Combination of Dissimilar Feature Scores for Image Quality Assessment Using Particle Swarm Optimization Algorithm

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Abstract In this paper, we propose a new combination technique for full-reference image quality assessment (IQA) by utilizing three better-recognized IQA methods. To select the IQA methods, we first pick up Most Apparent Distortion (MAD) as the most appropriate IQA index for image quality databases and then add two other indices, MS-SSIM and FSIM, which have the most dissimilar features from the first index MAD. The parameter values employed in the new IQA score are optimized using the particle swarm optimization algorithm. By experiments, it is validated that the proposed method gives the best performance for various databases and outperforms the other state-of-the-art methods.

Keywords: image quality assessment, particle swarm optimization

1. Introduction

These days, we are sharing photos via social media, sending and receiving photo messages and transmitting live videos every day for various reasons. These media facilities are feasible through digital cameras and photo editing systems. Digital images are, however, degraded by various types of distortion during processing. Thus, we need to measure the quality of images by image quality assessment (IQA). To fulfill this requirement, numerous methods for IQA have been searched for and proposed over the last two decades.

Objective IQA is more handy than subjective IQA because we can easily adjust the parameters of an image processing system by utilizing an objective IQA value in the system. The traditional IQA measures of mean squared error (MSE) and peak signal-to-noise ratio (PSNR) are the simplest and most widely used. However, they are not so well matched to evaluations with human eyes. In 2004, structural similarity (SSIM) [1] was designed to improve the traditional metrics such as PSNR and MSE. However, SSIM fails to give a satisfactory correlation with the human visual system (HVS) in the case of blurred images.

The improved version of SSIM, multiscale SSIM (MS-SSIM) [2], has better quality prediction accuracy than the original SSIM. Gradient-based structural similarity (GSSIM) [3] is also an improved version of SSIM where the contrast and structure components of SSIM are replaced by gradient-based contrast and structure components, respectively. GSSIM provides better performance than SSIM, especially for blurred images.

Visual information fidelity (VIF) [4] is based on the amount of information shared by reference and distorted images. VIF outperforms many of the existing full-reference IQA algorithms. However, the main drawback of VIF is its computational complexity. Visual signal to noise ratio (VSNR) [5] is a wavelet-based approach. It is good for full-reference images but its computation is quite complex.

Visual gradient similarity (VGS) [6] assesses the image quality by using magnitudes and directions of gradient vectors and evaluates changes in contrast by using the intensity of gradient vectors. VGS is effective for image denoising, contrast changes and JPEG compression images but unsatisfactory for local block-wise distorted images. In another metric LOGPSNR [7], images are filtered by the Laplacian of Gaussian (LOG) filter and then the image quality is measured.
by PSNR. LOGPSNR is effective for Gaussian noise, high-frequency noise and Gaussian blur images but ineffective for intensity shift images.

Furthermore, several new image quality measures have recently been proposed as better alternative indices. The 12 best-recognized IQA measures up to now are SSIM [1], MS-SSIM [2], VIF [4], VSNR [5], VGS [6], LOGPSNR [7], MAD [8], FSIM [9], NQM [10], IFC [11], PSNR and PSNR-HVS [12]. Each index provides an improvement relative to the traditional metrics, but the degree of improvement is limited by the insufficient consideration of HVS properties. This results in each single index having some shortcomings for certain types of distortion. Thus, the fusion of multiple IQA techniques has been a natural development. The combination of two scores, as shown in [7] is effective for some types of distortion in the TID2008 database but it cannot assess mean-shift images accurately. Even if one more score is added to the combination in [7], as in [13], the performance of the three-score combination is only a slight improvement relative to the two-score combination. Furthermore, these combination methods do not work well on other databases. Thus, a combination method that performs well with all types of distortion for any database is still an open issue.

Among the 12 best-recognized IQA indices described above, MAD is the most appropriate index for all six publicly available image quality databases [14]. In MAD, local luminance and contrast masking are used to estimate detection-based perceived distortion in high-quality images, whereas changes in the local statistics of spatial-frequency components are used to estimate appearance-based perceived distortion in low-quality images. Feature similarity (FSIM) [9] is used to understand low-level features that are minor details of the images such as lines or dots. Low-level features convey important visual information and are crucial to image understanding. Intuitively, combining multiple methods as a new score, combining methods that have similar features cannot produce significant benefit compared with the original single index. For instance, the two-score combination of PSNR and PSNR-HVS cannot give us better performance than each single index because both indices can only make good predictions for images with additive noise distortion.

In this paper, therefore, we combine MAD with other two indices, MS-SSIM and FSIM, which have the most dissimilar features from MAD, as a new score. The proposed method provides better predictability than other previous methods.

