# Objective Stereo Image Quality Assessment Model based on Matrix Decomposition

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*Abstract*—**Stereo image quality assessment (SIQA) is a key issue of stereo image processing. Image pixels have strong correlation and highly structured features, according to that an image quality mainly depends on the structure information distortion of the image, an objective stereo image quality assessment (OSIQA) model based on matrix decomposition is proposed. Firstly, the concavity and convexity maps of image are extracted through Hessian matrix decomposition, which reflects complexity of image, and the left-right image quality assessment (LR-IQA) value is gained by judging loss severity of concavity and convexity map, which is adopting singular value decomposition in the left and right images. Secondly, eigenvalues and eigenvectors of the absolute difference map that is the absolute differential value between the left image and right image in stereo image are extracted. Eigenvalues can reflect image energy of some directions, and eigenvectors can reflect the directionality of image. Depth perception quality assessment (DP-QA) value is gained by calculating the degree of the structure distortion under the edge and non-edge regions. Finally, OSIQA value is obtained through nonlinearly fitting of LR-IQA value and DP-QA value. Experimental results show that the proposed OSIQA model have a good consistency with subjective perception. The correlation coefficient and spearman rank order correlation coefficient between OSIQA model and subjective perception are more than 0.92, and rooted mean squared error is lower than 6.5.**

*Index Terms*—**Stereo image quality assessment, left-right image quality assessment, depth perception quality assessment, Hessian matrix**

## I. INTRODUCTION

With the rapid development of Internet, communications, image processing techniques are widely used [1]- [3], meanwhile, application prospect of stereo display technology will be more and more extensive [4]. During the collection, compression, transmission and so on, stereo images may be subject to various distortions. Therefore, how to establish an effective stereo image quality assessment (SIQA) model becomes a key issue of image processing field [5]. SIQA can be divided into subjective SIQA (SSIQA) [6] and objective SIQA (OSIQA) [7]. Up to now, many scholars had developed a series of researches on OSIQA. Yang et al. proposed an OSIQA method based on peak signal to noise ratio (PSNR) [8], because of different signals generate different visual effect in the human visual system, this model ignored depth perception characteristic and not well inconsistency with subjective perception. Based on structure similarity index (SSIM), an OSIQA method was proposed in [9]. Yim et al. [10] proposed the OSIQA model with a blocking effect factor (PSNR-B) model. Benoit et al. proposed the OSIQA model which was combined left-right view image quality assessment (LR-IQA) and depth perception image quality assessment (DP-QA) [11]. Campisi et al. proposed an OSIQA model also using two different combinations of LR-IQA and DP-QA under classic SSIM and C4 image quality assessment models [12]. Sazzad et al. [13] proposed the OSIQA based on assumptions that LR-IQA and DP-QA are strongly depend on local features, the parameters of models are gained through statistics of certain images, and remain further study. The OSIQA model based on human visual system is proposed [14], which the model took into account the absolute parallax and improved the forecast performance.

When human viewed an image, the structure information distortion can judge the image quality because that the natural images have highly structured [15]. In order to improve consistency between OSIQA and subjective perception, an OSIQA model based on matrix decomposition under comprised of LR-IQA and DP-QA is proposed, LR-IQA value is gained through assessing structure loss of image complexity map, and DP-QA value is gained by assessing structure loss of edge and non-edge regions under absolute difference map which is absolute differential value between the left image and right image in stereo image. Finally, the OSIQA value is gained through the nonlinear fitting between LR-IQA and DP-QA. The rest of the paper is organized as follows: Section 2 describes the details of the proposed OSIQA method, experimental results are discussed in Section 3, and finally, Section 4 concludes the paper.


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## II. THE PROPOSED OSIQA MODEL

Studies have shown that human eyes' sensitivities on different regions are different. Generally speaking, it is more sensitive for human eyes to edge regions than texture or smooth regions, if there is a slight difference have occurred in the edge regions, human can quickly perceive the change of image, so the quality changes of edge regions play an important role. Currently, it is limited understanding of extremely complex human visual system, many theories are based on certain assumptions [16]. On this basis, LR-IQA model and DP-QA model are proposed from the standpoint of assessing structure distortion. Then OSIQA model based matrix decomposition is proposed through nonlinear fitting. Fig. 1 shows the diagram of the OSIQA proposed. For simplicity, only the luminance component is considered, because it can make quality prediction of the color stereo images.

