stadium	3.2991	3.4945	3.0851	3.1491	3.0935	3.0730	**3.0058**	3.1869	3.0366	3.0273	3.0633
statue	3.3112	3.2304	3.1845	3.1519	3.2481	3.1415	3.1360	3.3260	3.1256	**3.1171**	3.1739
street	3.4985	3.1714	3.1231	3.2121	3.2572	3.3406	3.1011	3.5932	3.1124	3.2626	**3.0684**
sunset	3.0669	3.1436	2.9361	3.1152	2.9791	3.1254	2.9596	2.9539	2.9296	**2.8913**	2.9232
swan	3.3876	3.3307	3.2291	3.1559	3.1815	3.2333	3.1601	3.3623	**3.1458**	3.1497	3.2043
venice	3.6621	3.6594	3.4401	3.5969	3.8282	3.7203	3.4658	3.8453	**3.2090**	3.4636	3.2575
woman	3.0137	2.9681	2.8152	2.9066	2.9010	2.9492	2.8381	2.9075	**2.7875**	2.7887	2.8016
Mean	3.2909	3.3275	3.0469	3.1014	3.0891	3.3243	3.0200	3.1753	2.9930	2.9958	**2.9917**



(a) Input (b) NPE [12] (c) GOLW [10] (d) MF [3] (e) LIME [6] (f) SRIE [2] (g) WVM [4] (h) Ours

Figure 1: Comparison of illumination adjustment, including *archway*, *birds*, *block*, *campus*, *castle*, *desktop*, *dinner*, *driving*, *factory*, *gallery*, *girl*, *harbor* in each row respectively.

