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Quality Assessment of Visual Content

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Preface

Nowadays, the visual signals collected nationwide exceed 500,000 TB per day, accounting for 85% of the total Internet traffic. How to make full use of and deep mine the massive visual signals via advanced image processing techniques is the key to promote the rapid development of industries such as security surveillance, medical applications, distance education, social networking, and so on. During the past two decades, important image processing techniques, such as image quality assessment (QA) and enhancement, and object detection and recognition, have attracted extensive and in-depth studies from researchers in the fields of multimedia signal processing, computer image processing, pattern recognition and intelligent systems, automatic detection technology, etc., and have obtained a series of important research accomplishments. The acquisition equipment, storage media, transmission system, and processing algorithm inevitably have an impact on visual signals during the processes from collecting and generating to receiving visual signals, which causes the degradation of image quality and further inhibits the accuracy of subsequent object detection and recognition algorithms. Therefore, image QA is usually considered as the basis of the above-mentioned important image processing techniques, possessing two significant capabilities: One is that image QA can be used to monitor the whole procedure of visual signal processing and the other is that it can be employed to optimize the model structure and parameters of visual signal processing techniques. Based on the aforesaid analyses, this book mainly reviews the representative research on image QA during the past decade and analyzes their applications, performance, and prospects in various important fields, such as screen content images, 3D-synthesized images, sonar images, enhanced images, light-field images, virtual reality images, and super-resolution images, expecting to provide guidance and reference for engineering applications in various types of fields.

The main audiences of this book are graduate students, engineers, specialists, and scholars who are interested in image QA techniques in varied subject areas, e.g., optics, electronics, mathematics, photographic techniques, and computer technology. The authors anticipate that a systematic review of the current state of the technologies, key challenges, and future trends in QA of visual signals will enable the readers to obtain a deeper, more comprehensive, and more systematic understanding and appreciation of image QA and ideally will offer a positive impetus to the work and research.

In Chap. 1, the authors first outline the basic theories from the classification of image QA, namely subjective assessment and objective assessment, to the classification of objective image QA, namely full-reference assessment, reduced-reference assessment, and no-reference assessment according to the presence of distortion-free reference images or not. The authors then briefly analyze the research background, image characteristics, and cutting-edge technologies of different types of image QA in hot fields, such as screen content images, 3D-synthesized images, sonar images, enhanced images, light-field images, virtual reality images, and super-resolution images.

Screen content images are generated by computers, covering massive Internet information. Screen content images are composed of three kinds of complicated contents, namely texts, graphics, and illustrations, in each of which distortion causes various degrees of degradation. For the QA of screen content images, Chap. 2 first introduces the full-reference QA method based on structural similarity, in order to estimate structural changes and different statistical properties of regions. Second, it presents the reduced-reference QA method based on the fusion of macroscopic and microscopic features, in order to solve the problem of unsatisfactory prediction monotonicity. Third, it introduces the no-reference QA method based on adaptive multi-scale weighting and big data learning, in order to address the issues of monotonous color and simple shape in screen content images. Finally, the authors discuss the future research trend of QA of screen content image and point out that it is necessary to construct accurate and efficient objective QA models of screen content images.

3D-synthesized images possess the significant function of generating new viewpoints based on rendering technique, but tend to introduce specific geometric distortions that cause the quality degradation. For the QA of 3D-synthesized images, Chap. 3 first presents the no-reference QA method based on autoregressive modeling and multi-scale natural scene statistical analysis, in order to capture geometric distortion. Then, it introduces the no-reference QA method based on pixel-based changes in transform domains, in order to measure color and depth distortion. Finally, it presents the no-reference QA method on account of structural variations caused by geometric, sharpness, and color distortions, in order to assess the quality of blurred, discontinuous, and stretched 3D-synthesized images.

Sonar images contain important underwater information like submarine geomorphology, marine organism, and wreck remains in dim light and are prone to typical underwater distortion due to the poor underwater acoustic channel condition. For the QA of sonar images, Chap. 4 first introduces the sonar image quality database and the full-reference QA methods based on local entropy and statistical and structural information, in order to measure underwater distortion in sonar images. Second, it presents the task- and perception-oriented reduced-reference QA methods based on the human visual system, in order to assess the poor-quality sonar images in the complicated underwater environment. Finally, it describes the no-reference QA method based on contour degradation measurement, in order to overcome the difficulty of failure to acquire reference sonar images in the dynamic underwater environment.