As known, LR-IQA value $Q_s$ and DP-QA value $Q_d$ decrease with decreasing distortion degree. Therefore, let λ be a positive constant, then OSIQA value $Q$ is given by

$$Q = Q_s \times (Q_d)^{-\lambda} \tag{1}$$

### II.1. THE PROPOSED LR-IQA MODEL

### A. The Proposed LR-IQA Model

Hessian matrix decomposition (HMD) is a second partial derivative matrix of multi-dimensional variables function, which can reflect concavity and convexity of multi-dimensional variables function. If HMD is applied to the image processing field, it can reflect image fluctuations, which is the image complexity. Singular value decomposition (SVD) is a matrix diagonalization tool [16], and theory of SVD has been widely used in the image processing field. On this basis, LR-IQA model is proposed based on HMD and SVD, which is linear weighted between left image quality assessment (L-IQA) and right image quality assessment (R-IQA). While R-IQA value $Q_r$ is obtained in a similar approach of L-IQA value $Q_l$, L-IQA will detail in next, and Fig. 2 shows the diagram of L-IQA proposed.

### B. Regions Segmentation

Currently, the regions segmentation is got by processing the information of the grayscale image, for example, the gradient magnitude of the grayscale image is used to divide [17], and variance volatility between adjacent pixels is used [15]. In order to make better use of the information in color image, here, we adopted color classification method, which is under the hypothesis that gradient magnitude can well reflect the image edge and texture information [18]. The edge region of color image can be gained through computing gradient magnitude of each color component by Sobel operator. In order to avoid the problem of regions segmentation inaccuracy owing to large gradient magnitude of some color component may cover the small gradient that is gained in the other channels, so image edge regions are extracted in color vector space directly.

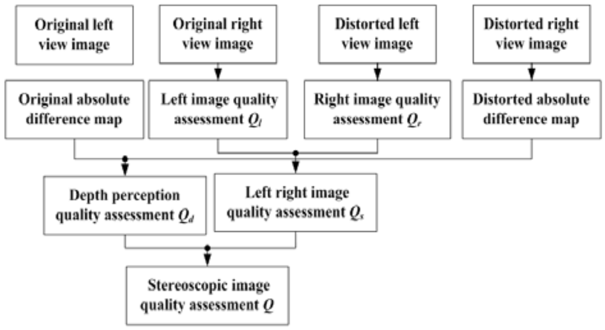



Figure 1. Diagram of the proposed OSIQA model

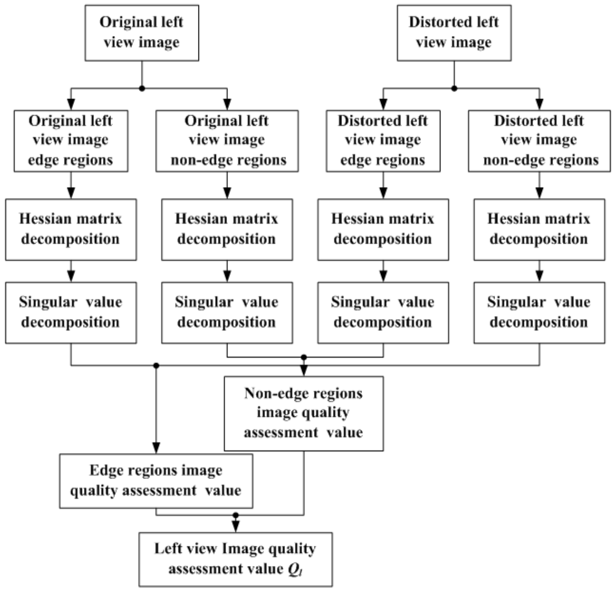



Figure 2. Diagram of left image quality assessment (L-IQA) model

Assuming that r, g and b mean the unit vector of three channels in RGB color image respectively. Let $u$ and $v$ denote the gradient vectors of horizontal and vertical directions, respectively, and they are calculated by

$$u = \frac{\partial R}{\partial x} r + \frac{\partial G}{\partial x} g + \frac{\partial B}{\partial x} b \tag{2}$$

$$v = \frac{\partial R}{\partial y} r + \frac{\partial G}{\partial y} g + \frac{\partial B}{\partial y} b \tag{3}$$

Let $g_{xx}$, $g_{yy}$ and $g_{xy}$ denote the gradient magnitudes of horizontal, vertical and crosswise directions, respectively, they are computed by

$$\mathrm{g}_{xx} = u \bullet u = u^T u = \left|\frac{\partial R}{\partial x}\right|^2 + \left|\frac{\partial G}{\partial x}\right|^2 + \left|\frac{\partial B}{\partial x}\right|^2 \tag{4}$$

$$\mathrm{g}_{yy} = v \bullet v = v^T v = \left|\frac{\partial R}{\partial y}\right|^2 + \left|\frac{\partial G}{\partial y}\right|^2 + \left|\frac{\partial B}{\partial y}\right|^2 \tag{5}$$

$$\mathrm{g}_{xy} = u \bullet v = u^T v = \frac{\partial R}{\partial x}\frac{\partial R}{\partial y} + \frac{\partial G}{\partial x}\frac{\partial G}{\partial y} + \frac{\partial B}{\partial x}\frac{\partial B}{\partial y} \tag{6}$$

