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광적응 효과와 시각 집중 효과를 이용한 새로운 객관적 영상 화질 측정 용 하이브리드 가중치 풀링 기법

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A New Hybrid Weight Pooling Method for Object Image Quality Assessment with Luminance Adaptation Effect and Visual Saliency Effect

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요 약

완전 참조 영상 화질(full-reference image quality assessment, FR-IQA)측정의 풀링 과정에 있어서, 한 영상의 전역 화질은 각 국부 패치의 측정된 화질값들로부터 측정된다. 그러나 한 영상의 전체 화질 값을 예측함에 있어서 국부 패치의 종류, 왜곡 타입, 왜곡의 인지 민감도, 국부 패치의 관심 집중(saliency) 정도에 따라 국부 패치가 전체 영상에 기여하는 왜곡의 정도가 다를 수 있다. 그 결과, 계산된 국부 패치 화질값에 대한 가중치 풀링 방법이 기존 FR-IQA 방법에서 고려되었다. 본 논문은 기존 FR-IQA 방법에서 고려되지 않은 시각인지시스템의 특성인, 광적응 효과 와 시각 관심 집중 효과를 고려한 새로운 가중치 풀링 방법을 제안한다. 실험 결과, 기존 FR-IQA 방법에 적용될 경우 예측 성능을 향상시킴을 확인하였으며, 이는 제안하는 가중치 풀링 방법은 사람의 시각인지 특성을 효과적으로 반영하기 때문으로 사료된다.

Abstract

In the pooling stage of a full reference image quality assessment (FR-IQA) technique, the global perceived quality for any distorted image is usually measured from the quality of its local image patches. But all the image patches do not have equal contribution when estimating the overall visual quality since the degree of degradation on those patches depends on various considerations i.e., types of the patches, types of the distortions, distortion sensitivities of the patches, saliency score of the patches, etc. As a result, weighted pooling strategy comes into account and different weighting mechanisms are used by the existing FR-IQA methods. This paper performs a thorough analysis and proposes a novel weighting function by considering the luminance adaptation as well as the visual saliency effect to offer more appropriate local weights, which can be adopted in the existing FR-IQA frameworks to improve their prediction accuracy. The extended experimental results show the effectiveness of the proposed weighting function.

Keyword : IQA, Hybrid Weight Pooling, Luminance Adaptation, Visual Saliency

Ⅰ. Introduction

The visual quality of digital images can easily be degraded by various types of distortions that are unavoidable due to the image sensing process as well as for different image operations like compression, transmission, and enhancement, etc. As a result, predicting the degree of perceived visual quality for distorted images becomes an indispensable step in many computer vision and image processing applications. Objective image quality assessment (IQA) techniques aim to predict the perceived visual quality of distorted images and have been studied for decades as a practical alternative for cumbersome, costly and time consuming subjective evaluation of image quality by human observers. There are three types of methods in the family of objective IQA that are categorized based on the degree of availability of distortion-free reference image: (i) full-reference (FR)-IQA method, where the reference image that is assumed to has the perfect quality, is fully present and the method predicts the quality of distorted image by comparing with that reference image; (ii) reduced-reference (RR)-IQA method, where the method has to evaluate the distorted image using some partial information about the reference image; (iii) no-reference (NR)-IQA, where the reference image is totally absent and the method has to predict the quality only by observing the distorted image. Our approach belongs to the FR-IQA method that estimates the subjective visual quality of a distorted image under its given reference image. Generally, the FR-IQA model takes the following mathematical structure:

$$\hat{y}=\frac{1}{W}\sum_{i=1}^{N} w_i,\phi(R_i,D_i;\theta) \tag{1}$$

where R_i, and D_i represents the i-th image patches from a reference image and its distorted image, respectively, with $i=1,2,\dots\ \dots,N$. ϕ is the local visual quality predictor with parameter θ. The predicted local visual quality values are pooled with the weight that is normalized by the sum of all the weights W calculated from the whole image patches. Finally, the pooled local visual quality values turn out to be the estimated overall visual quality value $\hat{y}$ of the distorted image D under its given reference image R.

