No-reference Image Quality Assessment Based on Regional Information

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Abstract. Human vision can quickly assess the quality of images because of the identity in a region and the divisibility between different regions. According to human visual characteristics, we propose a method of image quality assessment without reference information. Firstly, the image was segmented into a series of homogenous regions. Secondly, we analyzed statistical characteristics for each region. Lastly, the assessment model was constructed according to the statistical differences among regions. The results experimented on the LIVE database II show that this method is competitive to SSIM and PSNR.

1. Introduction
In storage and transmission processes, an image is easy to be attacked by noise, equipment and other factors, which result in image quality degradation. Degraded image has negative effect on high level image process, such as object recognition and image understanding. In order to assess image quality, researchers have proposed many methods, such as structural similarity index (SSIM), peak-signal-to-noise-ratio (PSNR). However, these methods need original image to be assessed. For no-reference image quality assessment (NR-IQA), it is still a challenge.

Image quality assessment (IQA) can be classified into subjective and objective method. The former uses subjective perception to assess the quality of objects. It can truly reflect the intuitive quality of the image, the assessment results are obtained without technical obstacles, but easily affected by subjective factors. The latter uses the quantitative index given by the model to simulate the perception mechanism of human visual system to measure the image quality. It is limited by technology and equipment, but the assessment results are not affected by human factors and more reliable.

Objective image quality assessment methods can be classified into two broad categories: reference and no-reference. The reference method needs full or parts of original image information to make comparisons. In terms of the overall situation, Picture Quality Scale (PQS) \cite{1} method measures main three aspects of images which are brightness, structure and contrast to assess image quality. Based on a single aspect, SSIM \cite{2} just uses structural information between data blocks to measure image quality. However, in practice, there is usually only one image and no reference information. Different from the reference methods, NR-IQA methods use image features as assessment criteria directly, which are more flexible and reliable. In space domain, an algorithm is designed to measure the degree of image blur by calculating the diffusion degree of image edge to its neighborhood pixels \cite{3, 4}. In the frequency domain, an algorithm based on block measures the chaos degree of low quality image according to the variation of energy transfer from high frequency to low frequency \cite{5}. Additionally,
according to the intensity of gradient value changed on the edge of image block after DCT compression, image quality can also be assessed [6, 7].

Visual masking effect is a kind of local effect, which is affected by background illumination, texture complexity and signal frequency. In complex external scenes, human vision can always quickly locate important target areas and make detailed analysis. On the basis of the characteristic, we propose a quality assessment method based on region for no-reference images. Firstly, an image is segmented according to the divisibility between regions. Then, regional statistical properties are computed. Finally, according to the contrast between regions, we calculate the assessment index. Our method is experienced on LIVE database II [8] to validate the performance.

This paper is organized as follows. In section 2, the mathematical background of constructing assessment model is given. Then, section 3 presents experience results of image quality assessment, which are experienced on the LIVE database II. Finally, conclusions are drawn in Section 4.

2. Assessment Model

Human vision has the identity and divisibility in region recognition. Combining visual characteristics and the contrast between image regions, we construct the assessment model:

\[
AR(u) = \text{contrast}(S(R_i(u)), S(R_j(u))), i \neq j
\]  

Here \(R(u)\) represents a region in \(u\) and \(S(\cdot)\) is the statistic information of a region.

2.1. Region Segmentation

When the human eye observe an image, the pixels with spatial continuity and color similarity are considered to be in the same region. According to these characteristics, an image with \(N\) pixels is segmented into \(k\) homogeneous regions:

\[
R_i = \{(u_i, u_j) | u_i = u_j, u_j \in \Omega_{u_i}, i = 1, \ldots, k \}
\]  

Here \(\Omega_{u_i}\) denotes the neighborhood of pixel \(u_i\).

The specific segmentation process will be described and we give a detailed graphic explanation about one region segmentation in figure 1:

- **Step1:** Calculate the gray of each pixel in the input image and sort it from low to high, the same gray value is the same level. In practice, we use gradient to represent gray level.
- **Step2:** Process all pixels of the first gray level. If the neighborhood of a pixel in the layer has been identified as belonging to a region, the pixel will be added to the first-in first-out (FIFO) queue.
- **Step3:** When the queue is non empty, the first pixel pops up and scans its neighborhood. If the gray level of the neighboring pixel belongs to the same layer (the gray value is equal), the identification of the pixel is refreshed according to the identification of the neighboring pixel. Loop until the queue is empty.
- **Step4:** Scan the pixels of the current gray level again. If another pixel is not identified, it means that it is a new minimum region, then the value of the current region (the value of the current area is counted from 0) plus 1 is assigned to the unidentified pixel. Then, starting from the pixel, continue with **step3** until no new minimal region exists.
- **Step5:** Return to **step2** to process pixels at the next gray level until all pixels at all levels are processed.
2.2. Region Merging
The number of regions is easily affected by the texture or other irregularities in the image, resulting in some small regions. Thus, the small regions need to be merged:

\[
\text{Number}(R_i) \geq \text{por} \cdot N
\] (3)

Here \(\text{por}\) is a proportion.

