Learning a Blind Measure of Perceptual Image Quality: Supplementary Material

Test result under the setup of [4] We first compare the Spearman correlation of our work under the specific training/test split of [4], exposed in [3]. We revised the source code of BIQI[1] to allow training on BLIINDS's specific setup, and also tested our LBIQ method on this setup. As shown in Fig., this specific configuration used is favourable to both our LBIQ method and the BIQI method[2], indicating that the actual performance of BLIINDS might be lower than 0.79. Even so, we observe our LBIQ measure and the BIQI measure to significantly outperform BLIINDS. Therefore, we believe it evident that both our LBIQ measure and BIQI measure are much more effective than BLIINDS.

Using LBIQ to sort images by quality Many applications require a reliable order of images based on quality, and typically these images has the same content. In Fig. 3, we show the sorting results of images of three reference images (Fig. 2) with our LBIQ measure. Fig. 3(a) shows an example where our LBIQ measure is very correlated with perceived quality (measured by DMOS) in order. Fig. 3(b) provides an example with a looser correlation, but perceptually still well correlated with perceived quality. Fig. 3(c)



Figure 1. Median Spearman Correlation under 150 test run and the correlation under the specific configuration of [4]. Darker colors corresponds to median of spearman correlation across 150 test runs, lighter colors corresponds to median of spearman correlation under the specific training/test split in [4]. Note that, compared to the median performance, both LBIQ and BIQI achieve similar or better correlation under this specific setting for each distortion type, and much better in the overall distortion type.

shows a failure example. The main reason it doesn't work very well is that this image is very sparse in gradients. Accordingly, a slightly noisy image would be misinterpreted by LBIQ measure as an image of well distributed gradients, and therefore prorated by LBIQ.

References

- A. K. Moorthy and A. C. Bovik. BIQI: Blind Image Quality Index (Matlab code), 2010. Software available at http://live.ece.utexas.edu/ research/quality/BIQI_release.zip.
- [2] A. K. Moorthy and A. C. Bovik. A two-step framework for constructing blind image quality indices. *IEEE Signal Processing Letters*, 17(5):513–516, 2010.
- [3] M. A. Saad, A. C. Bovik, and C. Charrier. BLIINDS: BLind Image Integrity Notator using DCT Statistic, 2010. Partial MATLAB code available at http://live.ece.utexas.edu/ research/Quality/BLIINDS.zip.
- [4] M. A. Saad, A. C. Bovik, and C. Charrier. A dct statistics-based blind image quality index. *IEEE Signal Processing Letters*, 17(6):583–586, 2010.



Figure 2. Example images used for sorting images by LBIQ. We use 10 reference images to train our LBIQ, and 5 reference images for selecting SVM parameter and tuning the weights. None of the above three images are used for training or tuning model parameters. The red boxes highlights areas we zoom-in in Fig. 3.

DMOS:-0.1 LBIQ:6.4	DMOS:-0.2 LBIQ:8.1	DMOS:11.0 LBIQ:10.0	DMOS:10.8 LBIQ:10.4	DMOS:13.7 LBIQ:11.2	DMOS:10.6 LBIQ:11.3	DMOS:6.7 LBIQ:12.4
		Photo and		DUGG DO S		
DMOS:19.7 LBIQ:18.6	DMOS:12.2 LBIQ:19.3	DMOS:36.7 LBIQ:25.8	DMOS:26.9 LBIQ:26.9	DMOS:36.5 LBIQ:36.2	DMOS:46.9 LBIQ:37.6	DMOS:40.8 LBIQ:41.3
DMOS:46.2	DMOS:49.8	DMOS:54.0	DMOS:55.6	DMOS:59.1	DMOS:67.2	DMOS:62.9
LBIQ:47.4	LBIQ:49.9	LBIQ:52.4	LBIQ:54.1	LBIQ:57.5	LBIQ:64.3	LBIQ:69.2
			6-53	653	12-57	
DMOS:70.9 LBIQ:76.9	DMOS:72.2 LBIQ:77.1	DMOS:71.8 LBIQ:84.1	DMOS:98.3 LBIQ:98.8	DMOS:92.7 LBIQ:100.8		
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(a) Success case: Spearman Correlation = 0.98						
DMOS:24.5 LBIQ:35.2	DMOS:8.3 LBIQ:38.1	DMOS:25.7 LBIQ:39.5	DMOS:33.2 LBIQ:40.0	DMOS:30.5 LBIQ:40.2	DMOS:33.8 LBIQ:43.6	DMOS:27.0 LBIQ:44.4
TORS EASE DMOS:42.5	DRS DMOS:52.3	DATE DATE DATE AND DATE DATE DATE DATE DATE DATE DATE DAT	DASE DMOS:57.4	DMOS:48.0	TORS FASE DMOS:41.0	TORS DALLOWER PASE DMOS:72.8
CORS STUDENT	CORS LEIGHT	TORS STATE	TORS DELEGISTIC		LBIQ:52.6	TORS FASE
DMOS:72.3 LBIQ:53.4	DMOS:60.8 LBIQ:56.3	DMOS:86.0 LBIQ:59.9	DMOS:77.3 LBIQ:62.5	DMOS:73.1 LBIQ:63.5	DMOS:64.7 LBIQ:67.8	DMOS:78.2 LBIQ:70.0
TORS DMOS:63.0	TORS MOS:70.9	DMOS:101.1	ORS DOS:86.8	DRS DMOS:109.6	IORS	
TORS		LEIQ.90.0	LDIQ.50.0			
(b) Typical case: Spearman Correlation = 0.92						
DMOS:15.4 LBIQ:7.7	DMOS:33.4 LBIQ:23.0	DMOS:5.7 LBIQ:34.2	DMOS:4.5 LBIQ:36.2	DMOS:14.5 LBIQ:36.5	DMOS:9.4 LBIQ:37.2	DMOS:18.6 LBIQ:40.2
DMOS:49.8 LBIQ:41.4	DMOS:19.9 LBIQ:41.8	DMOS:12.6 LBIQ:44.2	DMOS:76.0 LBIQ:47.5	DMOS:12.7 LBIQ:48.1	DMOS:41.0 LBIQ:48.4	DMOS:52.7 LBIQ:50.5
No.						
DMOS:37.3 LBIQ:52.4	DMOS:35.4 LBIQ:53.4	DMOS:64.7 LBIQ:57.3	DMOS:58.3 LBIQ:63.5	DMOS:96.0 LBIQ:66.3	DMOS:50.8 LBIQ:68.7	DMOS:62.5 LBIQ:69.6
DMOS:64.6 LBIQ:80.1	DMOS:70.8 LBIQ:81.0	DMOS:88.9 LBIQ:94.7	DMOS:72.8 LBIQ:95.9	DMOS:93.9 LBIQ:100.2		

(c) Failure case: Spearman Correlation = 0.81

Figure 3. Images sorted by quality with our LBIQ method