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Quantitative assessment of laser-dazzling effects through wavelet-weighted multi-scale SSIM measurements

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ABSTRACT

Laser active imaging systems are widespread tools used in region surveillance and threat identification. However, the photoelectric imaging detector in the imaging systems is easy to be disturbed and this leads to errors of the recognition and even the missing of the target. In this paper, a novel wavelet-weighted multi-scale structural similarity (WWMS-SSIM) algorithm is proposed. 2-D four-level wavelet decomposition is performed for the original and disturbed images. Each image can be partitioned into one low-frequency subband (LL) and a series of octave high-frequency subbands (HL, LH and HH). Luminance, contrast and structure comparison are computed in different subbands with different weighting factors. Based on the results of the above, we can construct a modified WWMS-SSIM. Cross-distorted image quality assessment experiments show that the WWMS-SSIM algorithm is more suitable for the subjective visual feeling comparing with NMSE and SSIM. In the laser-dazzling image quality assessment experiments, the WWMS-SSIM gives more reasonable evaluations to the images with different power and laser spot positions, which can be useful to give the guidance of the laser active imaging system defense and application.

1. Introduction

The laser active imaging systems have high contrast, high resolution and anti-interference capability. If the systems are influenced by laser or other external factors, the quality of the images will decline. How to evaluate the quality of the laser-dazzling images is a necessary step on the way to quantifying the dazzling effects. Image quality assessment (IQA) aims to design quality measures that can automatically predict the image quality. The most widely used objective quality algorithms are the mean squared error (MSE) and the peak signal-to-noise ratio (PSNR). They are simple to calculate and have clear physical meanings, but they do not correlate well with the subjective evaluations. The well known structural-similarity (SSIM) metric brings IQA from pixel-based stage to structure-based stage [1]. But unfortunately, it is inconsistent with the subjective rating on cross-distorted image assessment. On the basis of SSIM, there have been many improved algorithms. The multi-scale extension of SSIM (MS-SSIM) produces better results than its single-scale counterpart [2]. The three-component weighted structural similarity (three-SSIM) assigns different weights to the SSIM scores according to the local region types, such as edges, textures and smooth areas [3]. MSE operates on the intensity of the image directly. It is computed by averaging the squared intensity differences between original and distorted image pixels. SSIM is based on the average distortion. The laser-dazzling image is seriously distorted in the local area, which is different from the noise-distorted image. So the traditional algorithms do not correlate well with the quantitative assessment of the laser-dazzling image.

Based on the above analysis, we propose a novel wavelet-weighted multi-scale structural similarity, named WWMS-SSIM. We carry out the wavelet decomposition upon the both original and the distorted images for the frequency subbands firstly. Thereafter, the differences between the original subbands and the distorted subbands are measured by SSIM for their SSIM maps. The SSIM maps are weighted by taking characteristics of the human visual system into account. Finally, we use a mean WWMS-SSIM index to evaluate the image quality. To examine the performance of the proposed WWMS-SSIM algorithm, NMSE (Normalized Mean Square Error), SSIM and WWMS-SSIM are used to evaluate the image quality in the standard image database and the experiment is focused on the correlation, accuracy and consistency, respectively. In another experiment, the disturbed images of different laser irradiance power and different spot positions are obtained. The proposed WWMS-SSIM algorithm is used to evaluate the newly obtained laser-dazzling images. The results show that WWMS-SSIM gives more reasonable evaluation results for

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different laser-dazzling images. The evaluation results are more suitable for the subjective visual feeling.

2. Wavelet-weighted multi-scale SSIM

Human visual system has different response to different colors, directions and spatial frequency. Consequently, the multi-resolution analysis is very important in the image processing. It means the general structure is observed in the low-resolution and the detail information is observed in the high-resolution. Based on the above analysis, a wavelet-weighted multi-scale structural similarity (WWMS-SSIM) algorithm is proposed.

2.1. Wavelet decomposition

The multi-resolution analysis from rough to fine commonly uses octave division. Wavelet decomposition also uses octave division, which is close to the information processing mechanism of the human visual system. Wavelet decomposition can be used in the image quality assessment in order to get more accurate evaluation value. Wavelet decomposition not only has the ability to characterize the local signal characteristics in the time domain and frequency domain, but also has the multi-scale analysis ability and the direction-sensitive property. Therefore, the wavelet theory provides a simple approximation of how the human visual systems identify features in an image.

Five-level or six-level wavelet decomposition is more consistent with human visual characteristics, but the computation is too complex. Therefore, four-level wavelet decomposition is efficient in practice [4,5]. Wavelet bases such as Harris, Daubechies, Biorthgonal, Ceiflets and Symlets are commonly used. Considering the orthonormality, energy concentricity and wavelet reconstruction, the "Sym8" wavelet base is adopted in this paper [6,7]. Examples of the four-level wavelet decomposition can be found in Fig. 1.