The remainder of this paper is organized as follows. Section 2 thoroughly explains the current challenges of the IQA research field and the contribution of the proposed method. Section 3 presents the proposed method in detail. In Section 4, we evaluate the performance of the proposed method by experiments. Finally, Section 5 concludes the paper.

2. Related Works

The recent development of full-reference IQA measures has involved different combination strategies. Liu and Yang [15] combined SSIM, SNR, VSNR and VIF using canonical correlation analysis. Okarma [16, 17] nonlinearly combined three IQA metrics, MS-SSIM, VIF and R-SVD [18], as a full-reference image quality metric. In [19], Peng and Li proposed an approach based on a conditional Bayesian mixture of experts model that utilized a support vector machine classifier to predict the distortion type, and they combined SSIM, VSNR and VIF with k-nearest-neighbor regression. In 2013, a multimethod fusion technique was introduced in [14], and Oszust developed linearly combined similarity measures in [20]. Although these combinations achieved good evaluation results, the combination of different numbers of different IQA measures for each database is not straightforward in practice. To our best knowledge, therefore, all existing combination methods still have some shortcomings in terms of being able to obtain the highest performance for full-reference IQA.

To be able to overcome these major challenges in the current research trend, in this paper, we introduce a novel idea of combining dissimilar-feature scores by applying the particle swarm optimization (PSO) [21] algorithm. We first select MAD as the most correlated method for all types of distortion, applying the Biggest Index Ranking Difference (BIRD) algorithm [14] to select the most appropriate method for combination. After choosing the first combined IQA method, we choose the one that has the biggest index ranking difference from the first one as the second combined IQA method, since it has the most different characteristics from the first chosen combined IQA method. In the same way, we decide the third, fourth, and fifth combined IQA methods and so on. Although we experimentally compared the performance for combinations of up to 12 scores, the number of combined IQA scores that is best for all databases in terms of balancing the performance and complexity is three. Hence, in our combination, we combine MAD with two other indices, MS-SSIM and FSIM, which have the most dissimilar features from MAD, by employing exponentiated coefficients and weighted constant val-

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ues. Furthermore, we optimize these values by using the PSO algorithm, which is based on swarm intelligence. The calculation for PSO is very simple and the speed of searching is very high. Compared with the other developed algorithms, such as the genetic algorithm (GA), it has greater optimization ability and it can be completed easily. Thus, the main contribution of this paper is that we propose a very simple method with excellent performance compared with other state-of-the-art ones.

3. Proposed Method

In this section, we derive a new combination metric by adding MS-SSIM and FSIM to MAD. In the metric, we combine the three scores, which have dissimilar features, by employing the PSO algorithm for parameter optimization. In the combination of the three objective scores, we employ exponentiated coefficients and weighted constant values, which are free parameter values for each database. The calculation formula is defined as

\[ M_{\text{com}} = k_1 M_{\text{ms}}^\varphi + k_2 M_{\text{fs}}^\psi + M_{\text{ma}}^\rho + C \]  

where \( M_{\text{ms}} \), \( M_{\text{ma}} \) and \( M_{\text{fs}} \) are the objective scores of MAD, MS-SSIM and FSIM, respectively. \( k_1 \) and \( k_2 \) are weighting factors, \( \varphi \), \( \psi \) and \( \rho \) are exponentiated coefficients and \( C \) is a constant value. These parameters are optimized by employing PSO.

PSO is an artificial intelligence (AI) technique that can be used to find approximate solutions to extremely difficult or impossible numerical maximization and minimization problems. In recent years, PSO has become one of the most developed optimization algorithms. It searches for the optimal solution through continuous iteration, and it finally employs the size of the value of the objective function, or the function to be optimized (also known as the fitness function in the particle swarm), to evaluate the quality of the solution. Indeed, stochastic search techniques contain randomness in their process, so their performances can change from problem to problem. Many parameters can affect the performances of algorithms such as the problem size, number of constraint functions and constraint function type. the no free lunch theorems in [22]-[25] logically prove that an algorithm that can solve all optimization problems does not exist. This means that the success of an algorithm in solving a specific set of problems does not guarantee that it can solve all optimization problems with different types and natures. Thus, although there are many state-of-the-art swarm intelligence (SI)-based approaches for parameter optimization, we have to carry out an experiment first to decide the most suitable optimization algorithm for our specific problem. After extensive experiments, we select the PSO algorithm for parameter optimization in our nonlinear combination approach because it can provide faster convergence and find better solutions. Furthermore, the main advantage of the PSO algorithm is its ease of implementation since there is no crossover, decoding or encoding. In addition, PSO is simple in both its theory and numerical implementation and its computational time is inexpensive as compared with other optimal algorithms. The steps of the PSO to be implemented are as follows:

1) Create the initial particles and assign them initial velocities random uniformly. As 10 particles for each parameter is large enough to obtain good results for most cases, the population size used for optimization in our method is 60 (6 parameters \( \times \) 10 particles).

