New Concepts for Visual Perception Quality Assessment of Images —- Single-Image Visual Perception Quality Assessment and Visual Perception Quality Comparison Between Independent Images

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Abstract

Until now, image quality assessment has not addressed color issues. The literature on image quality assessment primarily evaluates the degree of degradation (deterioration) of image quality during image processing procedures such as compression and transmission. A planar image is essentially a two-dimensional luminance distribution. Luminance constitutes a core parameter of image visual quality; without luminance, there would be no image, and consequently, no basis for discussing image quality. This paper proposes three hierarchical metrics for image visual perceptual quality assessment (VPQA): Single-image Single-parameter Image Quality Assessment (SS_{IQA}), Single-image Five-parameter Fine Image Quality Assessment (SF_{IQA}), and Color Fidelity-aware Enhanced Image Quality Assessment (CF_{IQA}). From a horizontal perspective, it can be categorized into three aspects: single-image quality assessment (SIQA), multi-image quality comparison, and quality assessment in image enhancement. Image visual quality assessment serves as an indispensable tool for intelligently optimized image enhancement.

Full Text

New Concepts in Visual Perception Quality Assessment for Images–Single-Image Visual Perception Quality Assessment and Quality Comparison Among Independent Images

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Abstract

Until now, image quality assessment has not addressed color issues. The literature on image quality assessment primarily evaluates the degree of deterioration (degradation) of image quality during processing operations such as compression and transmission. A planar image is a two-dimensional luminance distribution, and luminance is the core parameter of image visual quality—without luminance, there is no image, and thus no basis for discussing image quality. This paper proposes three levels of image visual perception quality assessment (VPQA): single-parameter single-image quality assessment (SS-IQA), five-parameter fine image quality assessment (SF-IQA), and enhanced image quality assessment considering color fidelity (CF-IQA). Horizontally, these can be divided into three aspects: single-image quality assessment, multi-image quality comparison, and quality assessment in image enhancement. Visual quality assessment of images is an indispensable tool for intelligent optimization of image enhancement.

Keywords: Visual perception quality assessment (VPQA), Single-image-and-single-parameter image quality assessment, Single-image-and-multi-parameter fine image quality assessment, Visual quality assessment in image enhancement (considering color fidelity), Perturbation transformation, Optimization

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Image quality assessment is essentially visual perception quality assessment of images. An image is a two-dimensional optical stimulus for the visual system with a specific luminance distribution. Without vision (as in blindness), there is no light (only a segment of electromagnetic waves), no optics, and consequently no image. Human perception of one-dimensional optical stimuli involves sensing magnitude and quantity, whereas perception of two-dimensional optical stimuli involves assessing the quality of luminance distribution—that is, judging the goodness of that distribution. Human visual perception of image quality serves as the gold standard for image quality evaluation, for without vision, there would be no image [1,2]. While the Weber-Fechner law quantifies visual perception of light intensity [3,4], image quality assessment quantifies visual perception of luminance distribution quality [1-2].

Luminance is the most fundamental and core psychophysical parameter of an image. Since luminance may differ at every pixel, image luminance values can only be described using first-order statistics (i.e., the mean). Our research reveals that image visual quality is a function of average luminance. Visual quality increases with average luminance, reaches a maximum (optimal value), and then decreases with further increases in average luminance. Thus, image visual quality exhibits convex characteristics with respect to average luminance, as illustrated in the series of images in Figure 1(a)-(f).

Figure 1. The variation of image visual quality with average luminance possesses convex characteristics, logically inferring the existence of an optimal quality image.

This discovery of the existence of an optimal quality image enables us to create intelligent optimization methods for image enhancement based on average luminance transformation. Previously, no image enhancement methods optimized for visual perception quality existed precisely because the existence of an optimal quality image had not been discovered, lacking this conceptual foundation [1-4].

1. Two Conventions for Zero Visual Perception Quality

Human knowledge acquisition relies on sensation. Vision, being more complex than hearing, accounts for over 80% of human knowledge acquisition. Like hearing, vision has a sensory threshold—the minimum luminance required to elicit visual perception. Unfortunately, visual threshold values are not readily available. General sensory physiology and photometry research indicates that photopic vision occurs at ambient luminance ≥ 3 cd/m^2, while scotopic vision occurs at $\leq 10^{-3}$ cd/m^2, with further dependencies on wavelength. Auditory research includes pain thresholds, yet no corresponding data are reported for vision. Computer screens typically represent brightness using gray levels rather than physical quantities.

