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Adaptive grid-based confidence assessment for synthetic optoelectronic images by Physical Reasonable Infrared Scene Simulation Engine (PRISSE)

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HIGHLIGHTS

- Adaptive grids and 2D Gamma distributed weighting values are designed.
- Experiments on PRISSE simulation and filed MWIR data have been evaluated.
- The confidence of similarity assessments is compared to popularly-used traditional methods.

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ABSTRACT

Like visible spectrum, synthetic infrared scenes reflect the invisible world of infrared features. Propagation of a typical infrared radiation involves a variety of sources of different sizes, shapes, intensities, roughness, temperature, etc., all of which would impose impacts on the fidelity of the synthetic images. Assessing the confidence of a synthetic infrared scene is therefore not so intuitive as evaluating the quality of a visible image. An adaptive grid-based method is proposed in this paper for similarity assessments between synthetic infrared images and the corresponding real infrared images, which is on a grid-by-grid basis. Different from many traditional methods, each grid in our work is weighted by a value that is simulated by a 2D Gamma distribution. Introducing adaptive grids and exerting a weighting value on each grid are the aspects of our method. To investigate the effectiveness of our method, an experiment was conducted for taking real mid-wavelength infrared (MWIR) images, and the corresponding synthetic MWIR images were simulated by Physical Reasonable Infrared Scene Simulation Engine (PRISSE). The confidence of similarity assessments evaluated by our method is then compared to some popularly-used traditional assessment methods.

1. Introduction

Infrared (IR) scene simulation allows us to explore how radiation transfers in a thermal medium [1]. It has been widely applied in military and civilian realms to gain perception of environmental status, such as early warning system [2,3], target detection [4], urban's IR visualization [5–7], and crime analysis [8,9].

Computer graphics techniques make it possible to generate IR images that represent the thermal signature of different targets and backgrounds. For example, the well-known methods of IR image generation [10,11] are able to render fine IR scenes of a typical environment; Physical reasonable infrared scene simulation engine (PRISSE) [12–14] renders IR scenes by computing the "end-to-end" propagation of energy inclusive of self-radiation, reflection, ambient and/or atmospheric effects, and detector's noises; Digital imaging and remote sensing scene generation (DIRSIG) [15–18] is a synthetic image generator on a basis of first principle, which can generate spectral images in the electromagnetic wavelength of 0.3–20 μm. There are some more programs or models that have been developed for synthetic infrared image generations. Readers can be referred to [19–23].

Normally the synthetic IR images generated by computer graphics techniques comprise various sources, each of which has its own characteristics such as size, shape, emittance, roughness and temperature; all of these source characteristics impact the quality of the image simulation. The topic of this paper is to present a new method for similarity assessment between real images and synthetic images.

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Similarity assessment, named as confidence or fidelity assessment thereafter, for synthetic IR images has been studied for various purposes and applied in diverse situations [11,15,24,25]. Such an application, for instance in most military realms, investigates the fidelity of scene reproduction or physical accuracy of the simulation [21,26]. Therefore, both features and geometric structures in IR image processing play key roles in a confidence assessment that is employed for evaluation of synthetic IR images in comparison with the real scene images. Although there are several image assessment methods such as [27–31], what follows describe a couple of methods that are popularly used.

A method used in many applications is the mean square error (MSE) and peak signal-to-noise ratio (PSNR) [32–34]. It has also been employed to compare the simulated synthetic images to the ground truth data and to evaluate the fidelity of the rendering images created by DIRSIG model [15,35–37]. However, MSE and PSNR (denoted as MSE/PSNR thereafter) method has been shown to be inferior to human visual perception [38,39].

As an image quality index, the Structural SIMilarity index (SSIM) [40] has been applied in image/video processing and computer vision [27,41], and shows its favorability in evaluating the fidelity of various synthetic images [42–44]. However, it is still challenging to utilize SSIM as confidence assessment for synthetic IR images. There are two major issues as explained in the following. Firstly, SSIM is unstable at low variances and insensitive for high intensities [45], which makes it difficult to appraising the similarity extent between synthetic and real IR images. Secondly, the influence of SSIM's contrast and luminance components on image confidence mainly focuses on whether a particular region of interest (ROI) can be determined by human or machine vision.

Since the SSIM index is a single-scale method (i.e., treating the image as only one information source), which may lead to less compatible with different viewing conditions [28,39]. There are a couple of extension developments based on SSIM, such as the mean structural similarity (MSSIM) [46,47] and the multi-scale (i.e., handling the image as multiple information sources) structural similarity (MS-SSIM) [28]. The MSSIM calculates the mean of the SSIM values over all partitions in the image, where each partition is segmented on a basis of even-area grids in the whole image. The MS-SSIM assessment method was proposed by exerting different scale levels downscaled by several low-pass filters to provide more objectivity in image similarity assessment.