Thus, the angular of the maximum change rate in each pixel can be obtained according to the above formulas. Assuming that the angular of maximum change rate $\theta$

($x,y$) of the point ($x,y$) is given by

$$\theta(x,y) = \frac{1}{2}\arctan[\frac{2g_{xy}}{(g_{xx} - g_{yy})}] \tag{7}$$

The maximum change rate value $F(x,y)$ at direction ($x,y$) is given by

$$F_\theta(x,y) = \{\frac{1}{2}[(g_{xx}+g_{yy})+(g_{xx}-g_{yy})\cos 2\theta + 2g_{yy}\sin 2\theta]\}^{1/2} \tag{8}$$

Finally, the edge regions and non-edge regions can be gained according to those formulas and is given by

$$(x,y) \in \begin{cases} \text{edge} \quad region & F_\theta(x,y) > T \\ non-edge \quad region & F_\theta(x,y) \le T \end{cases} \tag{9}$$

where $M$ and $N$ means the width and height of the image, $\alpha$ is gained by simulations, and $T$ means a threshold, and $T = \alpha \times \frac{1}{M \times N}\sum_{x=1}^{M}\sum_{y=1}^{N} F_\theta(x,y)$.

### C. Hessian Matrix and SVD

The HMD of a real matrix $A_{m\times m}$ is given by

$$A = P \times H \times P' \tag{10}$$

where $H$ means the Hessian matrix, $P$ is the orthogonal matrix, and $P\times P'=E$, $E$ is an unit matrix.

The Hessian matrix represents the concavity and convexity of matrix $A$, and reflects the fluctuation of matrix $A$. In other words, The Hessian matrix reflects the complexity of matrix $A$. Due to the SVD can well characterize image structure information, the characterization of image SVD is intrinsic property not visual characteristic, and is very stable [17]. When the image is subject to small interference, the singular value of the image does not change dramatically. Therefore, the SVD can reflect structure distortion of Hessian matrix.

SVD on Hessian matrix $H_{m\times m}$ is given by

$$H = U \times S \times V \tag{11}$$

where $U$ and $V$ are the orthogonal matrix, and $S$ is a singular matrix, which is a diagonal matrix. Assuming that the rank of $S$ is $k$, and $S=diag(s_1,s_2,s_3,\ldots,s_k)$.

### D. Left-right Image Quality Assessment (LR-IQA) Index

Assuming that the luminance component of the left original image is $Y_{l,org}$, and the luminance component of the left distorted image is $Y_{l,dis}$. Firstly, $Y_{l,org}$ and $Y_{l,dis}$ are processed by Hessian decomposition in non-overlapping block, respectively. Assuming that the Hessian matrix of $Y_{l,org}$ is $H_{l,org}$, and the Hessian matrix of $Y_{l,dis}$ is $H_{l,dis}$. Secondly, $H_{l,org}$ and $H_{l,dis}$ is processed by the SVD in non-overlapping block, respectively. Assume that singular matrix of $H_{l,org}$ is $S_{l,org}$, and the Hessian matrix of $H_{l,dis}$ is $S_{l,dis}$. Thirdly, the assessment index $E_l(x,y)$ in block with initial point ($x,y$) is given by

$$E_l(x,y) = \sqrt{\sum_{i=1}^{4}\sum_{j=1}^{4}(S_{l,org}(x+i,y+j) - S_{l,org}(x+i,y+j))^2} \tag{12}$$

Fourthly, according to the way of regions segmentation, the edge and non-edge regions of left image are gained. Hence, the assessment index $E_{l,e}$ of edge regions in the left image is given by

$$E_{l,e} = \frac{1}{M_e}\sum_{(x,y)\in \text{edge}} E_l(x,y) \tag{13}$$

The assessment index $E_{l,ne}$ of non-edge regions in the left image is given by

$$E_{l,ne} = \frac{1}{M_{ne}}\sum_{(x,y)\in \text{non}-edge} E_l(x,y) \tag{14}$$

where $M_e$ and $M_{ne}$ mean the number of edge block and non-edge block, respectively.

