Contrast and visual saliency similarity induced index for image quality assessment

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Abstract

Perceptual image quality assessment (IQA) defines/utilizes a computational model to assess the image quality in consistent with human opinions. A good IQA model should consider both the effectiveness and efficiency, while most previous IQA models are hard to reach simultaneously. So we attempt to make another effort to develop an effective and efficiency image quality assessment metric. Considering that contrast is a distinctive visual attribute that indicates the quality of an image, and visual saliency (VS) attracts the most attention of the human visual system, the proposed model utilized these two features to characterize the image local quality. After obtaining the local contrast quality map and global visual saliency quality map, we add the weighted standard deviation of the previous two quality maps together to yield the final quality score. The experimental results on three benchmark database (LIVE, TID2008, CSIQ) showed that the proposed model yields the best performance in terms of the correlation with human judgments of visual quality. Furthermore, it is more efficient when compared with other competing IQA models.

Keywords: local contrast, image quality assessment, visual saliency, the summation of deviation-based pooling strategy, full reference.

1. Introduction

Image quality assessment occupies a very important position in numerous fields and applications, such as image acquisition, compression, transmission and restoration, etc. Human beings are the ultimate receivers of any visual stimulus, but subjective image quality assessment is often costly, slow, and difficult to integrate into real-time image processing systems. So it is essential to develop a perceptual model to closely correlate with the human visual system (HVS). According to the availability of a reference image, objective quality assessment methods can be classified into three types [1]: (1) full-reference (FR), where an ideal "reference" image is available for comparison; (2) reduced-reference (RR), where partial information about the reference image is available; and (3) no-reference (NR), where the reference image is not accessible. This paper

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☆The MATLAB source code of the proposed method is public available online at https://cn.mathworks.com/matlabcentral/profile/authors/4262696-tonghan-wang
focuses on the FR methods, which are widely used to evaluate kinds of image processing algorithms by measuring the quality of their output images.

In the past decades, great efforts and huge advances have been made in FR methods. The traditional metrics such as the peak signal-to-noise ratio (PSNR) and the mean squared error (MSE) are most widely used in image processing. But, because of non-considering the properties of human visual system, these metrics do not correlate well with human opinions [2]. Thus a flood of IQA metrics have been developed based on human visual system (HVS). The noise quality measure index (NQM) [3] and the visual signal-to-noise ratio index (VSNR) [4] pay attention to human visual system (HVS)’s sensitivity to different visual signals, such as the luminance, the contrast, the frequency content, and the interaction between them. As a milestone in the development of IQA models, the structural similarity (SSIM) [5] surpassed the previous ones since it had a better correlation with the human perception. It was based on the assumption that the HVS was highly adapted for extracting structural information. Then some SSIM-based metrics have been proposed in the literatures [6]-[8]. In [6], the authors presented a multi-scale SSIM, which produces better results than its single-scale counterpart. In [7], the authors proposed a 3-component weighted SSIM, which assigns different weights to the SSIM scores in accordance with the local region type: edge, texture or smooth area. In [8], Wang et al. improved the MS-SSIM to the information content weighted SSIM index, which adopts a new information content weighting-based quality score pooling strategy. The information fidelity criterion (IFC) [9] and the visual information fidelity (VIF) [10], took the FR IQA problem as an information fidelity problem by the information theory, and VIF was the developmental version of IFC. Larson and Chardler proposed a most apparent distortion (MAD) based IQA index [11], which was based on that the authors argued that the HVS performs two distinct strategies when assessing the image quality for high-quality images and for low-quality images. In [12]-[13], the studies have demonstrated that SSIM, MS-SSIM, and VIF have much better performance than the other IQA metrics. But SSIM and MS-SSIM share a common deficiency that all positions are considered to have the same importance when pooling a single quality score from the local quality map. And VIF, after images composed in different sub-bands can give these sub-bands different weights at the pooling stage, but, gives every position within each sub-band the same importance. According that different locations on an image can have different contributions to HVS’ perception of the image, such pooling strategies are needed to improve. Based on the observation that the visual information in an image is often redundant and the HVS understands an image mainly based on its low-level features, Zhang et al. proposed the feature-similarity (FSIM) index [14] unlike the SSIM’s average pooling which adopted a weighting strategy for the pooling. It employed two features (the phase congruency and the gradient magnitude) to compute the local similarity map and utilized the phase congruency map as a weighting function since it can reflect how perceptually important a local patch is to HVS. In their later work, Zhang et al. proposed a visual saliency-induced metric (VSI) [15], based on the assumption that an image’s visual saliency map had a close relationship with its perceptual quality. In the VSI, three components (visual saliency, gradient modulus and chrominance) were firstly computed by locally comparing the distorted image with the reference one via similarity function,
and then the visual saliency part was used as a weighting function to measure the importance of a local image region. Note that the weighting pooling may improve the IQA accuracy against those with average pooling to some extent, but it may be costly to compute the weights. In addition, this pooling could make the predicted quality scores more nonlinear to human opinions [16]. And the image gradient is a popular feature in IQA since it can effectively capture image local structures, to which the HVS is highly sensitive. Based on these observations, Xue et al. proposed the gradient magnitude similarity deviation (GMSD) index [16], where image gradient magnitude maps were firstly computed, then the standard deviation of these maps were treated as the overall image quality score.