1.1 High-End Boundary Condition for Zero Visual Perception Quality [1]

In typical 8-bit systems, screen brightness ranges from 0-255 gray levels. Image brightness is characterized by average gray level. We stipulate that an image with luminance but no luminance distribution has zero visual quality. Consequently, an image with average luminance of 255 gray levels has zero visual perception quality, as this value only occurs when every pixel has a brightness of 255 gray levels. Therefore, we establish 255 gray levels as the high-end boundary for visual perception. If VPQ represents visual perception quality, the high-end boundary condition is defined as:

$$VPQ = 0 \quad \text{when} \quad AL = 255$$

This represents the high-end boundary of visual perception.

1.2 Low-End Boundary Condition for Zero Visual Perception Quality [1]

Research further reveals that at approximately 3 gray levels average luminance, although gray-level distribution exists, the visual system cannot perceive image structure—this represents the visual threshold. At and below this threshold (average luminance ≤ 3 gray levels), despite the presence of gray-level distribution, visual perception is absent. Therefore, we also stipulate that images with average luminance of 3 gray levels or below have zero visual perception quality. The low-end boundary condition is defined as:

$$VPQ = 0 \quad \text{when} \quad AL \leq 3$$

This represents the low-end boundary of visual perception.

2. Single-Parameter Visual Perception Quality Equation for Independent Images

With these two conventions establishing zero visual perception quality at both high and low boundaries, we can construct a single-parameter equation (function) describing the visual perception quality of independent images [1]:

$$VPQ = k \cdot (AL - 3) \cdot (255 - AL)$$

where VPQ denotes visual perception quality. For color images, $k = 3$; otherwise, $k = 1$. This enables us to obtain the average luminance position of the optimal quality image and its functional relationship with the two boundary conditions:

$$AL_{optimal} = \frac{255 + 3}{2} = 129$$

as well as a direct evaluation metric for any image: the Visual Perception Quality Ratio ($VPQR$), which ranges from [0,100] and indicates proximity to the optimal quality image. Higher values denote better visual quality. $VPQR$ can evaluate both absolute image quality (closeness to optimal) and compare visual quality across multiple images (ranking). It assesses both improvement in enhanced images and degradation during compression or transmission.

Five example images are shown in Figure 2(a)-(e), captured from different objects under varying conditions. Their average luminance (AL) and $VPQR$ values are listed in Table 1, with rankings based on $VPQR$ values shown in the "Ranking" row.

3. Fine Assessment of Independent Image Visual Quality

3.1 Five-Parameter Fine Assessment Function (FAF)

Research demonstrates that independent image visual perception quality depends not only on average luminance (AL) but also on other parameters: average information entropy (AIE), average contrast (AC), average gray/color component count ($ACTT$), and average gray/color spectral bandwidth (ABW, i.e., average dynamic range). The Fine Assessment Function (FAF) is defined as [2]:

$$FAF = VPQR \times ISF$$

where ISF represents the Image Structure Function, determined by:

$$ISF = \frac{AIE}{AIE_{max}} \cdot \frac{AC}{AC_{max}} \cdot \frac{ACTT}{ACTT_{max}} \cdot \frac{ABW}{ABW_{max}}$$

Further research yields the following expressions: $AIE_{max} = \log_2(N)$, $AC_{max} = 255$, $ACTT_{max} = N$, and $ABW_{max} = 255$, where N represents the number of possible gray levels. Thus, FAF can be expressed in a more comprehensible form:

$$FAF = VPQR \cdot \frac{AIE}{\log_2(N)} \cdot \frac{AC}{255} \cdot \frac{ACTT}{N} \cdot \frac{ABW}{255}$$

The Image Structure Function (ISF) determines the maximum value of FAF, which varies for images of different objects. This is termed "fine quality assessment" because it enables detailed analysis of how the five parameters (AL, AIE, AC, $ACTT$, ABW) change before and after enhancement. The Visual Perception Quality Ratio ($VPQR$) acts as a trend factor, determining the FAF variation pattern of $0 \to$ maximum $\to 0$.

The FAF values for the original images in Figure 2(a)-(e) are listed in Table 1 under "FAFO" . Larger FAF values indicate better visual quality.