Fifthly, the left image assessment index is gained by linear weighted of $E_{l,e}$ and $E_{l,ne}$, and is given by

$$Q_l = \omega \times E_{l,n} + (1-\omega)\times E_{l,ne} \tag{15}$$

where $\omega$ is a weighted coefficient of edge region.

Finally, the right image assessment index $Q_r$ is gained by a similar approach with $Q_l$. LR-IQA index is given by

$$Q_s = \omega_l \times Q_l + (1-\omega_l)\times Q_r \tag{16}$$

where $\omega_l$ is a weighted coefficient of the left image assessment.

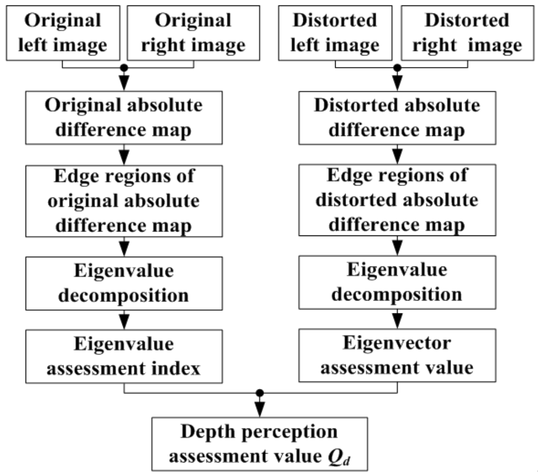



Figure 3. The diagram of depth perception quality assessment model

## II.2. THE PROPOSED DP-QA MODEL

The depth perception of stereo image is the relative displacement offset of identifying object. If stereo image have human standard parallax, the difference map of stereo image is similar to the image contour, and the parallax is the most obvious in the edge regions [19]. The absolute difference map can reflect strength of depth perception. The closer absolute difference map of distorted stereo image is to absolute difference map of original stereo image, the better depth perception quality is, and vice versa. According to the eigenvalues and eigenvectors can well characterize the structure distortion of image, DP-QA model is proposed from the standpoint of structure distortion in the edge regions. Fig. 3 shows the diagram of DP-QA model.

### A. Absolute Difference Map

Assume the original left image is $I_{l,org}$, and the original right image is $I_{r,org}$. The original absolute difference map $D_{org}$ is given by

$$D_{org} = \left| I_{l,org} - I_{r,org} \right| \tag{17}$$

Similarly, the distorted left image is $I_{l,dis}$, and the distorted right image is $I_{r,dis}$. The distorted absolute difference map $D_{dis}$ is given by

$$D_{dis} = \left| I_{l,dis} - I_{r,dis} \right| \tag{18}$$

*B. Regions Segmentation*

In the field of human's perception, the image can be divided into different regions, and the values of these regions are not the same, so the regions segmentation of the image can be conducted by the value of gradient value. Firstly, the original absolute difference map $D_{org}$ and distorted absolute difference map $D_{dis}$are processed by the Sobel operation, respectively, so the gradient amplitude map $G_{org}$of $D_{org}$ and the gradient amplitude map $G_{dis}$ of $D_{dis}$ are gained. Secondly, compute the threshold value $T_d$, and $T_d$=0.12×*max* ($G_{org}$). Finally, gain the edge regions map. Assume the gradient amplitude $G_{org}$ of pixel ($x$,$y$) is $G_{org}(x,y)$, and the gradient amplitude $G_{dis}$ of pixel ($x$,$y$) is $G_{dis}(x,y)$. If $G_{org}(x,y)> T_d$ or $G_{dis}(x,y)> T_d$, the pixel ($x$,$y$) is considered as an edge pixel. So the edge regions of $D_{org}$ and $D_{dis}$ are gained.

*C. Eigenvalue Decomposition*

The decomposition of real matrix $B$ is given by

$$B \times V = V \times U \tag{19}$$

where $U$ is a diagram matrix, the diagonal elements of matrix $U$ are the eigenvalues $P$, and $P$=*diag*($U$). $V$ is a modal matrix, and represents the right eigenvector of matrix $U$. The angle of the vector means linear correlation degree of two vectors, the smaller the angle of the vector, the closer linear correlation.