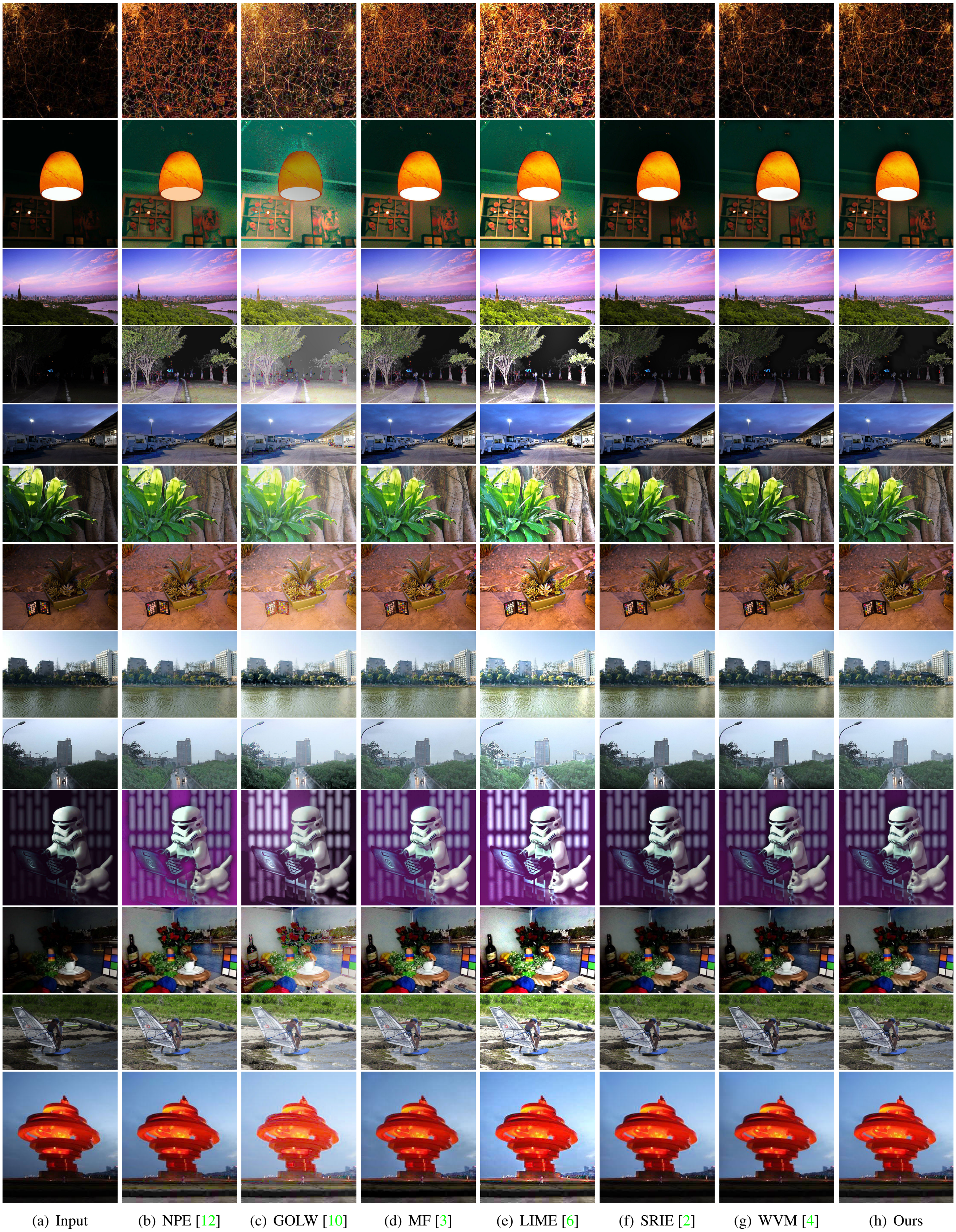
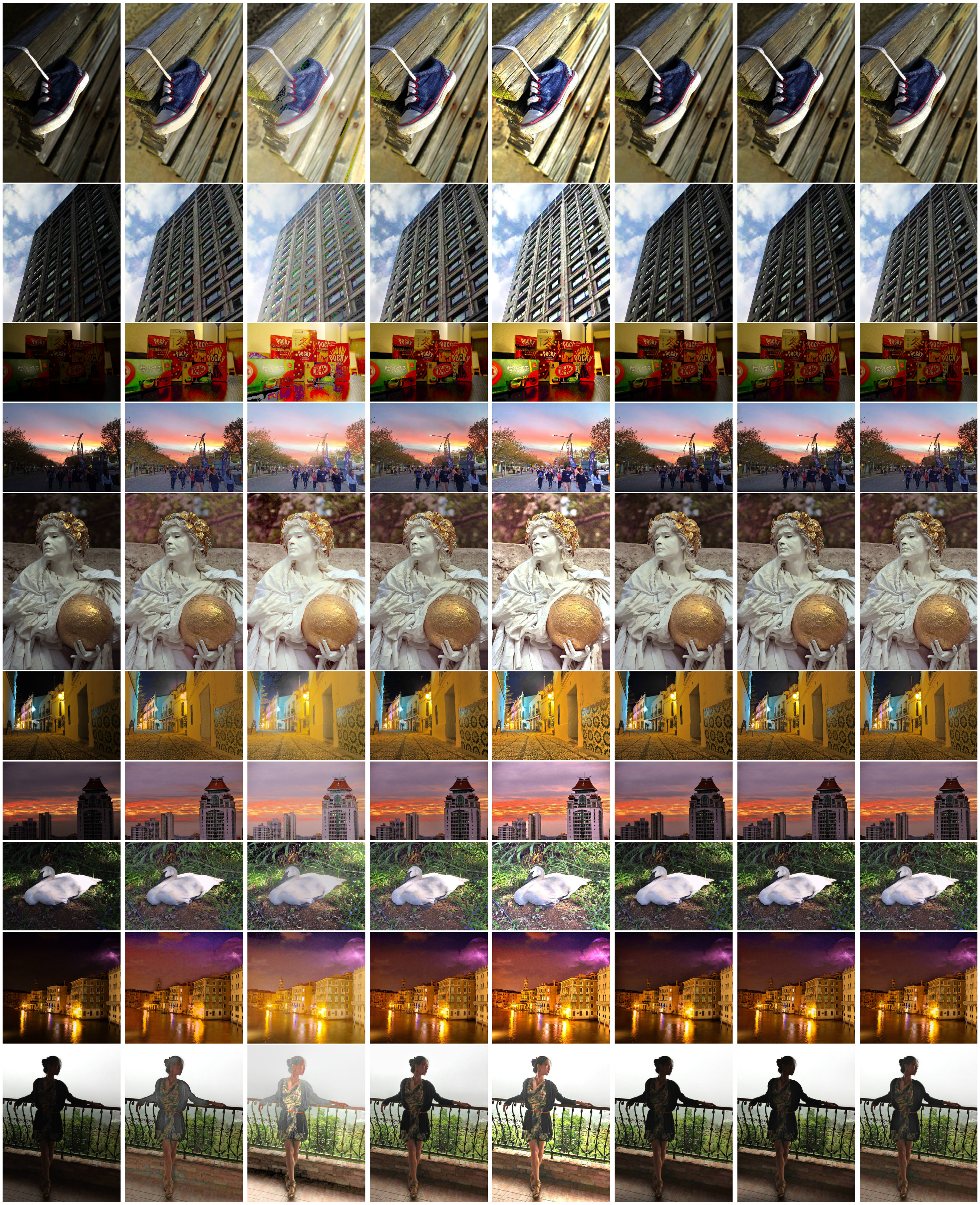


Figure 2: Comparison of illumination adjustment, including *laser*, *light*, *nightfall*, *nighttime*, *parking*, *plantain*, *potting*, *river*, *road*, *robot*, *room*, *sailing*, *sculpture* in each row respectively.



(a) Input (b) NPE [12] (c) GOLW [10] (d) MF [3] (e) LIME [6] (f) SRIE [2] (g) WVM [4] (h) Ours

Figure 3: Comparison of illumination adjustment, including *shoe*, *skyscraper*, *snacks*, *stadium*, *statue*, *street*, *sunset*, *swan*, *venice*, *woman* in each row respectively.