Based on the above analysis, we can see that the great success of state-of-the-art FR-IQA models owes to utilize features in relation to HVS or adopt a good pooling strategy in designing IQA models. The effectiveness and efficiency are two goals to design IQA models, however, most previous IQA models are hard to reach simultaneously two goals. So in this paper, we attempt to make another effort to fill this need, and develop an effective and efficient FR-IQA model which use contrast and visual saliency related closely to HVS and adopt the summation of deviation-based pooling strategy.

Using contrast and visual saliency to design IQA model is not new. Contrast has previously been utilized in SSIM [5], where it was used as a part of the features-luminance, contrast and structure. Contrast is a distinctive visual attribute that indicates the quality of an image. Proper contrast change can improve the perceptual quality of most images. In fact, we can define “high quality” as appropriate contrast and little distortion. And the contrast masking is a phenomena that flaws in an image being masked locally by the other stimulations in the image. Visual saliency (VS), however, is another good feature for IQA since HVS is quite sensitive to it. The salient regions of a visual scene are very important to human visual system since we pay more attention to them. Thus recently, researchers have been trying to utilize VS information to improve the performance of their proposed metrics in designing IQA model [17] and VS were mainly used as a weighting function for quality score pooling. For these reasons, we design our IQA model by using the contrast feature and visual saliency to characterize the image local quality, but we do not use VS as a weighting function unlike some previous studies.

After computing the local contrast similarity map and global visual saliency similarity map, it is needed to adopt a pooling strategy to yield a single overall quality score. Average pooling is a simplest and widely used pooling strategy, i.e., the overall quality prediction by taking the average of all elements in local quality map (LQM). Owing to considering that different regions may contribute differently to the overall quality of an image, weighting strategies are also widely adopted. Compared to average pooling, weighted pooling make the overall quality prediction accuracy to some extent, but it may be costly to compute the weights. In [16], deviation-based pooling strategy is used and supplies quite well quality prediction performance. But it may have good performance when using only one feature. So in this paper, we use the summation of deviation-based pooling strategy, which the fusion quality is computed after the overall qualities are given via the deviation-based pooling.

The main contribution of this work is that we utilize two features related closely to HVS - contrast and visual saliency, and to obtain good performance, we propose a new pooling strategy
which is the summation of standard deviation pooling which overcomes the fault of deviation-based pooling strategy when using only one feature, and breakthrough the limit that the visual saliency is commonly as a weighting function in designing the IQA models. The experiment results demonstrate that the proposed metric is efficient and promising compared with the state-of-the-art methods.

2. Proposed image quality assessment metric

The proposed metric has the same two-step framework with most of IQA models and is operated as follows. First, two similarity maps, namely, local contrast similarity map and global visual saliency map are generated. Then we add the weighted standard deviations of the two similarity maps together to yield the final quality score.