The best approach to calculate the local weights in Eq. (1) is to utilizing the psychophysical models such as contrast sensitivity function (CSF), luminance adaptation (LA) effect, contrast masking (CM) effect, and visual saliency (VS) property to well reflect the characteristics of human visual system (HVS). Most existing FR-IQA methods tried to reflect one of those psychophysical models. Structural Similarity Index (SSIM) [1] and many other FR-IQA methods were designed by incorporating the Weber's law in order to mimic the LA effect. The Weber's law states that the visibility threshold of the HVS to image signal difference increases along with the background luminance values and can be modeled as

$$\Delta L=\delta . L_f \tag{2}$$

where $\Delta L=|L_b-L_f|$ is the smallest visibility threshold of the HVS for the difference between a reference background luminance value L_b and its foreground luminance value L_f and δ is a constant value. ΔL can also be considered as a just noticeable difference (JND) threshold, which indicates that the visibility threshold of the HVS increases as the background luminance values increase. Bae et al [2] reveals that the LA effect has improperly been incorporated

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into the existing FR-IQA methods for example in SSIM. Because: (i) a recent study [3] has shown that the current LA model is unable to fit the measured experimental results for the LA effect; (ii) the Weber's law is applied in the luminance domain while the IQA methods operate in the pixel intensity domain. Consequently, Sung-Ho et. al. [13] proposed an appropriate way to imitate the LA effect in pixel intensity domain and used that LA model as a weighting function to adaptively apply weights for local image regions based on their sensitivity.

But the goal of IQA models is to be highly correlated with human perception and to do that, they should reflect the important HVS properties. VS is one of the most important characteristics of HVS which indicates that, HVS is highly sensitive to some specific image regions (salient regions) rather than all of the image regions. We reveal that the LA based weighting function is good for estimating the distortion sensitivity but unable to differentiate between the salient and less important regions in an image and thereby the weights to the local regions assigned by LA-LF is inappropriate. Therefore, this paper proposes a new weighting function by incorporating the VS properties along with the LA effect model to offer higher attention to significant image regions besides their noise sensitivity, when calculating the local weights that are used to estimate the overall quality. The experimental results show that the proposed weighting function is highly correlated with human perception and it improves the performance of existing IQA methods.

Ⅱ. Related Work

1. Luminance Adaptation based Local-weighting Function (LALF)

A recent study [3] revealed that, the Weber's law model defined in Eq. (2) cannot precisely be fitted to the measured visibility threshold values for various background luminance. The author found that $\Delta L/L_f$ in Eq. (2) cannot be fitted to a constant, but a decreasing function of ΔL and they devised a power-law model to solve the problem as

$$\frac{\Delta L}{L_f} = \eta \cdot L_b^{\xi} \cdot L_f^{-\xi} \tag{3}$$

where η, L_b and ξ are constants. However, the Weber's law model and the power law model operates on luminance values which have a non-linear relationship with pixel intensity values due to Gamma correction function [4] and the non-linear relationship can be represented as

$$L_f = \alpha + \beta \cdot \mu_f^{\gamma} \tag{4}$$

where α, β and γ are the model parameters of the Gamma correction function. By substituting L_f and μ_f with $L_f + \Delta L$ and $\mu_f + \Delta\mu$ in Eq. (4) and then applying first-order Taylor series expansions yields

$$L_f + \Delta L = \alpha + \beta \cdot \mu_f^{\gamma}\left(1 + \frac{\Delta\mu}{\mu_f}\right)^{\gamma} \tag{5}$$

Substituting ΔL in Eq. (3) and L_f in Eq. (4) into Eq. (5) yields

$$\Delta\mu(\mu_f) = a_1 \cdot \mu_f^{a_2} + a_3 \cdot \mu_f + a_4 \tag{6}$$

where $a_1 = -2.655$, $a_2 = 0.9259$, $a_3 = 1.709$ and $a_4 = 21.73$. The model represented in Eq. (6) reflects the LA effect in pixel intensity domain which is more appropriate to be used in IQA models [2]. Since some image regions are more sensitive to distortions than others in perceived quality, it is expected that those image regions will have higher weights compared to the less sensitive regions. Therefore, the newly devised LA model is used to assign the local weights in an adaptive manner. The distortion sensitivity of an image region can be found by the inverse of visibility threshold in Eq. (6) as

$$\delta_D(\mu_f) = \Delta\mu(\mu_f)^{-1} + \epsilon \tag{7}$$

where μ_f is the average pixel intensity of a local region, is a constant and $\epsilon = 1.5 \times 10^{-3}$. Now the distortion sensitivity $\delta_D(\mu_f)$ can be used in pooling stage as a replacement of weight ω_i as shown in Eq. (1). Between the sensitivity values of reference and distorted images, the higher one would be considered as the final weights for the local image regions.