2) Evaluate the objective function at each particle location and determine the best (lowest) function value and the best location.

3) Update the particle locations (the new locations are the old ones plus the velocity), velocities and neighbors.

4) Select particles randomly based on their fitness. In our proposed method, the particles with higher fitness values have higher probability of being selected.

5) Check whether the swarm of particles has converged or not.

In this paper, the maximum number of iterations is set to 1000. If the maximum iteration number or minimum error criterion is attained, the PSO is terminated. Otherwise, the velocities and positions are updated to create a new swarm.

4. Experimental Results and Discussion

In this section, we compare the performance of the proposed method with MAD [8], MS-SSIM [2] and FSIM [9] using six image quality databases (A57, CSIQ, TID2008, TID2013, LIVE and IVC). For a detailed performance evaluation, we compare the performance of the whole database and the performance of each distortion type based on each database.

The A57 Database [26] has three reference images and 54 distorted images, including six distortion types with five different levels, while the Categorical Image Quality (CSIQ) Database [27] has 30 reference images and 866 distorted images, including six types of distortions with four to five different levels.

The Tampere Image Database (TID2008) [28] has 25 reference images and 1700 distorted images, includ-
ing 17 types of distortion, as shown in Table 1, with four different levels. The Tampere Image Database (TID2008) [29] is an extended version of TID2008 and contains 3000 distorted images, including 24 types of distortion with five different levels as shown in Table 2.

The LIVE Image Quality Database [30] has 29 reference images and 779 distorted images, including five distortion types, while the IVC Database [31] has 10 reference images and 185 distorted images, including four types of distortion.

We use all images from one distortion group in one database for the training, and test the images from the same distortion group in the other remaining databases. For example, we build a trained dataset (for JPEG compression) from the LIVE database. Then, we use this trained dataset to do the testing on A57, CSIQ, TID2008, TID2013 and IVC. Moreover, we determine the values of parameters in Eq.(1) based on each database. The resulting parameter values for each database are summarized in Table 3.

The performances of the methods are calculated on the basis of Pearson’s correlation coefficient (PCC) and the Spearman rank-order correlation coefficient (SROCC). PCC is defined as

\[
PCC = \frac{\sum a_j b_j - J \bar{a} \bar{b}}{(J - 1)s_a s_b}
\]

where \( J \) is the data size, \( a_j \) and \( b_j \) are the single subjective and objective scores with index \( j \), \( s_a \) and \( s_b \) denote the standard deviations of the subjective and objective scores, and \( \bar{a} \) and \( \bar{b} \) denote the mean values of the subjective and objective scores, respectively. SROCC is defined as

\[
SROCC = 1 - \frac{6 \sum d^2}{J(J - 1)}
\]

where \( d \) is the difference between the subjective and objective score ranks.

In Tables 4-9, we compare the PCC and SROCC values of 20 IQA methods based on six databases. The experimental results show that the proposed method is more effective and better correlated with HVS than the state-of-the-art composed quality measure (CQM) [16], extended hybrid image similarity (EHIS) [17],

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**Table 1** Types of distortion in TID2008

| No. | Types                                |
|-----|--------------------------------------|
| 1   | Additive Gaussian noise              |
| 2   | Additive noise in color component    |
| 3   | Spatially correlated noise           |
| 4   | Masked noise                         |
| 5   | High-frequency noise                 |
| 6   | Impulse noise                        |
| 7   | Quantization noise                   |
| 8   | Gaussian blur                        |
| 9   | Image denoising                      |
| 10  | JPEG compression                     |
| 11  | JPEG2000 compression                 |
| 12  | JPEG2000 transmission errors        |
| 13  | JPEG transmission errors             |
| 14  | Non-eccentricity pattern noise       |
| 15  | Local blockwise distortions of different intensity |
| 16  | Mean shift (intensity shift)         |
| 17  | Contrast change                      |

**Table 2** Types of distortion in TID2013

| No. | Types                                |
|-----|--------------------------------------|
| 1   | Additive Gaussian noise              |
| 2   | Additive noise in color component    |
| 3   | Spatially correlated noise           |
| 4   | Masked noise                         |
| 5   | High-frequency noise                 |
| 6   | Impulse noise                        |
| 7   | Quantization noise                   |
| 8   | Gaussian blur                        |
| 9   | Image denoising                      |
| 10  | JPEG compression                     |
| 11  | JPEG2000 compression                 |
| 12  | JPEG2000 transmission errors        |
| 13  | JPEG transmission errors             |
| 14  | Non-eccentricity pattern noise       |
| 15  | Local blockwise distortions of different intensity |
| 16  | Mean shift (intensity shift)         |
| 17  | Contrast change                      |
| 18  | Change in color saturation           |
| 19  | Multiplicative Gaussian noise        |
| 20  | Comfort noise                        |
| 21  | Lossy compression of noisy images    |
| 22  | Image color quantization with dither |
| 23  | Chromatic aberrations                |
| 24  | Sparse sampling and reconstruction   |