2.1 Local contrast similarity map and Global Visual saliency Similarity map

There are different definitions for contrast [18], [19], such as Weber contrast, Michelson contrast, RMS (root-mean-square) contrast. The Weber contrast is used to measure the local contrast of a single target seen against a uniform background, while the Michelson contrast is mainly used to measure the contrast of periodic pattern. However, in complex images these uniformity or periodicity conditions are not always satisfied. RMS contrast is preferred for natural stimuli and efficiency calculations. And in [20], the experiment results also shows that RMS contrast with the subjective contrast of natural images has a better correlation than other contrast. So for natural images, we adopt RMS contrast which is also used by SSIM [5]. RMS contrast is defined as follows:

\[
c = \frac{1}{(N-1)} \sum_{i=1}^{N} (I_i - \bar{I})^2 \]  

(1)

where \( \bar{I} \) is mean.

Contrast maps are computed locally for reference image and its distorted one using formula (1). We denote by \( LC_r \) and \( LC_d \) the local contrast map for reference image and the distorted one, respectively. Then the local contrast similarity (LCS) for the two images being compared is defined as:

\[
LCS(r,d) = \frac{(2LC_rLC_d + c1)}{(LC_r^2 + LC_d^2 + c1)}
\]

(2)

where \( c1 \) is a positive constant to increase the instability of LCS, \( LC_r \) and \( LC_d \) are computed from a local patch of reference image \( r \) and the distorted one \( d \), respectively. For grayscale image, contrast is the difference in luminance that makes an object distinguishable. Contrast change is very important for image quality.

In this paper, we adopt the saliency map generator called spectral residual (SR) method [21] which was based on a Fourier transform to extract the spectral residual of the input image in spectral domain at first and to generate the corresponding saliency map in spatial domain. The reason is that one prominent advantage of this method compared with other methods is its low computational complexity. In order to make the algorithm more efficient, the VS map for the proposed model is conducted on the reduced resolutions
(first filtered by a $2 \times 2$ average filter, and then down-sampled by a factor of 2) not the original image scale, and this generated VS map is the global not local. The VS similarity is defined as follow.

$$GVSS(r,d) = \frac{2v_r \cdot v_d + c2}{v_r^2 + v_d^2 + c2}$$

(3)

where $c2$ is another positive constant, $v_r$ and $v_d$ are visual saliency map of reference image $r$ and the distorted one $d$, respectively. $GVSS$ is the global visual saliency similarity map.

2.2. Summation of Deviation-based Pooling

Pooling strategy is very important for full-reference image quality assessment (FR-IQA). The mean and weighted mean are the two common pooling in the literature. Compared with the average pooling, the weighted pooling make the overall quality prediction accuracy to some extent, but it may be costly to compute the weights. The standard deviation pooling proposed in [16] may reflect its overall quality more accurate than the mean pooling for gradient magnitude similarity. But when using only one feature to compute the local quality map (LQM), the conclusion can be made to that the standard deviation (SD) pooling could gain the performance instead of their nominal pooling method. When the LQM is generated using multiple and diverse types of features, the SD pooling is not suggested to apply for the reason that the interaction between these features may complicate the estimation of local image quality. Based on this consideration, we first generated the local contrast map and global VS map, and then SD summation pooling is utilized to score the final quality. The proposed method is different from VSI, in VSI the visual saliency part was used as a weighting function. By doing these, the proposed model yield the excellent performance. The final quality score with SD pooling is computed after the generation of the local contrast similarity map and the global VS similarity map.

$$S = w_1 \cdot SD(LCS) + w_2 \cdot SD(GVSS)$$

(4)

Subject to

$$w_1 + w_2 = 1$$

(5)

where $w_1$ and $w_2$ are the weight that indicate the importance of local contrast similarity map and global visual saliency similarity map, respectively, and

$$SD(LCS) = \frac{1}{N} \sum_{i=1}^{N} (lcs(i) - LCSM)^2$$

(6)

where

$$LCSM = \frac{1}{N} \sum_{i=1}^{N} lcs(i)$$

(7)

$$SD(GVSS) = \frac{1}{N} \sum_{i=1}^{N} (GVSS(i) - GVSSM)^2$$

(8)

where
\[ GVSSM = \frac{1}{N} \sum_{i=1}^{N} GVSS(i) \]

Therefore, the procedure to calculate the proposed metric is illustrated in Figure 1.