2. Visual Saliency (VS)

Human vision has an extraordinary ability that allows us to naturally focus on important regions in an image or scene. In order to empower the machine to mimic that facility, computational VS models aim to estimate the importance of various image regions based on their ability in attracting the attention of HVS. VS has been widely studied in several domains including psychology, neurobiology, computer vision, and image processing. Most recently it has attracted IQA researcher's attention since the distortions on salient regions have a significant effect on the perceived quality. Among numerous VS models [5] - [8], we have incorporated saliency detection using simple priors (SDSP) [8] in our model which is one of the best VS methods to fit in IQA techniques [9]. SDSP detects the salient regions in the viewing field by combining three simple priors: (i) the process of detecting salient objects by HVS in a visual scene can be well modeled by band-pass filtering mechanism; (ii) it is human nature to pay attention in the center of an image or scene; (iii) warm colors are more attractive to the HVS than cold colors. A given image $f(X)$ is converted to an opponent color space called CIEL*a*b* space and the resulted channels are denoted by $f_L(X), f_a(X)$ and $f_b(X)$ respectively. Then the frequency prior is defined as

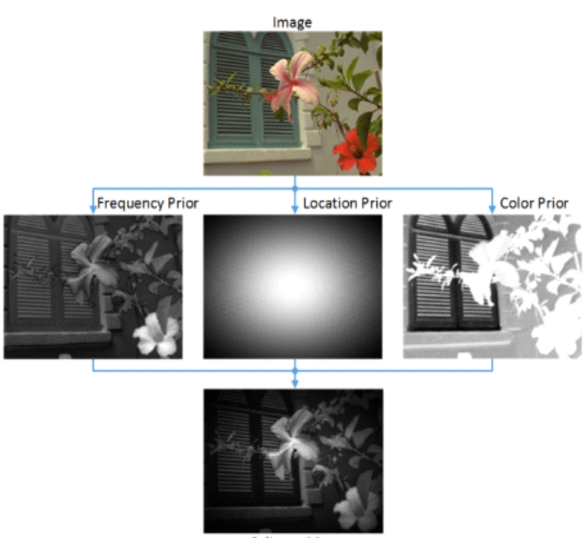

그림 1. SDSP를 사용한 시각적 중요성 감지
Fig. 1. Visual Saliency detection using SDSP

$$S_F(X) = \sqrt{(f_L * g)^2 + (f_a * g)^2 + (f_b * g)^2}\,(x) \tag{8}$$

where * denotes the convolution operation and g denotes the log-Gabor filter. In CIEL*a*b* space, a*-channel represents green-red color information and it will be greenish (reddish) if a* has smaller (higher) value. On the other hand, b*-channel represents the blue-yellow color information and it will be bluish (yellowish) if b* has smaller (higher) value. As a result, if a pixel has a higher a* or b* value it will be warmer. Otherwise it will be colder. In order to find the color prior, the a* and b* channels are first normalized as

$$f_{an}(X) = \frac{f_a(X) - a_{min}}{a_{max} - a_{min}} \tag{9}$$

$$f_{bn}(X) = \frac{f_b(X) - b_{min}}{b_{max} - b_{min}} \tag{10}$$

where a_{max} and a_{min} are the maximum and minimum value of a* and b_{max} and b_{min} are the maximum and minimum value of b*. Then the color prior can be defined as

$$S_c(X) = 1 - exp\left(-\frac{f_{an}^2(X) + f_{bn}^2(X)}{\sigma_c^2}\right) \tag{11}$$

where σ_c is a parameter. And the location prior can easily be modeled as a Gaussian map. If is a center of the image $f(X)$, then the location prior can be defined as

$$S_p(X) = exp\left(\frac{\| X - C \|_2^2}{\sigma_c^2}\right) \tag{12}$$

where σ_p is a parameter. Finally, using those three priors the visual saliency map $\delta_{VS}(X)$ for image $f(X)$, can be defined as

$$\delta_{VS}(X) = S_F(X).S_c(X).S_L(X) \tag{13}$$

Figure (1) shows an example of saliency detection using SDSP.