2.3. Quality Assessment
Pixels in homogenous regions do not change much, which can be represented by a regional mean:

\[
u_i = \frac{1}{N_i} \sum_{j=1}^{N_i} u_{ij}(j)
\] (4)

Here \(u_{ij}(j)\) is the value of the \(j\)-th pixel and \(N_i\) denotes the number of pixels in \(i\)-th region.

The contrast between different regions is expressed as:

\[d_{ij} = \left| u_i - u_j \right| \quad i, j = 1, 2 \cdots k
\] (5)

Here \(u_i\) and \(u_j\) denotes two regional means which are converted to gray values.

Then, sorting \(d_{ij}\) to get maximum, median and minimum:

\[
\begin{align*}
    d_0 &= \min \left\{ d_{ij}, i, j \in \{1, \cdots k\}, \text{and } i \neq j \right\} \\
    d_1 &= \text{med} \left\{ d_{ij}, i, j \in \{1, \cdots k\}, \text{and } i \neq j \right\} \\
    d_2 &= \max \left\{ d_{ij}, i, j \in \{1, \cdots k\}, \text{and } i \neq j \right\}
\end{align*}
\] (6)

In order to reduce the influence of shooting environment on image quality, the assessment index is calculated by:

\[
\text{index} = \frac{d_2 - d_1}{d_1 - d_0}
\] (7)

The overview of this method is shown in figure 2:
Regional information

Image quality assessment

Figure 2. The overview of image quality assessment. The given image is segmented into multiple homogeneous regions and computed regional information to assess image quality.

3. Experimental Result

The experiences are conducted using VC 6.0 on a PC with Intel-Core i5 @ 2.90 GHz and 16 GB of RAM. The tested images come from the LIVE database II. Natural scene image contains a lot of texture information, parts of degraded images were generated by Gaussian smoothing and mean filter methods, as shown in figure 3. The blur scale of the original image is set to 1, and then change the scale with 2 as the growth until it reaches 39. Each image in the test set is segmented and the contrast is calculated to get its own assessment index. In figure 4, results of the contrast about mean filter and Gaussian smoothing are given.

Figure 3. Degraded images by different blur methods. First row is mean filter images and the next is Gaussian smoothing images.

Figure 4. Results of the contrast. (a) is mean filter and (b) is Gaussian smoothing. The horizontal axis represents images with different blur scales, the vertical axis is the value of the contrast, and orange, gray and blue points represent the maximum, median and minimum respectively.
3.1. Parameter Discussion

The number of regions segmented is easily influenced by the details and edges of the image. The rough segmentation can’t retain more details and even loss some important information. The fine segmentation can retain more details, but it may cause the difficulties to calculate and degrades the efficiency because of too many regions. To avoid, we merge the regions which are the adjacent polar cells and get the final region segmentation results. In figure 5, we give a simple example of the segmentation results to discuss.

![Figure 5. Segmentation results.](image)

The results of assessment index with different segmentation conditions are shown in Table 1. It’s obvious that *por* has a great influence on our results. The size of the image in LIVE database II is 768 × 512. We choose *por* =0.1% as our merger condition. When the proportion of pixels in other regions is less than 0.1%, it is combined with adjacent regions.

| *por* (%) | 0.01 | 0.05 | 0.1 | 0.15 | 0.2 |
|----------|------|------|-----|------|-----|
| index    | 1.273| 2.481| 2.335| 2.257| 3.101|

Table 1. The assessment results in different segmentation conditions.

3.2. Comparison and Analysis

SSIM and PSNR are commonly used methods to assess image quality. SSIM measures image similarity from three aspects: brightness, contrast and structure. PSNR is based on the error between corresponding pixels to assess image quality. Visually, we give a result schematic to comparison for reference method and no-reference method about Gaussian smoothing in figure 6. And more detailed results are given in Table 2.

![Figure 6. The simple results schematic for reference method and no-reference method about Gaussian smoothing.](image)
Table 2. The results of assessment index, PSNR and SSIM experienced on two kinds of degraded images with different blur scales.

| Blur scale | 1      | 3      | 5      | 7      | 9      | 17     | 25     | 31     | 39     |
|------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Mean filter|        |        |        |        |        |        |        |        |        |
| PSNR       | 35.495 | 31.339 | 29.601 | 28.636 | 26.859 | 25.947 | 25.486 | 25.027 |        |
| SSIM       | 1      | 0.93   | 0.915  | 0.914  | 0.898  | 0.874  | 0.861  | 0.838  | 0.832  |
| Gaussian smoothing | |        |        |        |        |        |        |        |        |
| PSNR       | 34.451 | 30.63  | 28.901 | 27.889 | 25.918 | 24.85  | 24.307 | 23.771 |        |
| SSIM       | 1      | 0.929  | 0.913  | 0.912  | 0.916  | 0.866  | 0.87   | 0.826  | 0.797  |

SSIM and PSNR show monotonic decreasing characteristics as the degree of blur increases. However, from the experimental results, it is shown that the results of SSIM fluctuate slightly, although the overall trend is still decreasing with the increase of ambiguity.

4. Conclusion
We propose a quality assessment method according to the identity in a region and the contrast between regions for human vision. It uses the characteristics of image itself to assess image quality and doesn’t need any reference image. High quality images have higher indexes. But, in the process of region segmentation, gradient information is used as the segmentation criterion, which leads that the number of region is sensitive to noise. Therefore, a further research is the influence of noise in the image on this method.

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