To demonstrate the effectiveness of the proposed pooling strategy, we show the performance of different pooling strategy for the local contrast similarity map and global visual saliency similarity map in Figure 2. The “MEAN”, “STD”, “MAD” mean the mean, standard deviation and mean absolute deviation \([22]\) for the product of the two similarity maps, respectively. While the “Summation of mean-based pooling”, the “Summation of MAD-based pooling”, and the “Summation of deviation-based pooling” mean we add the mean, mean absolute deviations and standard deviations of the two similarity maps together as the quality score. We can see from Figure 2 that the proposed pooling strategy yield best performance on the three benchmark databases-LIVE, TID2008, and CSIQ. The reason may be that salient regions of a scene are paid more attentions by human beings, which is in line with the standard deviation pooling. Since the standard deviation indicates the range of distortion severities in an image. Furthermore, contrast is the range of luminance of image, so it can be elaborately captured by the standard deviation too.
3. Performance evaluation

3.1 Databases and evaluation protocols

To evaluate the performance of the proposed metric, we use the three publicly available image databases for algorithm validation and comparison, including LIVE [23], TID2008 [24] and CSIQ [11]. The characteristics of these three databases are summarized in Table I.

Table I Benchmark dataset for evaluating IQA indices

| Dataset | Reference Images | Distorted Images | Distortion Types | Observers |
|---------|------------------|------------------|------------------|-----------|
| TID2008| 25               | 1700             | 17               | 838       |
| CSIQ    | 30               | 866              | 6                | 35        |
| LIVE    | 29               | 779              | 5                | 161       |

We calculated four commonly used performance indices, i.e. the Spearman's rank ordered correlation coefficient (SROCC), the Kendall rank-order correlation coefficient (KROCC) which measure the prediction monotonicity, Pearson's (linear) correlation coefficient (LCC) which is related to the prediction linearity (considered as the measure of prediction accuracy), and the root mean square error (RMSE) which evaluates the prediction consistency. To computer the latter two indices, we used a logistic regression function to reduce the nonlinearity of predicted scores.

\[
p(x) = \alpha_1 \left( \frac{1}{2} - \frac{1}{1 + e^{\alpha_2(x - \alpha_3)}} \right) + \alpha_4 x + \alpha_5
\]

where \( \alpha_i \) are parameters to be fitted, \( x \) is the original score IQA scores, and \( p(x) \) is
the IQA score after regression. Denote by $s$ the subjective scores, $d$, the difference between the ranks of each pair in $x$ and $s$, $n$ is the total number of elements in data set, then:

$$SROCC = 1 - \frac{6 \sum_{i=1}^{n} d_i^2}{n(n^2-1)}$$

(11)

$$KROCC = \frac{n_c - n_d}{0.5n(n-1)}$$

(12)

where $n_c$ is the number of concordant pairs in the data set and $n_d$ is the number of discordant pairs in the data set. Let $(x_i, s_i), (x_j, s_j), \ldots(x_n, s_n)$ be a set of joint observations from two random variables IQA scores $X$ and subjective scores $S$, respectively. For any pair of observations $(x_i, s_i)$ and $(x_j, s_j)$,

If both $x_i > x_j$ and $s_i > s_j$ or if $x_i < x_j$ and $s_i < s_j$, then we call them concordant; else if $x_i = x_j$ or $s_i = s_j$, then they are nor concordant and discordant they are discordant; else they are discordant.

$$PLCC = \frac{\overline{p}^T \overline{s}}{\sqrt{\overline{p}^T \overline{p} \overline{s}^T \overline{s}}}$$

(13)

where $\overline{p}$ and $\overline{s}$ are the mean-removed vectors of $p$ and $s$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (s_i - p_i)^2}$$

(14)

A value close to 1 for SROCC, KROCC and LCC indicates a good performance for quality prediction. Whereas, for RMSE, the smaller the value is, the better prediction consistency it yields.