In this paper, we propose a new confidence assessment method base on SSIM. Adaptive (i.e., self-adjustable) grids in an ROI are built on the basis of scene contents and human vision, and applied to investigate the similarity between synthetic and real IR images. A local radiation distribution (LRD) is introduced to compute weight functions for the three components (i.e., structure, contrast and luminance) quoted in SSIM. The adaptive grids in an ROI are then automatically created by the proposed LRD. The contents in the images are segmented by the well-known Ostu's method [48] or by a human vision model [49]. Besides, in our work we performed an experiment to take real mid-wavelength infrared (MWIR) scene data by a real MWIR camera, and the corresponding synthetic MWIR scene images were generated by PRISSE. We subsequently applied our proposed assessment method as well as other traditional methods for similarity evaluation between real MWIR images and synthetic MWIR images.

The remaining of this paper is constructed as follows. Section 2 describes our proposed confidence assessment method and briefly delineates some other methods applied in our work. To demonstrate the effectiveness of all employed assessment methods, an experiment has been undertaken for data taking of MWIR scene images, which is depicted in Section 3. Our analysis and results of confidence assessments along with some remarks are then presented in Section 4. Finally conclusion is made in Section 5.

2. Methods

This section describes the similarity assessment methods introduced in Section 1.

2.1. MSE/PSNR method

PSNR is defined as the ratio of the maximum value of pixels in an image signal (MAX_s) to the extent of noise that distorts the representation of the image. In practice, PSNR is usually expressed in terms of the logarithmic decibel scale:

$$PSNR = 20\log_{10}\left(\frac{MAX_s}{\sqrt{MSE}}\right), \quad (1)$$

where MSE is expressed as:

$$MSE = \frac{1}{N}\sum_{k=1}^{N}\|f(k) - g(k)\|^2, \quad (2)$$

where N is the number of pixels in an image; $f(k)$ and $g(k)$ are denoted as the k-th pixel values for test and reference images, respectively. Considering the statistical features of PSNR and MSE, the confidence score can be derived as [34]:

$$Q_m = 1 - \frac{N \cdot MSE}{\sum_{k=1}^{N} g^2(k)}, \quad (3)$$

where $Q_m \in [0, 1]$ characterizes the similarity between the test and reference images. The larger the Q_m value, the more similar the two images, indicating a higher confidence score achieved.

2.2. SSIM-related methods

SSIM is a well-known full-reference method for image similarity assessment, which appraises a degraded image using three components: change of structure s, distortion of luminance l, and deformation of contrast c. For easier description of our method below, let $x = \{x_i | i = 1, 2, \ldots, N\}$ and $y = \{y_i | i = 1, 2, \ldots, N\}$ respectively be the ground truth and synthetic image signals, where x and y have the same number of pixels N. To evaluate the similarity between two images, SSIM index (Q) employs the following form [40]:

$$Q = s \cdot l \cdot c = \frac{\sigma_{xy}}{\sigma_x\sigma_y} \cdot \frac{2\bar{x}\bar{y}}{\bar{x}^2 + \bar{y}^2} \cdot \frac{2\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2}, \quad (4)$$

with

$$s = \frac{\sigma_{xy}}{\sigma_x\sigma_y}, l = \frac{2\bar{x}\bar{y}}{\bar{x}^2 + \bar{y}^2}, c = \frac{2\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2}, \quad (5)$$

where $\bar{x}$ and $\bar{y}$ represent the mean radiations of the ground truth image and synthetic image, respectively; the standard deviations of x and y are correspondingly denoted as σ_x and σ_y, while the covariance of x and y is indicated as σ_{xy}. The distinct effect of s, l, and c may not exert the same weighting contribution on Q. Three weighting parameters, α, β, and γ, are hence applied as powers to s, l, and c individually. Eq. (4) then becomes

$$Q_{SSIM} = (s)^{\alpha} \cdot (l)^{\beta} \cdot (c)^{\gamma}. \quad (6)$$

Both MSSIM and MS-SSIM methods inherit SSIM's fundamental character. Speaking of MSSIM method, the image is partitioned into grids, each of which has the same size. The MSSIM index is thus computed as the mean SSIM value over all grids, which is expressed as:

$$Q_{MSSIM} = \frac{1}{p}\sum_{i=1}^{p} Q_{SSIM}(i), \quad (7)$$