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**Table 3** Parameter values for each database by optimized PSO algorithm

| Parameter | A57  | CSIQ | TID 2008 | TID 2013 | LIVE | IVC |
|-----------|------|------|----------|----------|------|-----|
| \( k_1 \) | 1.122| 63.000| 0.010    | 0.278    | 83.675| 0.001|
| \( k_2 \) | 0.854| 0.001| 0.040    | 0.029    | 54.167| 0.001|
| \( \varphi \) | 0.001| 0.072| 0.001    | 0.094    | 0.001|
| \( v \)   | 0.001| 0.001| 9.190    | 13.502   | 0.001|
| \( \rho \) | 0.001| 0.001| 8.580    | 9.269    | 100  | 19.707|
| \( C \)   | 61.031| 0.071| 7.980    | 7.056    | 22.199| 63.880|

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### Table 4  PCC and SROCC performance comparison for A57 Database

| A57 Database (54 images) | | |
|--------------------------|--------------------------|--------------------------|
| **IQA Index**            | **PCC**                  | **SROCC**                |
| SSIM                     | 0.8019                   | 0.8067                   |
| MS-SSIM                  | 0.5596                   | 0.6673                   |
| VSNR                     | 0.9502                   | 0.9359                   |
| PSNR                     | 0.6347                   | 0.6189                   |
| PSNR-HVS                 | 0.8832                   | 0.8502                   |
| IFC                      | 0.4549                   | 0.3187                   |
| NQM                      | 0.8027                   | 0.7978                   |
| IW-SSIM                  | 0.9024                   | 0.8713                   |
| MAD                      | 0.5009                   | 0.8499                   |
| VIF                      | 0.6160                   | 0.6223                   |
| FSIM                     | 0.5566                   | 0.4962                   |
| [7]                      | -                        | -                        |
| CQM [16]                 | -                        | -                        |
| EHIS [17]                | -                        | -                        |
| GLD-PFT [32]             | -                        | -                        |
| LAF [33]                 | -                        | -                        |
| DOG-SSIM [34]            | -                        | -                        |
| ESIM [20]                | -                        | -                        |
| **Proposed**             | **0.9585**               | **0.9423**               |

### Table 5  PCC and SROCC performance comparison for CSIQ Database

| CSIQ Database (866 images) | | |
|---------------------------|--------------------------|--------------------------|
| **IQA Index**             | **PCC**                  | **SROCC**                |
| SSIM                      | 0.8594                   | 0.8755                   |
| MS-SSIM                   | 0.7837                   | 0.8734                   |
| VSNR                      | 0.8005                   | 0.8108                   |
| PSNR                      | 0.8001                   | 0.8057                   |
| PSNR-HVS                  | 0.8231                   | 0.8294                   |
| IFC                       | 0.8358                   | 0.7671                   |
| NQM                       | 0.7422                   | 0.7411                   |
| IW-SSIM                   | 0.9025                   | 0.9212                   |
| MAD                       | 0.9348                   | 0.9281                   |
| VIF                       | 0.9253                   | 0.9194                   |
| FSIM                      | 0.7999                   | 0.9192                   |
| [7]                       | -                        | -                        |
| CQM [16]                  | -                        | -                        |
| EHIS [17]                 | -                        | -                        |
| GLD-PFT [32]              | -                        | -                        |
| LAF [33]                  | -                        | -                        |
| DOG-SSIM [34]             | -                        | -                        |
| ESIM [20]                 | -                        | -                        |
| **Proposed**              | **0.9359**               | **0.9686**               |

### Table 6  PCC and SROCC performance comparison for TID2008 Database

| TID2008 Database (1700 images) | | |
|-------------------------------|--------------------------|--------------------------|
| **IQA Index**                 | **PCC**                  | **SROCC**                |
| SSIM                          | 0.8019                   | 0.8067                   |
| MS-SSIM                       | 0.5596                   | 0.6673                   |
| VSNR                          | 0.9502                   | 0.9359                   |
| PSNR                          | 0.6347                   | 0.6189                   |
| PSNR-HVS                      | 0.8832                   | 0.8502                   |
| IFC                           | 0.4549                   | 0.3187                   |
| NQM                           | 0.8027                   | 0.7978                   |
| IW-SSIM                       | 0.9024                   | 0.8713                   |
| MAD                           | 0.5009                   | 0.8499                   |
| VIF                           | 0.6160                   | 0.6223                   |
| FSIM                          | 0.5566                   | 0.4962                   |
| [7]                           | -                        | -                        |
| CQM [16]                      | -                        | -                        |
| EHIS [17]                     | -                        | -                        |
| GLD-PFT [32]                  | -                        | -                        |
| LAF [33]                      | -                        | -                        |
| DOG-SSIM [34]                 | -                        | -                        |
| ESIM [20]                     | -                        | -                        |
| **Proposed**                  | **0.9585**               | **0.9423**               |