Image enhancement has the function of changing the visual perceptual quality of images. How to optimize the model structures and parameters to achieve proper enhancement based on the QA of enhanced images has been a hot issue in recent years. For the QA of enhanced images, Chap. 5 first establishes the contrast-changed image QA database and presents the reduced-reference QA methods based on phase congruency and histogram statistics. Then, it introduces the no-reference QA methods that fuse non-structural information, sharpness, and naturalness and are based on feature extraction and regression. Finally, it shows evaluation criteria guidance-based automatic contrast enhancement technique.

Light-field images record the light intensity in different directions of the sensor, which is important for the research of next generation imaging technology. However, they tend to lose visual details in the processes of acquisition and transmission. For the QA of light-field images, Chap. 6 first introduces the full-reference QA method based on single- and multi-scale Gabor feature extraction, in order to address the problem of ignoring the perceived characteristic of the human visual system. Second, it illustrates the reduced-reference QA method based on depth map distortion measurement, in order to deal with different sizes of light-field images. Third, it presents the tensor-oriented no-reference QA methods based on spatial-angular measurement, in order to capture the high-dimensional characteristics of light-field images. In the end, the above-mentioned QA methods are validated on relevant databases, and the necessity of establishing efficient light-field image QA methods is pointed out.

Virtual reality images have attracted an amount of attention for providing an immersive experience. They have the characteristics of omnidirectional view, massive data, and so on, which are so vulnerable to external interference that their quality deteriorates. For the QA of virtual reality images, Chap. 7 first describes the databases that contain projection format, stitching, and double fisheye images, in order to fill the blank of lack of a virtual reality image database. Then, it presents the no-reference QA method based on the 3D convolutional neural network, in order to tackle the issue that the reference virtual reality images are inaccessible. Finally, it shows the no-reference QA method based on a multi-channel neural network, in order to overcome the problem of the full range of compression distortion in video coding technology.

It is important to generate a high-resolution image from a low-resolution image by super-resolution technique, but there often exist artifacts and blurring distortions during the process. For the QA of super-resolved images, Chap. 8 first introduces the super-resolution image database based on interpolation and image enhancement. Second, it presents the full-reference QA methods based on quality loss function and L_2 Norm. Finally, it introduces the QA approaches based on two-stage regression model, pixel similarity between image blocks, and natural scene statistical model.

This book collects the work programs of several research groups from all over the world. It introduces the image QA algorithms in various hot fields from different perspectives, which has scientific research value and engineering application value. This book is written by Ke Gu, Hongyan Liu, and Chengxu Zhou. We have received

great help from Jing Liu, Shuang Shi, and Shuangyi Xie, so we would like to express our sincere thanks to the experts, authors, teachers, and friends who have guided and supported us.

Beijing, China

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Contents

Acronyms

2D-CNN	2D convolutional neural network
3D-CNN	3D convolutional neural network
3DSWIM	3D-synthesized view image quality metric
ACR-HR	Absolute category rating-hidden reference
ADD-SSIM	Analysis of distortion distribution-based structural similarity
ADM	Accurate depth map
AGCWD	Adaptive gamma correction with weighting distribution
AGGD	Asymmetric generalized Gaussian distribution
APT	Autoregression-plus threshold
AR	Autoregression
ASIQE	Accelerated screen image quality evaluator
AVC	Advanced video coding
BER	Bit error rate
BIQME	Blind image quality measure of enhanced images
BL	Bi-lateral
BLL	Binarized low-frequency
BQMS	Blind quality measure for screen content images
BRISQUE	Blind/referenceless image spatial quality evaluator
CC	Contrast change
CCID2014	Contrast-changed image database
CC-NSIs	Camera-captured natural scene images
CCT	Cross-content-type
CDF	Cumulative normal distribution function
C-D-F 9/7	Cohen-Daubechies-Feauveau 9/7 wavelet transform
CGIs	Computer graphic images
CI-VSD	Color-involved view synthesis distortion
CNNs	Convolutional neural networks
C-PCQI	Colorfulness-based patch-based contrast quality index
CPP-PSNR	Craster parabolic projection-based peak signal-to-noise ratio
CP-PSNR	Content-based peak signal-to-noise ratio
CROSS	Cross-reference omnidirectional stitching dataset