*D. Depth Perception Quality Assessment Index*

Firstly, $D_{org}$ and $D_{dis}$ are processed by the eigenvalue decomposition with 4×4 block. Assume the eigenvector with initial point ($x$,$y$) of 4×4 block in $D_{org}$ is $V_{org}(x,y)$, and $V_{org}(x,y) = \{\overline{V}_{1,org}(x,y)\ \overline{V}_{2,org}(x,y)\ \overline{V}_{3,org}(x,y)\ \overline{V}_{4,org}(x,y)\}$. The diagonal elements of eigenvalue matrix is $P_{org}(x,y)$, and $P_{org}(x,y)=\{P_{1,org}(x,y), P_{2,org}(x,y), P_{3,org}(x,y), P_{4,org}(x,y)\}$. Similarly, the eigenvector with initial point ($x$,$y$) of 4×4 block in $D_{dis}$ is $V_{dis}(x,y)$, and $V_{dis}(x,y) = \{\overline{V}_{1,dis}(x,y)\ \overline{V}_{2,dis}(x,y)\ \overline{V}_{3,dis}(x,y)\ \overline{V}_{4,dis}(x,y)\}$. Diagonal elements of diagram matrix is $P_{dis}(x,y)$, and $P_{dis}(x,y)=\{P_{1,dis}(x,y), P_{2,dis}(x,y), P_{3,dis}(x,y), P_{4,dis}(x,y)\}$.

Secondly, the damage index $F$ ($x$, $y$) of eigenvalue with initial point ($x$,$y$) of block is given by

$$F(x,y) = \sqrt{\sum_{i=1}^{4} (P_{i,org}(x,y) - P_{i,dis}(x,y))^2} \tag{20}$$

Thirdly, the direction similarity $K$ ($x$, $y$) of eigenvector with initial point ($x$,$y$) of block is given by

$$K(x,y) = 1 - \frac{1}{4}\sum_{i=1}^{4} \frac{\overline{V}_{i,org}(x,y) \cdot \overline{V}_{i,dis}(x,y)}{\left|\overline{V}_{i,org}(x,y)\right| \times \left|\overline{V}_{i,dis}(x,y)\right|} \tag{21}$$

where $\left|\overline{V}_{i,org}(x,y)\right|$ and $\left|\overline{V}_{i,dis}(x,y)\right|$ mean module of $i$th original and distorted eigenvectors, respectively, $\overline{V}_{i,org}(x,y) \cdot \overline{V}_{i,dis}(x,y)$ means the dot product of the $i$th original and distorted eigenvectors.

Fourthly, depth perception assessment index $R$($x$, $y$) with initial point ($x$,$y$) of block is given by

$$R(x,y) = K(x,y) \times F(x,y) \tag{22}$$

Finally, according to the edge regions of absolute difference map mentioned above, depth perception assessment index $Q_s$ is given by

$$Q_s = \frac{1}{M_s} \sum_{(x,y) \in \text{edge}} R(x,y) \tag{23}$$

where $M_s$ means the number of edge regions in the absolute difference map.

(a) Horse (480×270) (b) Akko & Kayo (640×480) (c) Xmas (640×480)
(d) Puppy (720×480) (e) Soccer2 (720×480) (f) Door Flowers (1024×768)
(g) Alt Moabit (1024×768) (h) Leaving Laptop (1024×768) (i) Kendo (1024×768)
(j) Balloons (1024×768) (k) Lovebird1 (1024×768) (l) Newspaper (1024×768)

Figure 4.The contents of stereoscopic images used in the database

## III. Experimental Results and Discussions

In order to verify the proposed OSIQA model with the subjective perception assessment, the detail about stereo image database used can be found in [6], which includes 12 original stereo images, as shown in Figure 4, and 312 distorted stereo images. In the experiments, the left and right images are degraded with the same distorted degree. The distortion of these stereo images includes JPEG, JPEG2000, white noise, Gaussian blur and H264 coding. The subjective assessment scores are gotten from 23 observers, the quality of the stereo image is classified into five grades: very poor, poor, the general, good, and excellent in the subjective experiments. So each distorted stereo image can grain their Difference Mean Opinion Scores (DMOS), which is the D-value of Mean Opinion Score (MOS) and full mark (100), and the range of DMOS is from 0 to 100. Hence, the greater DMOS value is, the worse the image quality is, and vice versa. Hence, the subjective assessment scores are used to judge the effectiveness of the proposed model.