Ⅲ. Proposed Method

The local image regions that are highly sensitive to distortions and also located in the salient regions from the HVS viewpoint, should have higher weights compared to others. More specifically, some image regions are more sensitive to distortions than others and among those regions some are more attractive to the observer. So it is obvious that those significant regions play more important roles than others in perceiving the visual quality. Based on that assumption, we propose a more appropriate weight pooling mechanism called VSLA-LF by simultaneously incorporating the LA effect in pixel intensity domain along with the VS score to assign the local weights which are closer to the human perception. We assign the weights for local image regions adaptively based on the combined effect of distortion sensitivity and saliency score of those regions and can be defined as

$$w_{vsia} = \delta_D(\mu_f).\delta_{VS}(X)^{a_s} \tag{14}$$

where $\delta_D(\mu_f)$ is the distortions sensitivity, $\delta_{VS}(X)$ is the saliency score of any local image region and a_5 is a constant with value of . The local weight values for both reference and distorted images are calculated and the higher one between those values are used as the final weights for the local image regions. And to carry out the effects of the found local weights, we replace the w_i in Eq. (1) with w_{vsia} in Eq. (14). Figure 2 shows an example of assigning more appropriate weight by the proposed VSLA-LF and also shows the comparison with LA-LF method. In the reference and distorted images (1st and 2nd row), the regions that are highlighted by smaller blue and yellow boxes, indicate more distortion sensitive regions (gray) compared to the regions that is highlighted using smaller red box (dark) and the bigger boxes show the electronic zoom of those regions respectively. It is expected that the more sensitive regions should have higher weights compared to the less sensitive regions and that is handled by the proper LA model as shown in the 3rd row in the figure.

Also, it can be seen that the blue regions are more salient to the HVS compared to the yellow regions and as a result, they should have further higher weights compared to the yellow regions. But from the 3rd row in Figure 2 it is clear that the LA-LF is failed to reflect that property since it assigns similar weights for both the blue and yellow marked regions. While the proposed VSLA-LF well reflects that property and assigns lower weights to the less salient regions and higher weights to the more salient regions as shown by the 4th row in Figure 2.