CU	Coding unit
CVIQD	Compression virtual reality image quality database
DCT	Discrete cosine transform
DeepQA	Deep image quality assessment
DeepSim	Deep similarity
DIBR	Depth image-based rendering
DI-VSD	Depth-involved view synthesis distortion
DMOS	Differential mean opinion score
DWT	Discrete wave transform
EAP	Equal-area projection
EID	Enhanced image database
EOT	Existence of target
EOV	Variation of entropy
EPIs	Epi-polar images
ERP	Equirectangular projection
FES	Free energy excitation significance detection technology
FoV	Field of view
FR	Full-reference
FSIM	Feature similarity
FTQM	Fourier transform-based scalable image quality metric
FVV	Free viewpoint video
GB	Gaussian blur
GDD	Gradient direction distribution
GGD	General Gaussian distribution
GMSD	Gradient magnitude standard deviation
GN	Gaussian noise
GUI	Graphical user interface
HE	Histogram equalization
HEVC	High-efficiency video coding
HEVSQP	High-efficiency view synthesis quality prediction
HMD	Head-mounted display
HMF	Histogram modification framework
HOG	Histogram of oriented gradient
HR	High-resolution
HVS	Human visual system
IAM	Image activity measurement
IGM	Internal generative mechanism
ITU	International telecommunication union
IW-SSIM	Information weighted structural similarity
J2C	JPEG2000 compression
JC	JPEG compression
J-S	Jensen-Shannon
KRCC	Kendall rank correlation coefficient
LBP	Local binary pattern
LC	Layer segmentation backed coding

LCD	Liquid crystal display
LF	Light-field
LF IQM	Light-field image quality assessment metric
LFC	Light-field coherence
LFCIA	Light-field cyclopean image array
LGF-LFC	Log-Gabor feature-based light-field coherence
LL	Low-frequency
LOG	Laplacian of Gaussian
LOGS	Local geometric distortions and global sharpness
LPI	Laplace pyramid image
LR	Low-resolution
MAD	Most apparent distortion
MASM	Macrostructure measurement
MB	Motion blur
MC360IQA	Multi-channel neural network for blind 360-degree image quality assessment
MDID	Multiply distorted image database
MGGD	Multivariate generalized Gaussian distribution
MISM	Microstructure measurement
ML	Maximum likelihood
MLR	Multiple linear regression
MNSS	Multi-scale natural scene statistical analysis
MOSs	Mean opinion scores
MP-PSNR-RR	Morphological pyramid peak signal-to-noise ratio reduced reference
MRDM	Multi resolution depth map
MRF	Markov random field
MSCN	Mean subtracted and contrast normalized
MSE	Mean square error
MVD	Multi-view video plus depth
MW-PSNR	Morphological wavelet peak signal-to-noise ratio
NCP-PSNR	Non-content-based peak signal-to-noise ratio
NIQMC	No-reference image quality metric for contrast distortion
NQM	Noise quality measure
NR	No-reference
NRCDM	No-reference contour degradation measurement
NR-LFQA	No-reference light-field image quality assessment
NR-SRIQA	No-reference super-resolution image quality assessment
NSI	Natural scene image
NSIQM	No-reference sonar image quality metric
NSIs	Natural scene images
NSS	Natural scene statistics
OA	Opinion-aware
O-DMOS	Overall differential mean opinion score
OPT	Optical flow estimation

OR	Outlier ratio
OU	Opinion-unaware
OUT	Outliers in 3D-synthesized images
PC	Phase congruence
PCA	Principal component analysis
PCQI	Patch-based contrast quality index
PCS	Pair comparison sorting
PCSC	Principal component spatial characteristics
PDF	Probability density function
PLCC	Pearson linear correlation coefficient
PR	Partial-reference
PSIQP	Partial-reference sonar image quality predictor
PSNR	Peak signal-to-noise ratio
P-VQA	Perceptual video quality assessment
QA	Quality assessment
QACS	Quality assessment of compressed screen content image
QADS	Quality assessment database for super-resolution images
QMC	Quality assessment metric of contrast
QoE	Quality of experience
QP	Quantization parameter
RBF	Radial basis function
RD	Rate distortion
RDCT	Reconstructed discrete cosine transform
RDO	Rate distortion optimization
ReLU	Rectified linear unit
RICE	Robust image contrast enhancement
RIQMC	Reduced-reference image quality metric for contrast change
RMSE	Root mean square error
RR	Reduced-reference
RWQMS	Reduced-reference wavelet-domain quality measure of screen content pictures
SAIs	Sub-aperture images
SAS	Synthetic aperture sonar
SC	Screen content image compression
SCIs	Screen content images
SD	Standard deviation
SGD	Stochastic gradient descent
SI	Spatial information
SIFT	Scale-invariant feature transform
SIQA	Sonar image quality assessment
SIQAD	Screen image quality assessment database
SIQD	Sonar image quality database
SIQE	Screen image quality evaluator
SIQM	Structure-induced quality metric
SIQP	Sonar image quality predictor