### Table 7  PCC and SROCC performance comparison for TID2013 Database

| TID2013 Database (3000 images) | | |
|--------------------------------|--------------------------|--------------------------|
| **IQA Index**                  | **PCC**                  | **SROCC**                |
| SSIM                           | 0.6504                   | 0.6274                   |
| MS-SSIM                        | 0.7290                   | 0.7859                   |
| VSNR                           | -                        | -                        |
| PSNR                           | -                        | -                        |
| PSNR-HVS                       | -                        | -                        |
| IFC                            | -                        | -                        |
| NQM                            | -                        | -                        |
| IW-SSIM                        | -                        | -                        |
| MAD                            | 0.8070                   | 0.8380                   |
| VIF                            | 0.7720                   | 0.6769                   |
| FSIM                           | 0.8210                   | 0.8022                   |
| [7]                            | 0.7997                   | 0.7957                   |
| CQM [16]                       | -                        | -                        |
| EHIS [17]                      | -                        | -                        |
| GLD-PFT [32]                   | -                        | -                        |
| LAF [33]                       | -                        | -                        |
| DOG-SSIM [34]                  | -                        | 0.8942                   |
| ESIM [20]                      | -                        | 0.8804                   |
| **Proposed**                   | **0.8779**               | **0.8944**               |
Table 8  PCC and SROCC performance comparison for LIVE Database

| LIVE Database (779 images) | IQA Index | PCC | SROCC |
|----------------------------|-----------|-----|-------|
| SSIM                       | 0.9384    | 0.9479 |
| MS-SSIM                    | 0.9402    | 0.9521 |
| VSNR                       | 0.9235    | 0.9279 |
| PSNR                       | 0.8701    | 0.8756 |
| PSNR-HVS                   | 0.9134    | 0.9186 |
| IFC                        | 0.9261    | 0.9259 |
| NQM                        | 0.9128    | 0.9093 |
| IW-SSIM                    | 0.9425    | 0.9567 |
| MAD                        | 0.9672    | 0.9699 |
| VIF                        | 0.9597    | 0.9636 |
| FSIM                       | 0.9540    | 0.9634 |
| [7]                        | -         | -    |
| [13]                       | -         | -    |
| CQM [16]                   | -         | -    |
| EHIS [17]                  | -         | -    |
| GLD-PFT [32]               | -         | 0.9622 |
| LAF [33]                   | -         | 0.9570 |
| DOG-SSIM [34]              | -         | 0.9423 |
| ESIM [20]                  | -         | 0.9420 |
| Proposed                   | **0.9772**| **0.9806** |

global local distortion with PFT (GLD-PFT) [32], locally adaptive fusion (LAF) [33], difference of gaussian (DOG)-SSIM (DOG-SSIM) [34] and edge similarity (ESIM) [20].

Additionally, we compare the PCC and SROCC values of our proposed method with the values of MAD, MS-SSIM and FSIM for each distortion type in each database. The results are shown in Tables 10-21 in Appendix. According to these experimental results, although our proposed method has lower values for some distortion types, it is still powerful for almost all distortion types in every database.

Therefore, according to the experimental results, our proposed method consistently outperforms almost all types of distortion in six databases and is more robust than other previous combination methods.

5. Conclusion

To our best knowledge, there is no perfect single method that can give the best performance for all distortion types in every database. Similarly, there is no perfect single combination method that is very robust in predicting the quality of images of all databases. In this paper, therefore, we have proposed a new nonlinear combination method that combines MAD, MS-SSIM and FSIM scores using the particle swarm optimization algorithm. Our experimental results have demonstrated that our proposed method is a superior to not only other conventional single methods but also previous combination methods.

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Appendix

Table 9  PCC and SROCC performance comparison for IVC Database

| IVC Database (185 images) | IQA Index | PCC | SROCC |
|---------------------------|-----------|-----|-------|
| SSIM                      | 0.9117    | 0.9018 |
| MS-SSIM                   | 0.8435    | 0.8997 |
| VSNR                      | 0.8027    | 0.7993 |
| PSNR                      | 0.7192    | 0.6885 |
| PSNR-HVS                  | 0.8648    | 0.8590 |
| IFC                       | 0.9093    | 0.8993 |
| NQM                       | 0.8489    | 0.8343 |
| IW-SSIM                   | 0.9228    | 0.9125 |
| MAD                       | 0.8986    | 0.9082 |
| VIF                       | 0.9026    | 0.8964 |
| FSIM                      | 0.9376    | 0.9262 |
| [7]                       | -         | -    |
| [13]                      | -         | -    |
| CQM [16]                  | -         | -    |
| EHIS [17]                 | -         | -    |
| GLD-PFT [32]              | -         | 0.9631 |
| LAF [33]                  | -         | 0.9570 |
| DOG-SSIM [34]             | -         | 0.9423 |
| ESIM [20]                 | -         | 0.9420 |
| Proposed                  | **0.9534**| **0.9368** |