3.2 Performance comparison

In our experiment, we set $c_1 = 55$, $c_2 = 0.00008$, $w_1 = 0.545$, $w_2 = 0.455$. As in the implementations of SSIM [5], FSIM [14], and GMSD [16]. The images $r$ and $d$ are first filtered by a $2 \times 2$ average filter, and then down-sampled by a factor of 2. In other words, we use a $2\times2$ circular-symmetric Gaussian weighting function with its standard deviation of 1.5 and then rescaled to unit volume.

We compared the proposed method to eight state-of-the-art and representative FR-IQA models, including SSIM [5], MS-SSIM [6], IW-SSIM [8], VIF [10], MAD [11], FSIM [14], GMSD [16] and VSI [15]. In Table II, the best three ones are highlighted in boldface for each distortion for SROCC, KROCC, LCC and RMSE. Note that the source codes of all the other metrics were obtained from the original authors.

Table II. Performance of the proposed metric and the other eight competing FR-IQA metrics on three benchmark databases. The top three metrics for each criterion are highlighted in boldface.
In addition, as suggested by Wang and Li [8], in order to provide an evaluation of the overall performance of the evaluated IQA indices, in Table III we present their weighted-average SROCC, KROCC, PLCC, and RMSE results over three datasets and the weight assigned to each dataset linearly depends on the number of distorted images contained in that dataset, and we use boldface font to highlight the top 1 model.

Table III. Overall performance of IQA models over three databases

| IQA models | SROCC | KROCC | PLCC | RMSE |
|------------|-------|-------|------|------|
| SSIM       | 0.8413| 0.6574| 0.8360| 2.5504|
| MS-SSIM    | 0.8921| 0.7126| 0.8833| 2.4015|
| IW-SSIM    | 0.8963| 0.7226| 0.8945| 2.3219|
| VIF        | 0.8432| 0.6859| 0.8747| 2.1999|
| MAD        | 0.8942| 0.7301| 0.8939| 1.9767|
| FSIM       | 0.9128| 0.7462| 0.9056| 2.1466|
| GMSD       | 0.9241| 0.7633| 0.9173| 2.1207|
| VSI        | 0.9221| 0.7531| 0.9064| 2.3758|
| Proposed   | 0.9307| 0.7740| 0.9284| 1.9888|

The ranking of the weighted-average performances of the evaluated IQA indices based on four different performance metrics, SROCC, KROCC, PLCC, and RMSE, is presented in Table IV.

Table IV. Ranking of overall performance of IQA models

| IQA models | SROCC | KROCC | PLCC | RMSE |
|------------|-------|-------|------|------|
| SSIM       | 9     | 9     | 9    | 9    |
| MS-SSIM    | 7     | 7     | 7    | 8    |
| IW-SSIM    | 5     | 6     | 5    | 6    |
| VIF        | 8     | 8     | 8    | 4    |
| MAD        | 6     | 5     | 6    | 1    |
| FSIM       | 4     | 4     | 4    | 5    |
| GMSD       | 2     | 2     | 2    | 3    |
| VSI        | 3     | 3     | 3    | 7    |
| Proposed   | 1     | 1     | 1    | 2    |
From above tables, we can see that our proposed one performs consistently well on all the benchmark databases. Particularly, it performs greatly better compared with all the other metrics on the two largest databases, TID2008 and CSIQ. On LIVE, even though it is not the best, the proposed performs only slightly worse than the best results which MAD gets. MAD work well on LIVE database but fail to provide good result on other databases. Rather inspiring, the proposed achieve the best performance either in term of the individual database or the weighted-average over the three benchmark databases. The proposed model is followed by GMSD [16] and VSI [15]. It is noted that the performance of VSI on RMSE item is quite poor, whereas MAD [11] get the best performance for RMSE.