SLTDM	Stereo-like taxonomy depth map
SPIHT	Set partitioning in hierarchical trees
SPQA	Screen content perceptual quality assessment
S-PSNR	Spherical peak signal-to-noise ratio
SQI	Screen content image quality index
SQMS	Saliency-guided quality measure of screen content
SR	Super-resolution
SRCC	Spearman rank correlation coefficient
SS	Single stimulus
SSD	Sum of squared difference
SSDC	System-sparse set and disparity coding
SSIM	Structural similarity
SSIQE	Simplified screen image quality evaluator
SSMR	Single stimulus with multiple repetitions
STD	Structure-texture decomposition
SVD	Singular value decomposition
SVQI	Structural variation-based quality index
SVR	Support vector regression
TAVI	Tensor angular variation index
Tensor-NLFQ	Tensor-oriented no-reference light-field image quality evaluator
TH	Transmission loss under high-efficiency video coding compression
TPSIQA	Task- and perception-oriented sonar image quality assessment
TS	Transmission loss under screen content image compression
UAC	Underwater acoustic channel
UCA	Unified content-type adaptive
ULBP	Uniform local binary pattern
V-DMOS	Vectored differential mean opinion score
VIFP	Visual information fidelity in pixel domain
VQEG	BZVideo quality experts group
VR	Virtual reality
VSD	View synthesis distortion
VSNR	Visual signal-to-noise ratio
VSQA	View synthesis quality assessment
VSQP	View synthesis quality prediction
WLBP	Weighted local binary pattern
WN	White noise
WS-PSNR	Weighted-to-spherically uniform peak signal-to-noise ratio

Chapter 1
Introduction

1.1 Quality Assessment of Traditional Images

Image quality assessment (QA) is one of the basic techniques of image processing. It can evaluate the degree of image distortion by analyzing and studying the characteristics of images. In an image processing system, image QA plays an important role in system performance evaluation, algorithm analysis, and comparison.

For many decades, there has been a lot of research on image QA. These image QA approaches can be classified as subjective image QA and objective image QA based on whether a human is involved in quality evaluation. Subjective QA is expensive and time-consuming. In contrast, objective image QA uses the computational model to automatically evaluate the perceived quality of images, which is convenient and fast. Because of its advantages of high precision and strong robustness, objective image QA has been favored by a wide range of researchers. Objective image QA can be further classified into three types according to the utilization of the reference image information. They are, respectively, full-reference (FR) image QA, reduced-reference (RR) image QA, and no-reference (NR) image QA. The FR image QA utilizes complete pristine image information in the processing. The RR image QA only adopts part of the pristine image information to assess image quality. The NR image QA is totally different from the two models above-mentioned, due to its implementation of quality inferring without using any reference information. Several QA methods of traditional images are listed below, such as noise quality measure (NQM) [1], visual information fidelity in pixel domain (VIFP) [2], visual signal-to-noise ratio (VSNR) [3], the structural similarity (SSIM)-based QA method [4], the natural scene statistics (NSS)-based QA method, the information weighted structural similarity (IW-SSIM)-based QA method [5], peak signal-to-noise ratio (PSNR) [6], spherical PSNR (S-PSNR) [7], Craster parabolic projection-based PSNR (CPP-PSNR) [8], the VSNR based on the near-threshold and supra-threshold properties of human vision [3], the most apparent distortion based on the Fourier transformation and the Log-Gabor filtering [9], and so on. Most of these methods fail to effectively evaluate the

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quality of new types of visual signals such as screen content images, 3D-synthesized images, sonar images, enhanced images, light-field images, virtual reality images, and super-resolution images, so it is urgent to establish efficient QA methods that are specific to particular images.