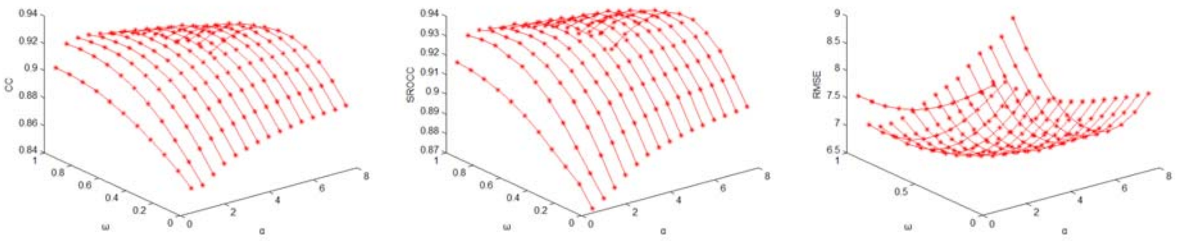
Firstly, the assessment scores of the distorted stereoscopic images are calculated with the proposed model. Then, three performance metrics [18] are used to evaluate the OSIQA model by measuring the consistency between the objective model and subjective stereoscopic perception. The first is the linear correlation coefficient (CC) between DMOS and the objective assessment scores following nonlinear regression [19], which is a four-parameter logistic regression function. CC reflects the forecast accuracy of an objective model. The second is the spearman rank order correlation coefficient (SROCC). SROCC is used to describe the variation relationship between DMOS and the output score of the proposed OSIQA model, and reflects the monotonic of OSIQA. In addition, the rage of CC and SROCC is from 0 to 1. If the value of CC and SROCC is closer to 1, it means that the performance of proposed OSIQA is better. If the value of CC and SROCC is close to 0, the model is invalid. The third is root mean squared error (RMSE). RMSE is used to describe the accuracy of proposed OSIQA. The smaller RMSE is, the more the performance of proposed OSIQA is, and vice versa.

Next, how to make sure the parameters $\lambda$, $\alpha$, $\omega$ and $\omega_l$ of proposed OSIQA, and the validity and dependability of OSIQA are discussed respectively.

### *A. Parameters Determination*

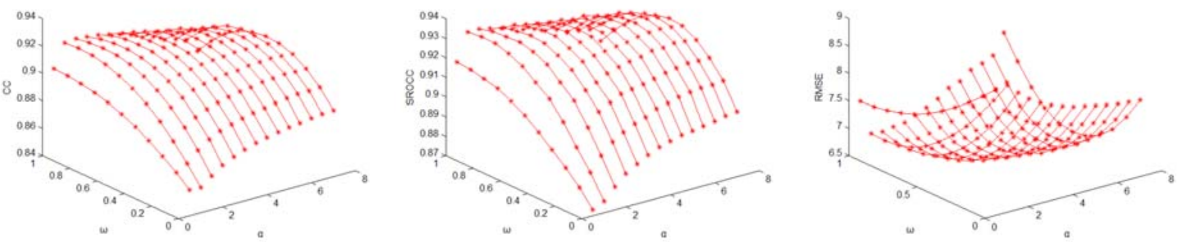
Firstly, how to make sure the parameters $\alpha$ and $\omega$ are discussed in detail. The parameter $\alpha$ can determine the image size of the edge and non-edge regions. If $\alpha$ value is too small, some edge regions can be mistaken for the non-edge regions. And if $\alpha$ value is too big, some non-edge regions can be mistaken for the edge regions. The gradient amplitude of the different image content is different. Fig 5 shows the graph between L-IQA value $Q_l$ of 312 distorted stereoscopic images and corresponding subjective perception assessment value DMOS under different $\alpha$ and $\omega$ values. Fig. 6 shows the graph between R-IQA value $Q_r$ of 312 distorted stereoscopic images and corresponding DMOS under different $\alpha$ and $\omega$ values. The range of $\alpha$ is from 0.5 to 7.5, and the interval is 0.5 in Fig. 5. The range of $\alpha$ is from 0.5 to 7 in Fig. 6. The range of $\omega$ is from 0 to 1, and the interval is 0.1 in Fig. 5 and Fig. 6.

As seen from Fig. 5 and Fig. 6, the change of parameters $\alpha$ and $\omega$ value have an impact on correlation between L-IQA or R-IQA and DMOS. When $\omega$ value is very small, CC and SROCC values are less than 0.9, and RMSE value is more than 7.5. CC and SROCC values get large with the increase of ω, and RMSE gets small with the increase of ω. When $\alpha$ and $\omega$ values are on a certain value, there is a good consistency between L-IQA or R-IQA and DMOS. Therefore, $\alpha$ value is 5, and $\omega$ value is 0.6 in the paper.