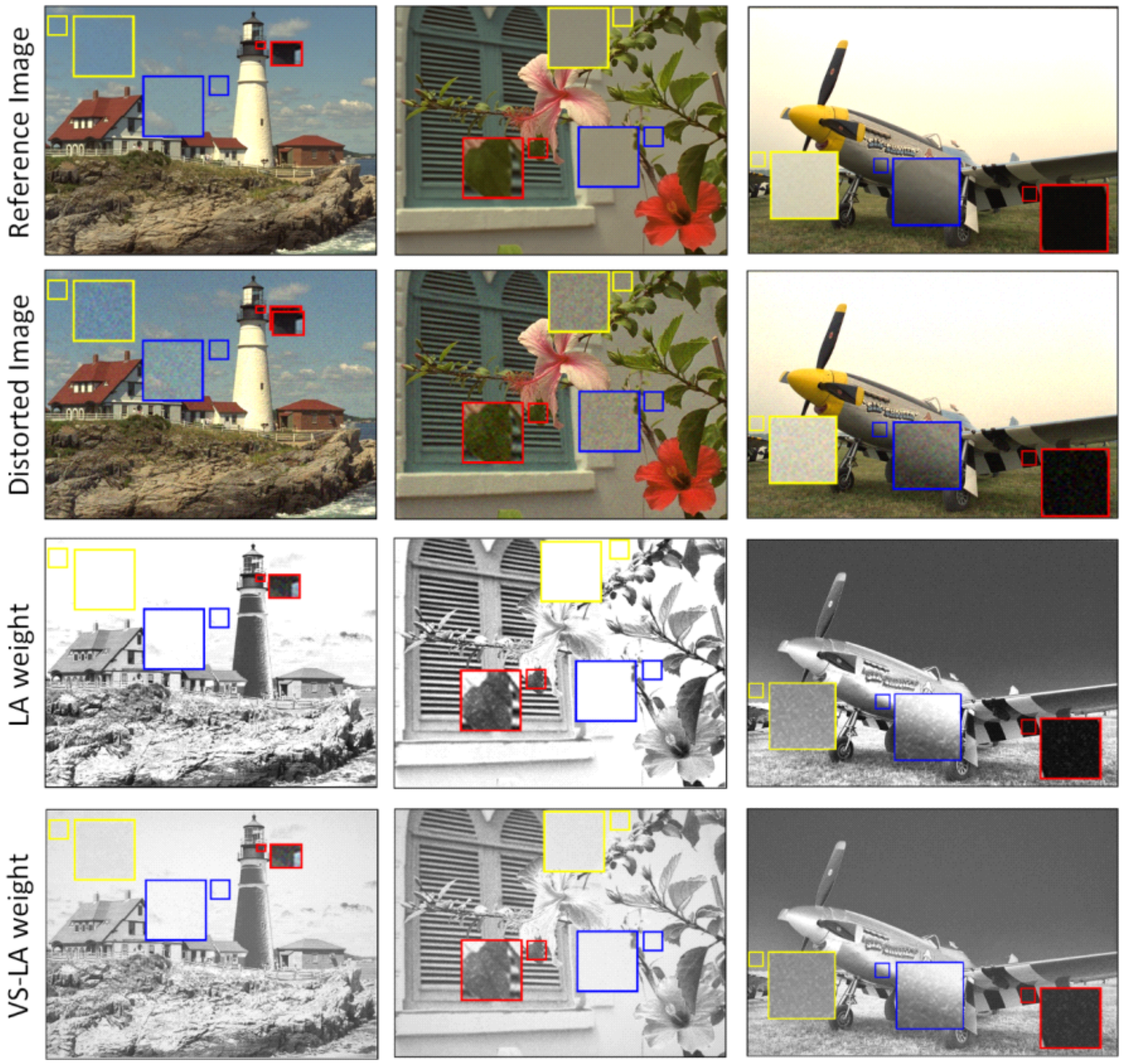

그림 2. 제안하는 VSLA-LF 방법에 의한 국소 가중치 할당의 예 및 LA-LF 방법과의 비교. 첫 번째 행의 첫 번째, 두 번째 이미지는 TID2013 데이터베이스에서 세 번째 이미지는 LIVE2 데이터베이스에서 가져온 참조 이미지이다. 두 번째 행은 참조 이미지에 가산성 백색 가우시안 잡음(AWGN)이 추가된 왜곡 이미지이고, 세 번째와 네 번째 행은 각각 LA-LF와 VSLA-LF 방법으로 찾은 가중치 맵이다.
Fig. 2. Examples of local weight assigning by the proposed VSLA-LF method and comparison with LA-LF method. The first row shows the reference images where the 1st and 2nd images are taken from TID2013 database and the 3rd image is taken from LIVE2 database. The Second row shows the corresponding AWGN-distorted images. And the third and fourth rows show the weight map found by LA-LF and VSLA-LF respectively.

Ⅳ. Experimental Results

Extensive experiments were conducted on four benchmark IQA datasets including TID2013 [10], TID2008 [11], CSIQ [12] and LIVE [1], to verify the effectiveness of the proposed VSLA-LF method. Table 1 summarizes the important information about these four datasets such as the number of reference and distorted images, the number of distortion types, the number of subjects performing the subjective evaluations, etc.

표 1. 실험에 사용된 네 가지 데이터 셋 요약
Table 1. Summary of the four datasets used for the experiments

Dataset	Number of reference images	Number of distorted Images	Number of distortion types	Number of subjects
TID2013	25	3000	24	971
TID2008	25	1700	17	838
CSIQ	30	866	6	35
LIVE	29	779	5	161

PSNR and SSIM are two widely accepted and mostly used FR-IQA methods on which the proposed weighting function is applied and they are denoted as VSLA-PSNR and VSLA-SSIM respectively. But in VSLA-SSIM, the luminance similarity component of the original SSIM is excluded because of its inappropriate LA effect. The model parameters are the same as mentioned in their original papers. Four well-known performance metrics such as Spearman Rank-Order Correlation coefficient (SROC), Kendall Rank- Order Correlation coefficient (KROC), Pearson Linear Correlation coefficient (PLCC) and Root Mean Squared Error (RMSE) are adopted to measure the per-formance of the methods under test. For RMSE, the lower values indicate better prediction accuracy and for the rest of the three metrics i.e., SROC, KROC and PLCC, the higher values indicate better prediction accuracy. SROC and KROC measure the prediction monotonicity of an IQA index and they operate only on the rank of data points regardless of their relative distance. But PLCC and RMSE need a non-linear mapping between the objective scores and subjective mean opinion scores (MOS). So, in order to map the predicted objective scores to the MOS, we adopt a logistic regression [1].