1.2 Quality Assessment of Screen Content Images

With the rapid development of computer technology and the popularity of electronic devices, screen content images (SCIs) have received much attention from researchers as the main computer-generated signals. The visual quality of SCIs, which is the basis for image processing techniques, is inevitably subject to external interference during image compression, transmission, display, and so on, further resulting in poor image quality. Therefore, it is necessary to first evaluate the quality of SCIs in order to ensure the efficiency and accuracy of image processing systems. Most of the existing image QA metrics were designed based on the assumption that the human visual system (HVS) is highly adapted to deriving the scene's structural information. Besides, various QA methods of natural scene images (NSIs) have been proposed recently, most of which can effectively evaluate the quality of NSIs rather than SCIs. There are few studies on SCIs which contain complicated content like texts, graphics, and illustrations, and the distortion causes varying degrees of degradation in different areas.

This book elaborately introduces two FR QA, a RR QA and two NR QA methods of SCIs proposed in recent years, and the details are illustrated in Chap. 2. One of the FR QA models of SCIs is named structural variation-based quality index (SVQI) on account of the association between the perceived quality and the structural variation [10]. The other FR QA model of SCIs incorporates both visual field adaptation and information content weighting into structural similarity-based local QA [11]. The RR QA method of SCIs extracts the macroscopic and microscopic structures in the original and distorted SCIs separately and compares the differences between them in order to obtain the overall quality score [12]. One of the NR QA models of SCIs named unified content-type adaptive (UCA) is applicable across content types [13]. The other NR QA model of SCIs is based on big data learning and uses four types of features including the picture complexity, the screen content statistics, the global brightness quality, and the sharpness of details to predict the perceived quality of SCIs [14]. In addition, there are some methods that can be learned by any interested readers, such as screen content perceptual quality assessment (SPQA) [15], reduced-reference wavelet-domain quality measure of screen content pictures (RWQMS) [16], blind quality measure for screen content images (BQMS) [17], and so on.

1.3 Quality Assessment of 3D-Synthesized Images

Technological advances in 3D visual signals continue to make 3D imaging and display techniques draw a large amount of attention in several different fields, such as remote education, security monitoring, entertainment, and so on. The depth image-based rendering (DIBR) technique is utilized to synthesize new viewpoint images of the same scene from a limited number of reference-free multiple views, solving the problems of high cost and complexity [18]. The introduction of DIBR causes geometric distortion in 3D-synthesized images, which results in a decrease in the perceived quality of 3D-synthesized images. With this concern, it is imperative to design efficient perceptual QA methods for 3D-synthesized images before processing these images to avoid operating on low-quality images and reducing the efficiency of the whole process. The DIBR technologies introduce particular distortions when utilizing depth information to transfer occluded regions on the outlines of foreground objects, which are more likely to destroy the semantic structure of images. Several image QA approaches are tailored to particular scenes or common distortions (i.e., blur and noise) and, thus, are not applicable to evaluate the perceived quality of 3D-synthesized images.

To solve the problems mentioned above, the researchers have been concerned about 3D-synthesized image QA approaches based on DIBR. This book elaborately introduces six NR 3D-synthesized image QA approaches, and the details are illustrated in Chap. 3. These methods are mainly classified into three categories, namely the models based on NSS, domain transformation, and structural transformation. The first type includes two blind image QA models based on the autoregression (AR) with local image description [19] and the multi-scale natural scene statistical analysis (MNSS) using two new NSS models [20]. One of the second-type methods is the high-efficiency view synthesis quality prediction (HEVSQP) QA model that quantifies the effects of color and depth distortion in 3D-synthesized images [21]. The other one is the new QA model which combines local and global models to evaluate geometric distortion and sharpness changes in wavelet domain [22]. The third type includes two image quality prediction models based on local changes in structure and color and global changes in brightness [23] as well as the image complexity [24]. In addition, there are some methods that can be learned by any interested readers. For example, the 3D-synthesized view image quality metric (3DSWIM) [25] measures local geometric distortion and global sharpness changes [26]. The view synthesis quality assessment (VSQA) modifies the distorted view or similarity view from the reference view and the composite view [27]. The reduced version of morphological pyramid peak signal-to-noise ratio (MP-PSNR-RR) image QA can evaluate the geometric distortion in 3D-synthesized images influence generated by DIBR [28].

