Frequency-Consistent Optimization for Image Enhancement Networks

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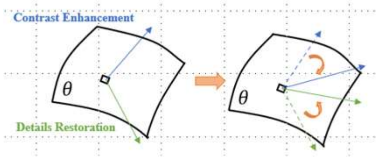
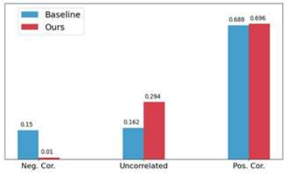
Introduction

Motivation:

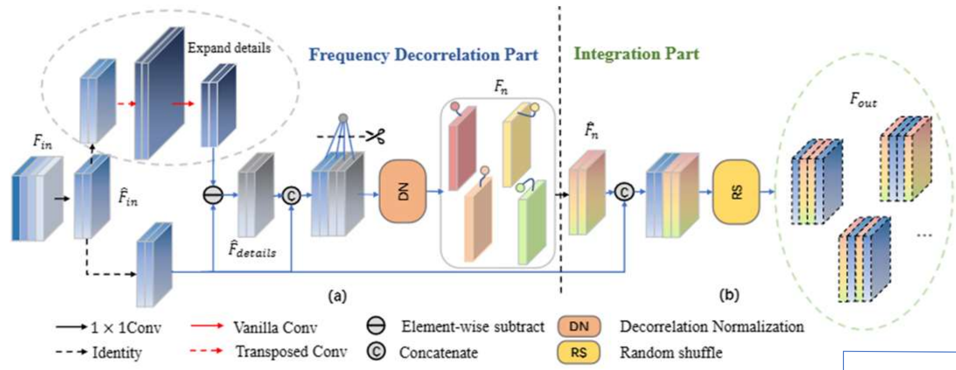
- Image enhancement aims at enhancing the overall contrast (low frequency) while reconstructing details (high frequency). Existing studies typically achieve these two objectives with a heuristically constructed complex architecture (i.e., two-stage or two-branch).
- However, the complex designs result in unsatisfactory flexibility and transferability. What's more, two-stage approaches lead to the accumulation of errors, resulting in sub-optimization.





- Our aims is to perform the image enhancement task within a single-stage and single-branch network.
- However, directly employing a single network to optimize the two objectives simultaneously will lead to an optimization conflict.
- To alleviate this problem, we construct a frequency-independent feature space for maintaining optimization consistency

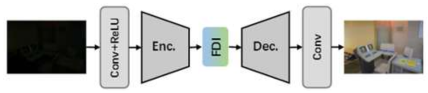
Method



- The overview of our proposed FDI module, which formulates a frequency-independent feature space with (a) a frequency decorrelation part and (b) an integration part.
- The frequency decorrelation part maps frequency-dependent features to the frequency-independent features.
- The integration part compensates for the information loss caused by decorrelation normalization, which introduces a random channel shuffle operator to reduce the sensitivity to frequency during the training process.

Decorrelation Normalization (DN): given the input features $X \in R^{C\times HW}$, we perform DN by:

$$\mu = \frac{1}{HW} X \cdot \mathbf{1} \qquad \Sigma = \frac{1}{HW}(X - \mu \cdot \mathbf{1}^T)(X - \mu \cdot \mathbf{1}^T)^T \qquad \hat{X} = \Sigma^{-\frac{1}{2}}(X - \mu \cdot \mathbf{1}^T)$$



The plug-in strategy

Experiments

Figure 4: Visual comparison on LOL dataset. M-SID and M-MPRNet denote SID and MPR-Net incorporated with the proposed FDI module by strategy (ii) mentioned in Sec. 3.4.

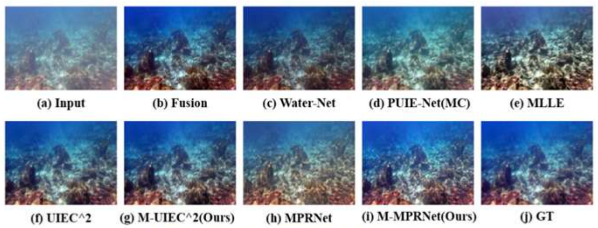


Figure 5: Visual comparison on UIEB dataset.

Method	Fusion	Water-Net	PUIE-Net(MC)	MLLE	UIEC^2	M-UIEC^2	MPRNet	M-MPRNet
PSNR(↑)	21.47	18.92	22.09	18.58	21.41	22.27(+0.86)	21.33	**23.39**(+2.06)
SSIM(↑)	0.8739	0.8533	0.8441	0.7706	0.9357	**0.9433**(+0.0076)	0.9154	0.9387(+0.0233)
LPIPS(↓)	0.158	0.158	0.156	0.312	0.128	**0.125**(+0.003)	0.178	0.147(+0.031)
#Param	N/A	4.16M	61.5M	N/A	2.05M	2.32M	17.5M	18.2M

Table 1: Quantitative results on LOL dataset. The best results are highlighted in bold.