3.3 Performance comparison on individual distortion types

To more comprehensively evaluate an IQA model’s ability to predict image quality degradations caused by specific types of distortions, we compare the performance of competing methods on each type of distortion. The results are listed Table V. To save space, only the SROCC scores are shown, because by using the other measures, such as KROCC, PLCC and RMSE, the conclusions are similar. In Table V, we use boldface font to highlight the top 3 models in each group.

| Distortion Type | SSIM | MS-SSIM | IW-SSIM | VIF | MAD | FSIM | GMSD | VSI | Proposed |
|-----------------|------|---------|---------|-----|-----|------|------|-----|----------|
| TID2008         |      |         |         |     |     |      |      |     |          |
| AGN             | 0.8107 | 0.8086 | 0.7869 | 0.8804 | 0.8388 | 0.8574 | 0.9180 | 0.9229 | 0.9202 |
| ANC             | 0.8029 | 0.8054 | 0.7920 | 0.8768 | 0.8258 | 0.8515 | 0.8977 | 0.9118 | 0.8972 |
| SCN             | 0.8145 | 0.8209 | 0.7714 | 0.8709 | 0.8678 | 0.8485 | 0.9132 | 0.9296 | 0.9048 |
| MN              | 0.7795 | 0.8107 | 0.8087 | 0.8683 | 0.7336 | 0.8023 | 0.7087 | 0.7734 | 0.7696 |
| HFN             | 0.8729 | 0.8694 | 0.8662 | 0.9075 | 0.8864 | 0.9093 | 0.9189 | 0.9253 | 0.9184 |
| IN              | 0.6732 | 0.6907 | 0.6465 | 0.8326 | 0.0650 | 0.7456 | 0.6611 | 0.8298 | 0.7006 |
| QN              | 0.8531 | 0.8593 | 0.8177 | 0.7970 | 0.8160 | 0.8555 | 0.8875 | 0.8731 | 0.8883 |
| GB              | 0.9544 | 0.9563 | 0.9636 | 0.9540 | 0.9197 | 0.9472 | 0.8968 | 0.9529 | 0.9304 |
| DEN             | 0.9530 | 0.9582 | 0.9473 | 0.9161 | 0.9434 | 0.9604 | 0.9752 | 0.9693 | 0.9695 |
| JPEG            | 0.9252 | 0.9322 | 0.9184 | 0.9168 | 0.9275 | 0.9282 | 0.9525 | 0.9616 | 0.9452 |
| JP2K            | 0.9625 | 0.9700 | 0.9738 | 0.9709 | 0.9707 | 0.9775 | 0.9795 | 0.9848 | 0.9778 |
| JGTE            | 0.8678 | 0.8681 | 0.8588 | 0.8583 | 0.8661 | 0.8708 | 0.8621 | 0.9160 | 0.8893 |
| J2TE            | 0.8577 | 0.8606 | 0.8203 | 0.8501 | 0.8394 | 0.8542 | 0.8825 | 0.8942 | 0.8696 |
| NEPN            | 0.7107 | 0.7377 | 0.7724 | 0.7619 | 0.8287 | 0.7494 | 0.7601 | 0.7699 | 0.7658 |
| Block           | 0.8462 | 0.7546 | 0.7623 | 0.8324 | 0.7970 | 0.8489 | 0.8967 | 0.6295 | 0.8414 |
| MS              | 0.7231 | 0.7338 | 0.7067 | 0.5102 | 0.5161 | 0.6695 | 0.6486 | 0.6714 | 0.6724 |
| CTC             | 0.5246 | 0.6381 | 0.6301 | 0.8188 | 0.2723 | 0.6480 | 0.4659 | 0.6557 | 0.4662 |
| CSIQ            |      |         |         |     |     |      |      |     |          |
| AGWN            | 0.8974 | 0.9471 | 0.9380 | 0.9575 | 0.9541 | 0.9262 | 0.9676 | 0.9636 | 0.9670 |
| JPEG            | 0.9546 | 0.9634 | 0.9662 | 0.9705 | 0.9615 | 0.9654 | 0.9651 | 0.9618 | 0.9689 |
| JP2K            | 0.9606 | 0.9683 | 0.9683 | 0.9672 | 0.9752 | 0.9685 | 0.9717 | 0.9694 | 0.9777 |
| AGPN            | 0.8922 | 0.9331 | 0.9059 | 0.9511 | 0.9570 | 0.9234 | 0.9502 | 0.9638 | 0.9516 |
| GB              | 0.9609 | 0.9711 | 0.9782 | 0.9745 | 0.9602 | 0.9729 | 0.9712 | 0.9679 | 0.9789 |
| GCD             | 0.7922 | 0.9526 | 0.9539 | 0.9345 | 0.9207 | 0.9420 | 0.9037 | 0.9504 | 0.9324 |
| JP2K            | 0.9614 | 0.9627 | 0.9649 | 0.9696 | 0.9692 | 0.9717 | 0.9711 | 0.9604 | 0.9719 |
One can see that the proposed model is among the top 3 models 19 times, followed by VSI and GMSD, which are among the top 3 models 17 times and 13 times, respectively. Thus, we can have the conclusion that the proposed performs the best, while VSI and GMSD can have comparable performance when the distortion is of a specific type. A good IQA model should also predict the image quality consistently across different types of distortions. So we also show the scatter plots on the TID2008 database in Figure 3.