1.4 Quality Assessment of Sonar Images

It is possible to obtain important information by observing sonar images, such as submarine geomorphology, marine organism, and wreck remains, so the sonar imaging technique is widely utilized in the field of ocean exploration, underwater rescue [29, 30], etc. The sonar imaging technique can acquire clearer images in a dim environment based on the temporal distribution of echo received by sonar equipment. However, the sonar images are inevitably distorted due to the influence of the complex underwater environment in the formation and propagation processes, resulting in poor sonar image quality. Therefore, the QA prior to the analysis of sonar images can exclude low-quality sonar images with information loss, further increasing the efficiency of performing underwater tasks. Generally speaking, images obtained in different scenes possess various characteristics. For example, NSIs have rich color changes, complex textures, and coarse lines. Sonar images are gray and simple due to the unavailability of natural light, which differ dramatically from NSIs [31]. In addition, more attention has been paid to the structural features of sonar images containing task information in underwater detection and scene rendering. Most of the previous QA studies focus on camera-captured natural scene images (CC-NSIs) and are not suitable for effectively assessing the visual quality of sonar images.

In order to fill the gap in the study of sonar image QA, this book introduces an FR image QA, two RR image QA, and an NR image QA methods of sonar images presented in recent years, and the details are illustrated in Chap. 4. The FR image QA approach named the sonar image quality predictor (SIQP) combines the statistical and structural information [32]. One of the RR image QA approaches is the task- and perception-oriented sonar image quality assessment (TPSIQA), which considers the underwater tasks and better estimates the perceptual quality of sonar images [33]. The other RR image QA approach is the partial-reference sonar image quality predictor (PSIQP) that can predict the image quality by using image information, comfort index, and SSIM index [34]. The NR image QA approach is the no-reference contour degradation measurement (NRCDM), which can evaluate the sonar image quality on the basis of the degree of contour degradation [35]. In addition, there are some classical QA methods of sonar images, namely the QA method of synthetic aperture sonar (SAS) based on navigation error degree [36]; the method based on sonar platform motion, navigation error level, and environmental characteristics [37]; and the method called no-reference sonar image quality metric (NSIQM) that measures the contour degradation degree of the test and the filtered images [38].

1.5 Quality Assessment of Enhanced Images

In many real-world applications, such as object detection and recognition, original images require to be enhanced appropriately to improve the perceptual quality [39]. Image enhancement is the frequently used technique for improving the visual quality of images. Among, contrast enhancement is a popular type of image enhancement method that can improve the perceived quality of most images. Its goal is to create more aesthetically beautiful or visually instructive images or both. The contrast of an image can be dramatically increased by reassigning pixel values. Due to its ease of use and speed, histogram equalization is commonly employed in many image post-processing systems. However, the problem in these methods such as over-enhancement still requires attention. Therefore, it has been a hot issue in recent years to optimize the model structures and parameters in order to realize appropriate enhancement using enhanced image QA. The classic image QA methods may be separated into subjective and objective evaluation. For current image enhancement studies, the quality of enhanced images is mostly determined by subjective tests, which are time-consuming and costly. To overcome the limitations of subjective assessment, researchers have turned their research priorities to the design of objective assessment. Despite the emergence of hundreds of objective image QA models, very few efforts have been made for the issue of contrast-changed image QA.

This book elaborately introduces two enhanced image databases, two NR QA approaches of enhanced images, and two contrast enhancement methods, and the details are illustrated in Chap. 5. One enhanced image database is based on five image enhancement algorithms and three image processing software [40]. The other database includes 655 images which are created by five categories of contrast-oriented transfer functions [41]. One of NR QA approaches of enhanced images is the first opinion-unaware (OU) blind image QA metric named blind image quality measure of enhanced images (BIQME), which can effectively obtain the prediction quality of enhanced image [39]. The other NR QA approach is based on the theory of information maximization to realize the judgment of images having better contrast and quality [42]. One of the contrast enhancement methods is an automatic robust image contrast enhancement (RICE) model based on saliency preservation [43]. The other image contrast enhancement framework is based on cloud images, solving the difficulty of multi-criteria optimization [44].

1.6 Quality Assessment of Light-Field Images

In recent years, the light-field (LF) imaging technology has attracted wide attention in many practical applications, such as underwater imaging, 3D object recognition, super-resolution (SR) imaging, and so on. Yet, the LF images will inevitably damage visual details in the acquisition, coding, denoising, transmission, rendering, and display, which will affect the perceived quality of low-frequency images.