Table 10  PCC performance evaluation for each distortion type based on A57 Database

| No. | Distortions       | MAD | MS-SSIM | FSIM   | Proposed |
|-----|-------------------|-----|---------|--------|----------|
| 1   | Flat allocation   | 0.5460 | 0.6187 | 0.6226 | **0.7945** |
| 2   | JPEG compression  | 0.4732 | 0.5028 | 0.5591 | **0.8667** |
| 3   | JPEG-2000         | 0.4733 | 0.4898 | 0.4838 | **0.9333** |
| 4   | JPEG-2000+DCQ     | 0.5238 | 0.4556 | 0.5445 | **0.9333** |
| 5   | Gaussian blur     | 0.5672 | 0.4848 | 0.5759 | **0.8541** |
| 6   | Gaussian white noise | **0.8011** | 0.6825 | 0.8425 | 0.7119 |
### Table 11  SROCC performance evaluation for each distortion type based on A57 Database

| No. | Distortions                  | MAD   | MS-SSIM | FSIM   | Proposed |
|-----|------------------------------|-------|---------|--------|----------|
| 1   | Flat allocation              | 0.6557| 0.6724  | 0.7057 | 0.4391   |
| 2   | JPEG compression              | 0.5391| 0.3724  | 0.6724 | 0.7667   |
| 3   | JPEG-2000 compression        | 0.5557| 0.4224  | 0.6224 | 0.8833   |
| 4   | JPEG-2000+DCQ compression    | 0.4224| 0.5391  | 0.3724 | 0.9633   |
| 5   | Gaussian blur                 | 0.4224| 0.4891  | 0.3891 | 0.8767   |
| 6   | Gaussian white noise          | 0.3891| 0.5891  | 0.5224 | 0.4891   |

### Table 12  PCC performance evaluation for each distortion type based on CSIQ Database

| No. | Distortions                  | MAD   | MS-SSIM | FSIM   | Proposed |
|-----|------------------------------|-------|---------|--------|----------|
| 1   | Additive Gaussian white noise| 0.9486| 0.9018  | 0.7643 | 0.9496   |
| 2   | Gaussian blurring             | 0.9713| 0.8367  | 0.8822 | 0.9723   |
| 3   | Global contrast decrement     | 0.7632| 0.7470  | 0.6514 | 0.7667   |
| 4   | Additive Gaussian pink noise  | 0.8663| 0.7269  | 0.7254 | 0.8665   |
| 5   | JPEG compression              | 0.9595| 0.8991  | 0.8493 | 0.9585   |
| 6   | JPEG-2000 compression         | 0.9808| 0.8663  | 0.9073 | 0.9813   |

### Table 13  SROCC performance evaluation for each distortion type based on CSIQ Database

| No. | Distortions                  | MAD   | MS-SSIM | FSIM   | Proposed |
|-----|------------------------------|-------|---------|--------|----------|
| 1   | Additive Gaussian white noise| 0.9540| 0.9317  | 0.9258 | 0.9551   |
| 2   | Gaussian blurring             | 0.9680| 0.9174  | 0.9721 | 0.9690   |
| 3   | Global contrast decrement     | 0.8044| 0.8149  | 0.8057 | 0.7950   |
| 4   | Additive Gaussian pink noise  | 0.8191| 0.7636  | 0.7921 | 0.8191   |
| 5   | JPEG compression              | 0.9581| 0.9459  | 0.9544 | 0.9590   |
| 6   | JPEG-2000 compression         | 0.9752| 0.9129  | 0.9684 | 0.9754   |

### Table 14  PCC performance evaluation for each distortion type based on LIVE Database

| No. | Distortions                  | MAD   | MS-SSIM | FSIM   | Proposed |
|-----|------------------------------|-------|---------|--------|----------|
| 1   | Bit errors in JPEG2000 bit stream | 0.7359| 0.8366  | 0.8497 | 0.9859   |
| 2   | Gaussian blur                 | 0.9545| 0.8739  | 0.9810 | 0.6198   |
| 3   | JPEG2000                      | 0.4309| 0.5557  | 0.6997 | 0.9102   |
| 4   | JPEG compression               | 0.4191| 0.5269  | 0.6586 | 0.7822   |
| 5   | White noise                    | 0.9418| 0.9663  | 0.8494 | 0.7177   |