|       | MOS    | MOS    | MOS    | MOS    | MOS    |
|-------|--------|--------|--------|--------|--------|
| JPEG  | 0.9764 | 0.9815 | 0.9808 | **0.9846** | 0.9786 | **0.9834** | 0.9782 | 0.9761 | **0.9836** |
| AWGN  | 0.9694 | 0.9733 | 0.9667 | **0.9858** | **0.9873** | 0.9652 | 0.9737 | **0.9835** | 0.9809 |
| GB    | 0.9517 | 0.9542 | **0.9720** | **0.9728** | 0.9510 | **0.9708** | 0.9567 | 0.9527 | 0.9662 |
| FF    | 0.9556 | 0.9471 | 0.9442 | **0.9650** | **0.9589** | 0.9499 | 0.9416 | 0.9430 | **0.9592** |

Figure 3. Scatter plots of predicted quality scores against the subjective quality scores (MOS) by representative FR-IQA models on the TID2008 database.

We can see that the proposed model is more concentrated across different groups of distortion types than the other competitors.

### 3.4 Computational cost

In application, particularly, such as real-time image/video quality monitoring and prediction, the complexity of implemented IQA models becomes crucial. So we do the experiment of the time cost. In Table VI we list the amount of time (in seconds) to compute each quality measure on a color image of resolution 512×512 (taken from CSIQ database) on a 2.66 GHz Intel Core2 Quad CPU with 5 GB of RAM, and we use boldface...
font to highlight the top 3 models. Note that all the IQA models but VSI (it is specially designed for color image) need transform the color image to grayscale one.

### Table VI. Running time of the competing IQA models

| IQA models | Running time (s) |
|------------|-----------------|
| SSIM       | 0.0367          |
| MS-SSIM    | 0.1643          |
| IW-SSIM    | 0.8721          |
| VIF        | 1.8774          |
| MAD        | 2.7192          |
| FSIM       | 0.5367          |
| GMSD       | 0.0129          |
| VSI        | 0.3044          |
| Proposed   | 0.0443          |

We can see from Table VI that GMSD, SSIM and the proposed are the top three efficient IQA models and ran much faster than other competing IQA models. For example, our proposed is almost 9 times faster than the excellent model VSI which could achieve state-of-the-art prediction performances.

### 4. Conclusion

The effectiveness and efficiency are two goals to design IQA models, however, most previous IQA models are hard to reach simultaneously two goals. To fill the end, in this paper, we propose a new highly effective and efficient full-reference image quality assessment (FR-IQA) by using the summation of deviation-based pooling strategy for local contrast similarity map and global visual saliency similarity map. It is based on the assumption that contrast is a distinctive visual attribute that indicates the quality of an image, and the visual saliency (VS) map correlates highly with its perceptual quality. Moreover, the proposed pooling strategy could make full advantage of these two features. Compared with other eight state-of-the-art FR-IQA models, experiment results show that the proposed model performs better in terms of both accuracy and efficiency, making it an ideal choice for high performance IQA applications. In addition, the proposed methods can be improved with the advent of even more efficient VS models.

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