In order to better assess the quality of LF images, a large number of researchers have done work to design different LF image QA approaches. This book elaborately introduces an FR LF image QA, a RR LF image QA, and two NR LF image QA methods proposed in recent years, and the details are illustrated in Chap. 6. The FR LF image QA methods measure the LF coherence between the pristine LF image and the corrupted LF image to evaluate the image quality [45]. The RR LF image QA methods investigate the association between the perceptual quality of LF images and the distortion of the estimated depth map [46]. One of the NR LF image QA methods named no-reference light-field image quality assessment (NR-LFQA) evaluates the quality degradation of LF images on the basis of the spatial information and the angular consistency [47]. The other NR LF image QA method is a novel tensor-oriented no-reference light-field image quality evaluator named Tensor-NLFQ that is based on tensor theory. In addition, there are some methods that can be learned by any interested readers. For example, [48] came up with an FR image QA model called the multi-order derivative feature-based model to explore the multi-order derivative features. Huang et al. [49] presented an FR LF image QA algorithm that is based on dense distortion curve analysis and scene information statistics.

1.7 Quality Assessment of Virtual Reality Images

With the development of multimedia techniques, virtual reality (VR) technologies, such as 3D real-time image display and 3D positioning tracking, have attracted a lot of attention. The images generated by VR technologies can provide observers with an immersive and realistic viewing experience and further improve the efficiency of human-machine interaction. However, the omnidirectional view characteristics lead to high resolution and massive data of 360-degree images, which in turn make images so sensitive to external interference that their quality deteriorates. Based on this consideration, it is significant to design efficient image QA methods for VR images to prevent low-quality images from causing undesirable user experience. Traditional image QA methods have poor performance due to the limitation of VR image databases and cannot effectively assess the perceptual quality of VR images with high-dimensional characteristics.

In order to fill the gap in the research of QA methods of VR images, this book elaborately introduces four different QA methods of VR images proposed in recent years, and the details are illustrated in Chap. 7. These VR image QA approaches are classified into four categories according to the different observing subjects, namely subjective QA, objective QA, subjective-objective QA, and cross-reference stitching QA, respectively. The subjective QA method is based on the database named compression VR image quality database (CVIQD) [50] that consists of raw images and images with JPEG compression to evaluate the VR image quality. The objective QA approach named weighted-to-spherically uniform peak signal-to-noise ratio (WS-PSNR) assesses the visual quality of VR images in terms of the reweighting of pixels according to their position in space [51]. For subjective-objective QA, deep learning is employed to assess the omnidirectional images quality. Two typical image QA methods named vectored differential mean opinion score (V-DMOS) and overall differential mean opinion score (O-DMOS) are presented to effectively assess the panoramic image quality [52]. For cross-reference stitching QA method, which focuses on evaluating the area of stitched omnidirectional images, [53] designed a typically used method. The method concentrates on the stitching regions by convolutional sparse coding and compound feature selection to quantify ghosting and structure.

1.8 Quality Assessment of Super-Resolution Images

With the increasing demand for image or video resolution, the SR technique is widely utilized in medical image processing, infrared imaging, security monitoring, and other fields. The high-resolution images can be generated from the given low-resolution images via the image SR techniques like bilinear interpolation, bicubic interpolation, and the Lanczos resampling. However, these pixel integration operations cause serious mixed artifacts and fuzzy distortion in the edge and high-frequency regions, resulting in poor image perception quality. Therefore, it is essential to effectively assess the SR image perceptual quality before further analysis of SR images, in order to improve the accuracy of processing systems. The commonly used image QA methods do not systematically consider the artifacts and distortions that appear in SR images, so they are not applicable to assess the SR image quality.

Deep learning, especially convolutional neural networks (CNNs), has been broadly applied to image processing tasks [54]. Therefore, this book elaborately introduces two QA methods based on deep learning and a QA method based on NSS of SR images presented recently, and the details are illustrated in Chap. 8. One of the deep learning-based QA methods of SR images is the method based on a cascade regression, which establishes the mapping relationship between multiple natural statistical features and visual perception scores by learning a two-layer regression model [55]. The other deep learning-based QA method of SR images is the method based on the combination of SR image QA loss function and L_2 Norm, which can effectively assess the visual perceptual quality of SR images [56]. The NSS-based QA method of SR images is the method that quantifies the degradation of image quality using deviations from statistical models of frequency energy falloff and spatial continuity of high-quality natural images [57]. In addition, there are also some approaches, such as the metric named the deep similarity (DeepSim) [58], the dual-stream siamese network used to assess the distorted image perceptual quality score [59], and the model called the deep image quality assessment (DeepQA) [60]. The interested readers can learn these above-mentioned methods on their own.

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