The image is decomposed into a set of subband images whose resolutions reduce gradually. The low-frequency subband (LL) is decomposed into secondary subbands. LL subband represents the low-frequency information including most of the energy of the image. LH subband represents the horizontal edge information (horizontal low frequency and vertical high frequency). HL subband reflects the vertical edge information (horizontal high frequency and vertical low frequency). HH subband reflects the diagonal edge information including the horizontal and vertical high frequency detail.

2.2. Wavelet multi-scale SSIM algorithm

Distorted images are classified into two categories, namely non-structural distortion and structural distortion. After the wavelet decomposition, the images are decomposed into several subbands with different spatial frequencies. Fig. 2 shows different types of distorted images. Fig. 2(a) shows an original image. Fig. 2(b) shows a luminance distorted image. Fig. 2(c) shows a contrast distorted image. They are all non-structural distorted images. Fig. 2(d)–(f) shows white noise, Gaussian blur, JPEG compression distorted images, respectively. They are all structural distorted images. For convenience, original and distorted images are decomposed into subband images by one-level wavelet decomposition. Each image is decomposed into a low-frequency subband (LL) and three high-frequency subbands (HL, LH, and HH). Combining the high-frequency subbands obtains:

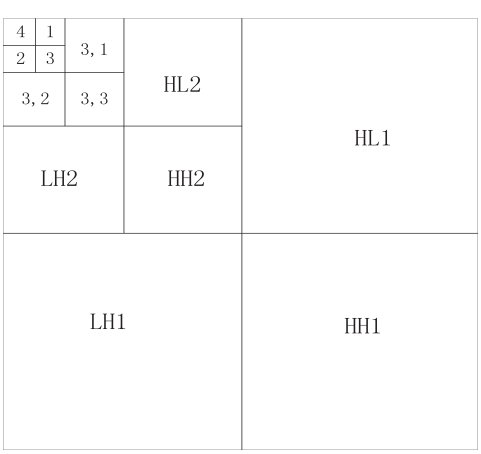

Fig. 1. A four-level wavelet decomposition map.

$$\mathrm{highmap}=\sqrt{\mathrm{HL}^2+\mathrm{LH}^2+\mathrm{HH}^2} \tag{1}$$

The SSIM algorithm is composed of luminance comparison, contrast comparison and structure comparison [1].

Luminance comparison is defined as

$$l(x,y)=\frac{2\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1} \tag{2}$$

Contrast comparison is defined as

$$c(x,y)=\frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2+\sigma_y^2+C_2} \tag{3}$$

Structure comparison is defined as

$$s(x,y)=\frac{\sigma_{xy}+C_3}{\sigma_x^2\sigma_y^2+C_3} \tag{4}$$

Suppose x and y are two non-negative image signals. μ_x and μ_y represent the mean gray value of the subband images x and y. σ_x and σ_y represent the standard deviation of x and y. σ_{xy} represents the covariance between x and y. C_1, C_2 and C_3 are included to avoid instability when denominators are very close to zero. $C_1=(K_1G)^2$, $C_2=(K_2G)^2$, $C_3=(C_2/2)^2$, G is the dynamic range of the pixel values, and $K_1 \ll 1$, $K_2 \ll 1$, they are small constant. LL and highmap are considered as subband images. They are calculated using Eqs. (2)–(4). After that, the comparison functions of the low and high frequency in various distorted images are presented in Table 1.

From the underlined values in Table 1, we can see that the changes of the luminance have more effects on the low frequency components, but the changes of the contrast and the structure distortions have fewer effects. The high frequency components are just the reverse of the low frequency. It is not sensitive to the distortion of the luminance, but it is sensitive to the contrast and structure distortions. Consequently, wavelet multi-scale structural similarity (WMS-SSIM) algorithm only calculates the luminance comparison in the low-frequency subband and calculates the contrast and structure comparison in the high-frequency subbands. Four-level low-frequency wavelet subband structural similarity is defined as

$$\mathrm{WMS-SSIM}_4^{LL}(x,y)=\left[l_4^{(LL)}(x,y)\right]^{\alpha} \tag{5}$$

Four-level high-frequency wavelet subband structural similarity is defined as

$$\mathrm{WMS-SSIM}_j^{(i)}(x,y)=\left[c_j^{(i)}(x,y)\right]^{\beta}\left[s_j^{(i)}(x,y)\right]^{\gamma}$$
$$(i)=\{\mathrm{LH},\mathrm{HL},\mathrm{HH}\}, j=\{1,2,3,4\} \tag{6}$$

where l, c and s is defined in Eqs. (2)–(4), i is the wavelet decomposition direction, j is the wavelet decomposition level. $\alpha>0$, $\beta>0$ and $\gamma>0$ are parameters used to adjust the relative importance of the three components. In this paper, three comparisons are equally important and in order to simplify the expression, we set $\alpha=\beta=\gamma=1$. If the readers pay more attention to the luminance, the parameters can be adjusted to $\alpha=1$ and $\beta=\gamma=0.5$.