### Table 15  SROCC performance evaluation for each distortion type based on LIVE Database

| No. | Distortions                  | MAD   | MS-SSIM | FSIM   | Proposed |
|-----|------------------------------|-------|---------|--------|----------|
| 1   | Bit errors in JPEG2000 bit stream | 0.8628| 0.7964  | 0.8463 | 0.9531   |
| 2   | Gaussian blur                 | 0.9621| 0.8521  | 0.9717 | 0.8396   |
| 3   | JPEG2000                      | 0.7295| 0.8567  | 0.7103 | 0.8908   |
| 4   | JPEG compression               | 0.6046| 0.7665  | 0.6440 | 0.8661   |
| 5   | White noise                    | 0.9501| 0.9524  | 0.9448 | 0.8033   |

### Table 16  PCC performance evaluation for each distortion type based on IVC Database

| No. | Distortions                  | MAD   | MS-SSIM | FSIM   | Proposed |
|-----|------------------------------|-------|---------|--------|----------|
| 1   | Blurring                      | 0.9714| 0.8815  | 0.8904 | 0.9864   |
| 2   | JPEG2000 compression          | 0.9160| 0.9145  | 0.9296 | 0.9657   |
| 3   | JPEG compression              | 0.9401| 0.9270  | 0.9601 | 0.9923   |
| 4   | Locally adaptive resolution (LAR) | 0.9558| 0.9414  | 0.9352 | 0.9384   |

### Table 17  SROCC performance evaluation for each distortion type based on IVC Database

| No. | Distortions                  | MAD   | MS-SSIM | FSIM   | Proposed |
|-----|------------------------------|-------|---------|--------|----------|
| 1   | Blurring                      | 0.9630| 0.8526  | 0.9625 | 0.9640   |
| 2   | JPEG2000 compression          | 0.9098| 0.9383  | 0.9620 | 0.9624   |
| 3   | JPEG compression              | 0.8962| 0.9143  | 0.9805 | 0.9805   |
| 4   | Locally adaptive resolution (LAR) | 0.9489| 0.9474  | 0.8857 | 0.8857   |

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Table 18  PCC performance evaluation for each distortion type based on TID2008 Database

| Distortions | MAD  | MS-SSIM | FSIM   | Proposed |
|-------------|------|---------|--------|----------|
| 1           | 0.8165 | 0.7743  | 0.7828 | 0.8582   |
| 2           | 0.8267 | 0.7982  | 0.8198 | 0.8654   |
| 3           | 0.8598 | 0.7908  | 0.7938 | 0.8783   |
| 4           | 0.7566 | 0.8086  | 0.7689 | 0.8104   |
| 5           | 0.8931 | 0.8522  | 0.8383 | 0.9369   |
| 6           | 0.0417 | 0.7231  | 0.6740 | 0.7558   |
| 7           | 0.7981 | 0.7641  | 0.7831 | 0.8803   |
| 8           | 0.9227 | 0.9075  | 0.9079 | 0.9597   |
| 9           | 0.9612 | 0.8974  | 0.9320 | 0.9878   |
| 10          | 0.9487 | 0.8999  | 0.9253 | 0.9959   |
| 11          | 0.0733 | 0.8498  | 0.9534 | 0.9732   |
| 12          | 0.8556 | 0.8140  | 0.8418 | 0.9002   |
| 13          | 0.8295 | 0.8089  | 0.7877 | 0.8566   |
| 14          | 0.8242 | 0.6661  | 0.7264 | 0.7659   |
| 15          | 0.8007 | 0.8902  | 0.8410 | 0.8757   |
| 16          | 0.5709 | 0.6832  | 0.6704 | 0.7176   |
| 17          | 0.2573 | 0.5890  | 0.7285 | 0.7294   |

Table 19  SROCC performance evaluation for each distortion type based on TID2008 Database

| Distortions | MAD  | MS-SSIM | FSIM   | Proposed |
|-------------|------|---------|--------|----------|
| 1           | 0.8389 | 0.8027  | 0.8577 | 0.8777   |
| 2           | 0.8257 | 0.8129  | 0.8517 | 0.8805   |
| 3           | 0.8671 | 0.8280  | 0.8479 | 0.8678   |
| 4           | 0.7339 | 0.8140  | 0.8022 | 0.8241   |
| 5           | 0.8865 | 0.8451  | 0.9095 | 0.9295   |
| 6           | 0.0644 | 0.7543  | 0.7455 | 0.7655   |
| 7           | 0.8158 | 0.7963  | 0.8550 | 0.8750   |
| 8           | 0.9195 | 0.9396  | 0.9470 | 0.9671   |
| 9           | 0.9433 | 0.9229  | 0.9604 | 0.9802   |
| 10          | 0.9276 | 0.8973  | 0.9283 | 0.9485   |
| 11          | 0.9708 | 0.8830  | 0.9776 | 0.9976   |
| 12          | 0.8657 | 0.8203  | 0.8705 | 0.8905   |
| 13          | 0.8400 | 0.8393  | 0.8551 | 0.8751   |
| 14          | 0.8287 | 0.6921  | 0.7497 | 0.7695   |
| 15          | 0.7959 | 0.8963  | 0.8478 | 0.8678   |
| 16          | 0.5170 | 0.7192  | 0.6700 | 0.6940   |
| 17          | 0.2722 | 0.5535  | 0.6482 | 0.6687   |

