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A Fuzzy-logic-based Theoretical Framework for Quantitative Fidelity Evaluation of Infrared Camera Simulators

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Abstract: Aiming to improve the current situation of the simulator fidelity evaluation system, a new theoretical framework based on fuzzy logic and fuzzy set theory is introduced to quantitatively evaluate the simulation fidelity of infrared camera simulators. This framework is an objective and multi-parameter evaluation system, which is related to many fields such as fuzzy logic, curve similarity evaluation, image quality assessment, and information theory, etc. Compared with those available, a multi-scale fidelity evaluation analysis, which includes performance characteristic evaluation of the total system and image quality assessment of the camera outputs, is considered more compromisingly in this evaluation system. Consequently, the new framework here has better task flexibility and it is easier to quantify and compare the fidelity results between different camera simulators with the same or similar mission requirements.

Key words: Imaging system; Infrared camera simulator; Fidelity evaluation; Image quality metrics

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0 Introduction

Since prototyping a real infrared camera is costly and time-consuming, there is a growing demand for infrared image sensor designers and imaging system analysts to optimize design tradeoffs and predict image quality via computer simulation before an actual camera becomes available. Hence, during the past several decades, a great variety of infrared virtual camera simulators[1-5] have been developed to achieve such a goal. These simulators show different performance for different applications. The concept "simulation fidelity" relates to what extent the simulator's characteristics meet the features of a real camera. Ideally, the camera simulator should be all the same as its real counterpart under any conditions. However, such a perfect simulation may not be feasible and may not always be necessary. The simulator has to make a mission-driven compromise. So that, how to reliably evaluate the simulation fidelity of a virtual camera has become a great challenge. Traditionally, the subjective evaluation methods that rely on human observers are generally adopted. The subjective methods may have some benefits like good flexibility and high creditability. However, the subjective evaluation is usually costly and inefficient, and it is difficult to quantify or compare the results in practice. While the objective evaluation methods, which can provide the quantitation, repeatability and reliability lacking in the subjective evaluation processes, have been widely used. The current objective evaluation system for infrared simulators has conventionally developed in the following aspects: 1) a comparison of performance characteristic parameters/curves between the simulated and actual cameras[6-7]; 2) a comparison of the captured images obtained from a specific bar target or other simple scenes between the simulated and actual cameras[7-8]; 3) a comparison of the temperature response characteristics between the measured data collected from specific locations and the simulator generated results[9-10].

However, each aspect of the above objective

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evaluation index is considered separately in the simulator fidelity evaluation system available now. It is determined that the fidelity evaluation methods mentioned above have poor mission flexibility, and it is difficult to obtain an intuitionistic result to make a comparison between different camera simulators. Here a new fuzzy-logic-based theoretical framework, which is a comprehensive, objective, multi-parameter evaluation system, is introduced to quantitatively evaluate the fidelity of infrared camera simulators. The primary performance characteristic evaluation of the camera and the image quality assessment of the output images obtained from a specific bar target are both included in the framework.

1 Performance characteristic scale

The performance of thermal imagers is described in general by resolution, response and noise sensitivity, and subjective perceive characteristics[11-14], including the modulation transfer function (MTF), slit response function (SRF), signal transfer function (SiTF), noise equivalent temperature difference (NETD), minimum resolvable temperature difference (MRTD), minimum detectable temperature difference (MDTD) and so on. In consideration of the significance, measurement, and relationship of those, the MTF and SiTF, which characterize resolution and response performance respectively, are chosen as the primary characteristic scales herein.

1.1 The MTF and SiTF curves

The MTF[15], which is generally used to characterize resolution performance of an infrared camera, is the ratio of the contrast of the output to the input image as a function of spatial frequency (an exemplary MTF plot is shown in Fig. 1).

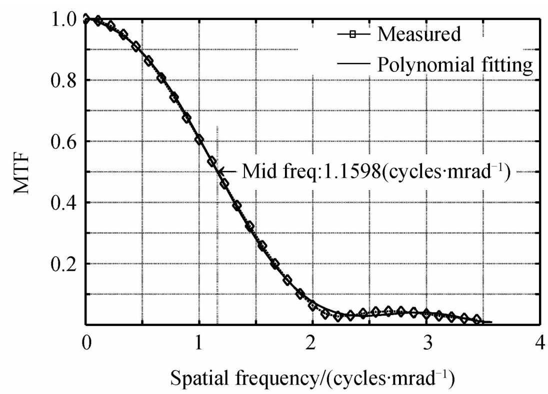

Fig. 1 A measured curve of MTF against spatial frequency is obtained which characterizes the resolution performance of the infrared cameras. Then a sixth-order polynomial fit is applied to the smoothed MTF versus spatial frequency curve

Spatial frequency is typically measured in cycles per milliradians. The MTF is inversely related to the MRTD, which is a subjective measure of an infrared sensor′s ability to resolve temperature difference. The MTF is defined as the Discrete Fourier Transform (DFT) of the line spread function (LSF). Given the LSF, the MTF is approximately calculated via DFT. The 50% cutoff frequency is determined to yield the corresponding middle spatial frequency.

The SiTF, which determines the responsivity of an infrared imager, is a measure of the signal output (usually the output voltage) versus the signal input (usually the differential temperature). It provides information on gain, linearity, dynamic range, and noise and saturation level. The SiTF curve, which is shown in Fig. 2, is typically shaped like a sideways "S". There are many general applications of the SiTF. Specifically, it can be used to estimate the NETD, which is a typical measure of sensitivity/noise for infrared imaging systems.