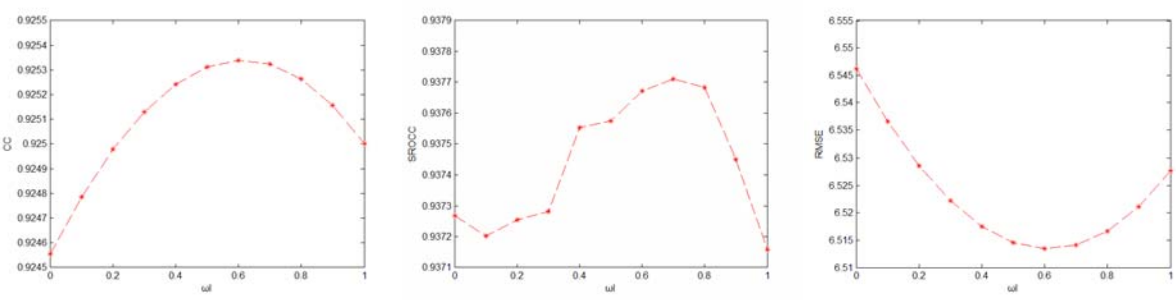

CC SROCC RMSE

Figure 5. The graph between L-IQA and subjective perception under different $\alpha$ and $\omega$ value



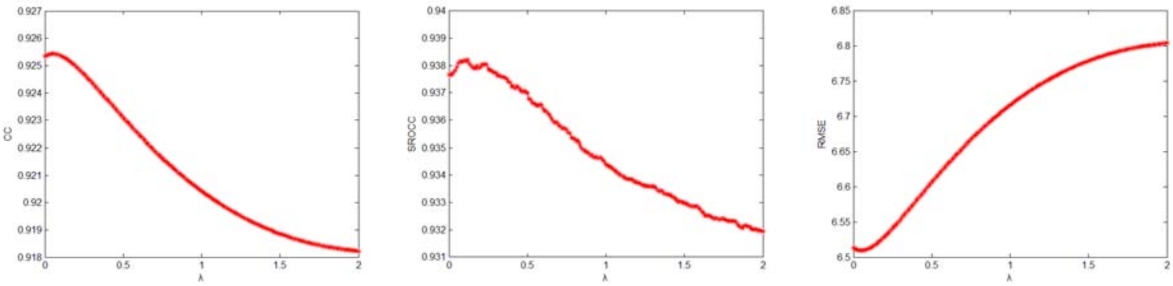

CC SROCC RMSE

Figure 6. The graph between R-IQA and subjective perception under different $\alpha$ and $\omega$ value



CC SROCC RMSE

Figure 7. The graph between LR-IQA and subjective perception under different $\omega_1$ value

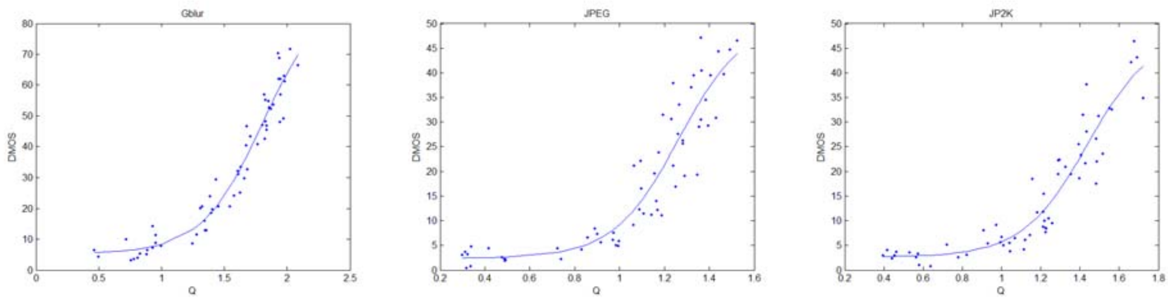


CC SROCC RMSE

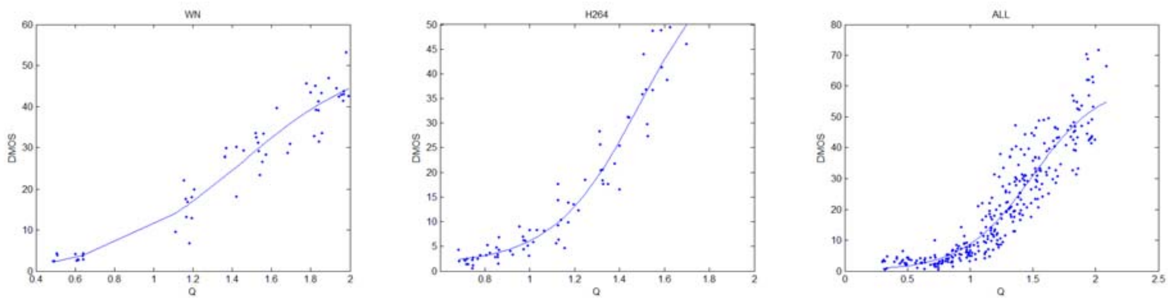
Figure 8. The graph between proposed OSIQA and subjective perception under difference $\lambda$ value