Method	RetinexNet	KinD	KinD++	RUAS	DRBN	EnlightenGAN	SCI
PSNR(↑)	16.77	20.87	18.97	18.23	19.86	17.48	14.78
SSIM(↑)	0.5671	0.7988	0.8441	0.7170	0.8342	0.7330	0.6350
LPIPS(↓)	0.474	0.207	0.175	0.257	0.155	0.306	0.3334
#Param	0.62M	8.03M	9.63M	45K	2.21M	8.64M	43k
Method	**SID**	**SID-L**	**M-SID**	**MPRNet**	**MPRNet-L**	**M-MPRNet**	**LEDNet**
PSNR(↑)	19.16	18.99	21.07(+1.91)	20.13	20.22	21.59(+1.46)	20.94
SSIM(↑)	0.7862	0.8242	0.8360(+0.0498)	0.8170	0.8095	0.8512(+0.0342)	0.8506
LPIPS(↓)	0.440	0.258	0.227(+0.213)	0.266	0.261	0.154(+0.112)	0.2609
#Param	29.6M	118M	35.1M	17.5M	34.3M	18.2M	28.4M
Method	**LEDNet-FDI**	**Restormer**	**Restormer-FDI**	**NAFNet**	**NAFNet-FDI**	**IAT**	**IAT-FDI**
PSNR(↑)	21.59(+0.65)	20.67	20.79(+0.12)	22.44	22.79(+0.35)	23.38	**23.59**(+0.21)
SSIM(↑)	0.8618(+0.0112)	0.8193	0.8212(+0.0019)	0.8608	0.8620(+0.0012)	0.8675	**0.8704**(+0.0029)
LPIPS(↓)	0.2484(+0.0125)	0.2145	0.2107(+0.0038)	0.1482	**0.1467**(+0.0015)	0.2158	0.2049(+0.0109)
#Param	28.7M	99.8M	102.9M	65.5M	71.0M	0.41M	0.43M

Table 4: Quantitative results on LOL dataset. H-, R-, and M- denote incorporating the FDI module at the head, rear, and middle of networks, respectively.

Method	PSNR(↑)	SSIM(↑)	LPIPS(↓)	#Param(M)
SID	19.16	0.7862	0.439	29.6
H-SID	19.24(+0.08)	0.7846(-0.0016)	0.288(+0.218)	29.6
R-SID	20.18(+1.02)	0.8330(+0.0468)	**0.221**(+0.218)	29.6
M-SID	**21.07**(+1.91)	**0.8360**(+0.0498)	0.227(+0.212)	35.1
MPRNet	20.13	0.8170	0.266	17.5
H-MPRNet	20.72(+0.59)	0.8040(-0.0130)	0.259(+0.007)	17.6
R-MPRNet	20.63(+0.50)	0.8192(+0.0022)	0.231(+0.035)	17.6
M-MPRNet	**21.59**(+1.46)	**0.8512**(+0.0342)	**0.154**(+0.112)	18.2

Ablations

Table 5: Ablation study with decorrelation normalization on LOL dataset.

Method	PSNR(↑)	SSIM(↑)	LPIPS(↓)
baseline	20.13	0.8170	0.266
LN	21.14(+1.01)	0.8281(+0.0111)	0.204(+0.062)
IN	21.10(+0.97)	0.8330(+0.0208)	0.208(+0.058)
PCA	19.51(-0.62)	0.8241(+0.0071)	0.191(+0.075)
ZCA	**21.59**(+1.91)	**0.8360**(+0.0498)	**0.154**(+0.112)

Normalization	LN	PCA	ZCA	Expand	down-up	up-down
PSNR(dB)↑	21.14	19.51	**21.59**	PSNR(dB)↑	21.02	**21.59**
SSIM↓	0.8281	0.8241	**0.8512**	SSIM↓	0.8239	**0.8512**
LPIPS↓	0.204	0.191	**0.154**	LPIPS↓	0.190	**0.154**

Table 2. Ablation studies with decorrelation normalization and expand operator on LOL dataset (using MPRNet as the backbone).

Table 3: Ablation study for investigating the components of the FDI module. DN, DE, and RS stand for Decorrelation Normalization, Details Expanding, and Random Shuffle, respectively.

DN	DE	RS	PSNR (↑)	SSIM(↑)	LPIPS(↓)
			20.13	0.8170	0.266
	✓	✓	20.37	0.8199	0.250
✓		✓	20.82	0.8202	0.243
✓	✓		20.61	0.8243	0.244
✓	✓	✓	**21.59**	**0.8512**	**0.154**

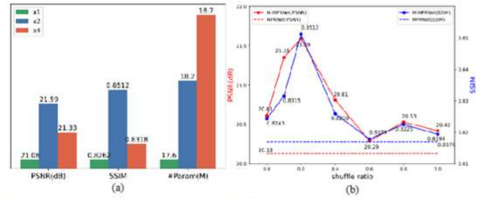


Figure 6: Ablation studies on LOL dataset. (a) Performance versus expanding resolution; (b) performance versus shuffle ratio.

Conclusions

- We point out the optimization inconsistency between contrast enhancement and texture restoration in image enhancement. To this end, we construct a frequency-independent feature space with a Frequency Decorrelation and Integration (FDI) module.
- Within the FDI module, we design a frequency decorrelation part for mapping features to a frequency-independent space, and an integration part for reducing the sensitivity to the frequency during the optimization process.
- Our FDI module is general and can be integrated into the existing image enhancement methods with negligible parameters. Extensive experiments demonstrate consistent performance gains by introducing our proposed module.