The overall performance is measured by taking the weighted average based on the number of images containing in each of the datasets. For overall performance, we do not consider the RMSE because it cannot offer meaningful indication since the MOS scales for different datasets are different. First, we evaluate the proposed VSLA-LF model by applying it on traditional PSNR. Table 2

표 2. PSNR, VS-PSNR, LS-PSNR, VSLA-PSNR의 성능 측정 비교
Table 2. Performance measurement of VSLA-PSNR and comparison with PSNR, VS-PSNR and LA-PSNR

		PSNR	VS-PSNR	LA-PSNR	VSLA-PSNR
TID2013	SROC	0.6868	0.6900	0.6889	0.6896
	KROC	0.4960	0.4994	0.4963	0.4970
	PLCC	0.6778	0.6765	0.6847	0.6849
	RMSE	0.9110	0.9129	0.9036	0.9033
TID2008	SROC	0.5371	0.5522	0.5529	0.5540
	KROC	0.3795	0.3912	0.3907	0.3915
	PLCC	0.5387	0.5418	0.5507	0.5511
	RMSE	1.1297	1.1279	1.1201	1.1197
CSIQ	SROC	0.8409	0.8434	0.8522	0.8534
	KROC	0.6401	0.6415	0.6493	0.6512
	PLCC	0.8280	0.8273	0.8309	0.8311
	RMSE	0.1470	0.1473	0.1461	0.1459
LIVE	SROC	0.8994	0.9003	0.8999	0.9002
	KROC	0.7348	0.7353	0.7343	0.7348
	PLCC	0.7919	0.7921	0.7922	0.7922
	RMSE	14.0959	14.1092	14.1058	14.1059
Overall	SROC	0.7002	0.7061	0.7068	0.7076
	KROC	0.5206	0.5255	0.5248	0.5257
	PLCC	0.6787	0.6789	0.6853	0.6856
	RMSE	-	-	-	-

shows the performance comparison of the proposed VSLA-PSNR with the traditional PSNR, VS-PSNR, and LA-PSNR, where VS-PSNR is found by applying only VS as a weighting function in PSNR. Both the VS-PSNR and LA-PSNR improves the prediction accuracy compared to the traditional PSNR in all the cases, where LA-PSNR shows little bit higher accuracy than VS-PSNR. On the other hand, VSLA -PSNR shows its superiority than VS-PSNR and LA-PSNR in most of the cases and also outperforms in case of overall prediction accuracy. Next, we apply the VSLA-LF model in SSIM that is the most widely accepted FR-IQA method and the performance comparison is shown in Table 3. Similar to the previous experiment, VS-SSIM, and LA- SSIM improves the traditional SSIM performance where VS-PSNR outperforms for CSIQ dataset. VSLA- SSIM also shows promising results and for all the cases it improves the prediction accuracy than the LA-SSIM. Except the CSIQ dataset VSLA-SSIM shows the best accuracy in all the cases and also on average it outperforms all other methods.

표 3. SSIM, VS-SSIM, LA-SSIM, VSLA-SSIM의 성능 측정 비교
Table 3. Performance measurement of VSLA-SSIM and comparison with SSIM, VS-SSIM and LA-SSIM

		SSIM	VS-SSIM	LA-SSIM	VSLA-SSIM
TID2013	SROC	0.7417	0.7593	0.7596	0.7607
	KROC	0.5588	0.5731	0.5710	0.5733
	PLCC	0.7895	0.8062	0.8061	0.8076
	RMSE	0.7417	0.7334	0.7336	0.7310
TID2008	SROC	0.7749	0.8220	0.8234	0.8273
	KROC	0.5768	0.6192	0.6182	0.6234
	PLCC	0.7732	0.8131	0.8159	0.8189
	RMSE	0.8511	0.7812	0.7758	0.7702
CSIQ	SROC	0.8756	0.9286	0.9244	0.9249
	KROC	0.6907	0.7583	0.7514	0.7526
	PLCC	0.8613	0.9152	0.9107	0.9112
	RMSE	0.1334	0.1058	0.1084	0.1082
LIVE	SROC	0.946	0.9501	0.9507	0.9510
	KROC	0.8057	0.8159	0.8172	0.8179
	PLCC	0.9385	0.9458	0.9463	0.9464
	RMSE	7.9838	7.5048	7.4740	7.4682
Overall	SROC	0.7987	0.8266	0.8266	0.8282
	KROC	0.6179	0.6459	0.6440	0.6467
	PLCC	0.8171	0.8433	0.8435	0.8451
	RMSE	-	-	-	-

V. Conclusion

In this paper, we found that the properly assigned local weights in pooling strategy can improve the prediction accuracy of the existing FR-IQA methods. The impact of local quality on global visual quality perception depends on various HVS properties i.e., the distortion sensitivity as well as the visual saliency score of that local region. The proposed weighting function offers the combined effect of distortion sensitivity and visual saliency to well reflect the HVS properties. Then we effectively incorporated that weighting function into the pooling strategy of conventional FR-IQA frameworks to adaptively assign higher weights to the more sensitive local regions and relatively lower weights to the less sensitive regions which improves the underlying FR-IQA methods.

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