TABLE I
ASSESSMENT PERFORMANCE TABLE BETWEEN PROPOSED OSIQA AND SUBJECTIVE PERCEPTION

| | Gblur | JP2K | JPEG | WN | H264 |
|---|---|---|---|---|---|
| Image Number | 60 | 60 | 60 | 60 | 72 |
| CC | 0.9725 | 0.9419 | 0.9271 | 0.9613 | 0.9667 |
| SROCC | 0.9666 | 0.9425 | 0.9341 | 0.9278 | 0.9470 |
| RMSE | 4.9081 | 4.0248 | 5.3376 | 4.1834 | 3.5890 |



Gblur JPEG JP2K



WN H264 ALL

Figure 9. The scatter between proposed OSIQA and subjective perception

Secondly, how to make sure the parameter $\omega_l$ is discussed in detail. The contribution of LR-IQA is different to stereoscopic images under different distortion type [20]. Such as stereoscopic image quality mainly depends largely on the image of better quality in left and right image of stereoscopic image under Gaussian blur distortion. But for the block effects, stereoscopic image quality depends largely on half of left image quality and right image quality.

Fig. 7 shows the change graph between LR-IQA value $Q_s$ of 312 distorted stereoscopic images and corresponding DMOS under different $\omega_l$ value. The range $\omega_l$ is from 0 to 1, and the interval is 0.5. The change of CC, SROCC and RMSE values is very small with the change of $\omega_l$. This is because that the left and right images are subject to distortion in the same distorted level. Therefore, $\omega_l$ value is 0.6, and $\omega_r$ value is 0.4 in the paper.

Finally, how to make sure the parameter $\lambda$ is discussed in detail, $\lambda$ value determines the contribution of stereoscopic image quality on LR-IQA and DP-QA. At the same time, all the LR-IQA and DP-QA values are increased with the increase of the distortion degree. So $\lambda$ is a real number being greater than zero. Fig. 8 shows the change graph between OSIQA value of 312 distorted stereoscopic images and corresponding DMOS under different $\lambda$ value.

From Fig. 8, the change of $\lambda$ value has little influence on assessment performance between proposed OSIQA and DMOS. When $\lambda$ value is less than the threshold, CC and SROCC values are increased, and RMSE value is reduced with the increase of $\lambda$ value. When $\lambda$ value is more than the threshold, CC and SROCC values are reduced, and RMSE is increased with the increase of $\lambda$ value. Therefore, $\lambda$ value is 0.08 in the paper.

### B. *Assessment Performance between Proposed OSIQA and DMOS*

According to the parameters $\lambda$, $\alpha$, $\omega$ and $\omega_l$ values are obtained through section 3.1, 312 distorted stereoscopic image assessment values are obtained. Experimental results show in Fig. 9 and Table 1. Fig. 9 shows the scatter between proposed OSIQA and DMOS under Gaussian blur, Gaussian white noise, JPEG, JP2K, H264 coding and mixture distortion type. Table 1 shows the quantitative assessment performance index between proposed OSIQA and DMOS under the various distortion types.

As shown in Fig. 9, the scatter is very concentrated under the various distortion types, and it can visually reflect the validity of proposed OSIQA. To analyze the accuracy of proposed OSIQA model, three indicators are used to illustrate the correlation with the DMOS. As seen in Table 1, CC and SROCC values are all more than 0.92, and RMSE values are all less than 6.5. It means that the judgment of the proposed OSIQA model is highly consistent with DMOS, and it can effectively assess stereoscopic image quality.

## IV. CONCLUSION

An objective stereo image quality assessment (OSIQA) model based on matrix decomposition is proposed by judgment of image structure information, which is organically composed of the left-right image quality assessment (LR-IQA) and the depth perception quality assessment (DP-QA). LR-IQA mainly considers the characteristic of HMD and SVD, and human visual property of different regions with different sensitivity. Hessian matrix can well reflect the image complexity. In addition, SVD can well reflect the image structural information and the stability performance. DP-QA mainly considers the damage of eigenvalue and deflection of eigenvector in edge regions of absolute difference map. The experimental results shows that proposed OSIQA and subjective perception have well consistent. All the correlate coefficient and spearman rank order correlation coefficient are more than 0.92, and root mean squared error is less than 6.5 under JPEG, JP2K, Gaussian white noise, Gaussian blur, H264 coding distortion and mixture distortion type. However, the parameters of proposed OSIQA are gained by experiments based on some stereo image, and they are needed to be further improved.

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