3.2 Visual Quality Comparison and Ranking Among Arbitrary Images

Since FAF exhibits the property that larger values correspond to better visual quality, it can be used for comparison and ranking among arbitrary images—accomplishing what appears to be a very difficult task. Table 1' s "Ranking" row shows ordering by $VPQR$ values, mixing original and perturbation-transformed images. "Ranking1" orders by original image FAF (FAFO) values. "Ranking2" orders by perturbation-transformed image FAF (FAFTur) values (without considering color distortion in enhanced images). "Ranking3" orders by unified FAF (TFAF) values for both original and transformed images. Compared with the $VPQR$-based Ranking, this approach better approximates visual evaluation.

Table 2 contains numerical values, characters, and images—a novel data format representing an extended "structured" data type in database technology, which can be called an expanded structure type. Table 2' s "Ranking3" data are sorted in descending order by TFAF. The "TImageR" row shows images corresponding to Ranking3, clearly demonstrating the TFAF sorting effect.

4. Quality Assessment in Image Enhancement [5-7]

We categorize quality assessment in image enhancement into two aspects: performance evaluation of enhancement methods and visual quality evaluation of enhanced images. Previously, no reports on performance evaluation of enhancement methods have been seen.

4.1 Performance Evaluation of Image Enhancement Methods

We propose three fidelity criteria specifically for evaluating enhancement method performance, with particular emphasis on quantifying color distortion for performance assessment, detailed in references [8-9]. These criteria establish a veto mechanism for image enhancement methods.

4.2 Enhanced Image Quality Assessment: Seven-Parameter Method

Enhanced image quality assessment employs a seven-parameter method, with the evaluation function $CFAF$ defined as:

$$CFAF = VPQR \cdot \frac{AIE}{\log_2(N)} \cdot \frac{AC}{255} \cdot \frac{ACTT}{N} \cdot \frac{ABW}{255} \cdot (1 - d_1) \cdot (1 - d_2)$$

where d_1 and d_2 represent color distortion parameters [8-9]. This evaluation metric 首次包含了评价彩色失真的参数和 [8-9] (*Note: This phrase appears incomplete in the original*). It emphasizes that color distortion reduces enhanced image visual quality. This assessment method is an indispensable and powerful tool for achieving intelligent optimal image enhancement.

The CFAFTur values for enhanced images 1a)-1e) in Figure 2 are shown in Table 1' s CFAFTur row.

4.3 Quality Comparison and Hybrid Ranking of Enhanced vs. Original Images Using TFAFTur

Table 1' s TFAFTur includes original image FAF values and FAF values calculated after considering color distortion parameters ($1dCorr$ and $2dCorr$) in perturbation-transformed images (FAFTur). Table 1' s "Ranking4" row provides unified sorting by FAFTur values. Compared with Ranking3, positions 2 and 3 are swapped. Table 1' s TFAF2Tur includes original image FAF and FAF values calculated after considering color distortion parameters from the second perturbation transformation ($1dCorr2Tur$ and $2dCorr2Tur$), denoted as CFAF2Tur. Ranking5 shows ordering by TFAF2Tur values, where positions 8 and 9 are swapped compared with Ranking4.

4.4 Brightness-Preserving Image Enhancement Is Impossible

Image enhancement typically increases contrast (AC), thereby also increasing local average contrast (LAC), which is why it is often called contrast enhancement. For our proposed IOALT (Intelligent Optimization Average Luminance Transformation) method, AIE and $ACTT$ do not increase, complying with the first and second fidelity criteria in image enhancement (non-increasing entropy and non-increasing gray/color component criteria). Image enhancement trades entropy reduction for contrast enhancement.

Since image visual quality is a function of AL, any enhancement necessarily changes AL. For low-AL images (Figures 3a, 3b, 3c, 3e), AL increases after enhancement; for high-AL images (Figure 3d), AL decreases after enhancement. Therefore, brightness-preserving image enhancement proposed in literature [10-12] cannot exist. Such methods are fundamentally impossible.

5. Concept of Narrow-Sense Image Enhancement

We define narrow-sense image enhancement as visual quality enhancement required due to luminance-related degradation. It excludes enhancements for noise, various types of blur, or component loss, which have dedicated denoising, deblurring, and inpainting methods collectively termed image restoration. If restored images have not yet achieved optimal visual quality, optimal image enhancement methods can be further applied.

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Note: Figure translations are in progress. See original paper for figures.