Table 20  PCC performance evaluation for each distortion type based on TID2013 Database

| Distortions | MAD  | MS-SSIM | FSIM   | Proposed |
|-------------|------|---------|--------|----------|
| 1           | 0.8704 | 0.8492  | 0.8282 | 0.8792   |
| 2           | 0.8232 | 0.8016  | 0.8172 | 0.6564   |
| 3           | 0.8813 | 0.8257  | 0.8088 | 0.8900   |
| 4           | 0.7974 | 0.8150  | 0.8163 | 0.4242   |
| 5           | 0.9067 | 0.8878  | 0.8468 | 0.9107   |
| 6           | 0.2676 | 0.7602  | 0.6881 | 0.7707   |
| 7           | 0.8552 | 0.8791  | 0.8377 | 0.9011   |
| 14          | 0.8545 | 0.7839  | 0.8221 | 0.8264   |
| 15          | 0.3042 | 0.6075  | 0.5114 | 0.5200   |
| 16          | 0.6882 | 0.7317  | 0.6986 | 0.2519   |
| 17          | 0.2612 | 0.5433  | 0.6796 | 0.6288   |
| 18          | 0.0581 | 0.476   | 0.3814 | 0.0549   |
| 19          | 0.8436 | 0.7866  | 0.7900 | 0.8373   |
| 20          | 0.9279 | 0.8564  | 0.924  | 0.9452   |
| 21          | 0.9513 | 0.9231  | 0.9392 | 0.9570   |
| 22          | 0.8691 | 0.7817  | 0.8149 | 0.9015   |
| 23          | 0.9549 | 0.9444  | 0.9409 | 0.9646   |
| 24          | 0.9653 | 0.8870  | 0.9441 | 0.9608   |

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Table 21 SROCC performance evaluation for each distortion type based on TID2013 Database

| Distortion Type | MAD | MS-| SSIM | FSIM | Proposed |
|-----------------|-----|----|------|------|----------|
|                 | 1   | 0.8812 | 0.8708 | 0.9002 | 0.9402  |
|                 | 2   | 0.7896 | 0.7836 | 0.8196 | 0.7573  |
|                 | 3   | 0.8931 | 0.8774 | 0.8813 | 0.9213  |
|                 | 4   | 0.7521 | 0.8041 | 0.8168 | 0.6601  |
|                 | 5   | 0.8805 | 0.8557 | 0.8959 | 0.9387  |
|                 | 6   | 0.2664 | 0.8081 | 0.8018 | 0.8418  |
|                 | 7   | 0.8726 | 0.9134 | 0.9060 | 0.9460  |
|                 | 8   | 0.9408 | 0.9673 | 0.9590 | 0.9792  |
|                 | 9   | 0.9242 | 0.9442 | 0.9497 | 0.9897  |
|                 | 10  | 0.9215 | 0.9330 | 0.9330 | 0.9739  |
|                 | 11  | 0.9543 | 0.9043 | 0.9579 | 0.9785  |
|                 | 12  | 0.8393 | 0.8215 | 0.8453 | 0.8914  |
|                 | 13  | 0.8794 | 0.8724 | 0.8886 | 0.9286  |
|                 | 14  | 0.8322 | 0.7972 | 0.8139 | 0.8539  |
|                 | 15  | 0.2590 | 0.6281 | 0.5355 | 0.5755  |
|                 | 16  | 0.6591 | 0.7813 | 0.7606 | 0.4949  |
|                 | 17  | 0.1997 | 0.3859 | 0.4648 | 0.5048  |
|                 | 18  | 0.0091 | 0.4436 | 0.3950 | 0.3940  |
|                 | 19  | 0.8430 | 0.8021 | 0.8543 | 0.8946  |
|                 | 20  | 0.9024 | 0.8596 | 0.9165 | 0.9526  |
|                 | 21  | 0.9439 | 0.9295 | 0.9564 | 0.9664  |
|                 | 22  | 0.8792 | 0.7993 | 0.8947 | 0.9344  |
|                 | 23  | 0.8375 | 0.8881 | 0.8779 | 0.9241  |
|                 | 24  | 0.9564 | 0.9072 | 0.9646 | 0.9646  |

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