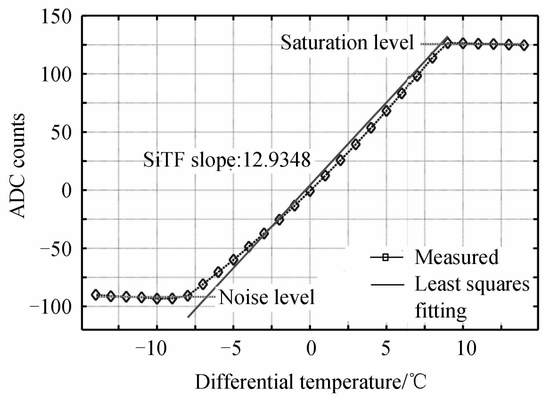

Fig. 2 A measured curve of SiTF is obtained which characterizes the response performance of the infrared cameras. The slope of the linear portion of the SiTF curve is calculated and marked

1.2 Curve similarity evaluation

This section deals with how to calculate the similarity between two simple curves, specially the simulated and measured performance characteristic curves herein. Firstly, a multi-dimension feature vector $x=\{x_1, x_2, \cdots\cdots, x_n\}$ is created by selecting feature points from the horizontal axis X of the curve, where n is the total feature point number. The vector $r=\{r_1, r_2, \cdots\cdots, r_n\}$ represents the corresponding vector of the feature vector x on the actual measured characteristic curve CR; the vector $s=\{s_1, s_2, \cdots\cdots, s_n\}$ represents the corresponding on the simulated one CS. The covariance between r and s is defined as

$$\mathrm{cov}(r,s)=E[(r-\bar{r})\cdot(s-\bar{s})] \tag{1}$$

where E is the mathematical expectation operator and $\bar{r}=Er$, $\bar{s}=Es$. The correlation coefficient ρ between two vectors r and s with standard deviations σ_r and σ_s is given by

$$\rho_{\mathrm{CR,CS}}=\mathrm{corrcoef}(r,s)=\frac{\mathrm{cov}(r,s)}{\sigma_r\cdot\sigma_s}=\frac{\sum_{i=1}^{n}[(r_i-\bar{r})\cdot(s_i-\bar{s})]}{\sqrt{\sum_{i=1}^{n}[(r_i-\bar{r})^2]}\cdot\sqrt{\sum_{i=1}^{n}[(s_i-\bar{s})^2]}} \qquad (2)$$

The curve similarity between the actual measured characteristic curve CR and the simulated curve CS is defined as

$$f(\mathrm{CR,CS})=\mu_{\mathrm{CR,CS}}^{c\alpha}\left|\rho_{\mathrm{CR,CS}}\right|^{c\beta} \qquad (3)$$

where μ is a crucial value that may represent the similarity of the numerical characteristic parameters of the two curves; the correlation coefficient ρ is a measure of curve shape similarity; $c\alpha>0$ and $c\beta>0$ are constant parameters used to adjust the relative importance between the two components μ and ρ. Generally, we can set $c\alpha=c\beta=1$ in this paper. In Eq. (3), μ may be generally defined as

$$\mu_{\mathrm{CR,CS}}=\frac{2|\bar{r}|\cdot|\bar{s}|}{\bar{r}^2+\bar{s}^2} \qquad (4)$$

Note that the dynamic range of the value μ defined above is [0, 1] and the best value 1 is achieved if and only if $\bar{r}$ and $\bar{s}$ are the same. However, the above definition of μ in Eq. (4) is not used in this paper. For the calculation of the similarity of the two MTF curves, we use the middle spatial frequency (marked in Fig. 1) of each curve to take place of the mathematical expectation $\bar{r}$ and $\bar{s}$ in Eq. (4); and for that of the SiTF curves, the slope of the linear portion (shown in Fig. 2) of each SiTF curve is used instead.

2 Image quality metrics

Besides the system performance characteristics, the output images are also obtained to assess the simulation fidelity between the actual and virtual cameras. Due to the complexity of theoretical calculation of infrared radiation, a simple target with a relatively regular shape, for example, a standard four-bar target pattern is usually used in the simulation scene. The output image quality cannot be quantified completely by a single metric. We can, however, quantify different aspects of image quality by different metrics which are as follows.

2.1 Peak signal-to-noise ratio

Peak signal-to-noise ratio (PSNR) is one of the most popular image quality metrics[16-17], which is widely used as a measure of image reconstruction quality between two images before and after compression. Thus, we use it as one of the quality metrics to evaluate the similarity between the actual and simulated images. The actual image data acts as the reference signal that has perfect quality in this case, and the noise is the error introduced by simulation. The PSNR between the actual image R and the simulated image S, which is usually expressed in terms of the logarithmic decibel scale, is defined by the following equation

$$\mathrm{PSNR}(S,R)=10\log_{10}\left(\frac{S_{\mathrm{peak}}^2}{\mathrm{MSE}(S,R)}\right)=10\log_{10}\left(\frac{S_{\mathrm{peak}}^2}{E[(S-R)^2]}\right) \qquad (5)$$

Here, S_{peak} is the maximum possible gray value of the image. Generally, when the image is using b bits per sample, this is 2^b-1. The MSE in Eq. (5) represents the mean square error between the simulated image and the actual image, and E herein is also the mathematical expectation operator. A larger value of PSNR means that the simulated image is more similar to the real one. Its dynamic range is $[0,\infty]$ and the best value ∞ is achieved if and only if the two images are the same. These values do not adjust to the quality parameter definition, so it needs to be normalized. Generally, human eyes can not distinguish the distortion between the two images when the PSNR value is greater than 30 dB. Usually, typical values for the PSNR in image compression are between 30 and 50 dB, and a compressed image is considered to be acceptable if PSNR is at least 45 dB. So that we assume that the normalized value is 0.9 when PSNR is 30 dB and the normalized value is 0.99 when PSNR is 45 dB. A principle of mapping normalization, which is shown in Fig. 3, is proposed following the Eq. (6)

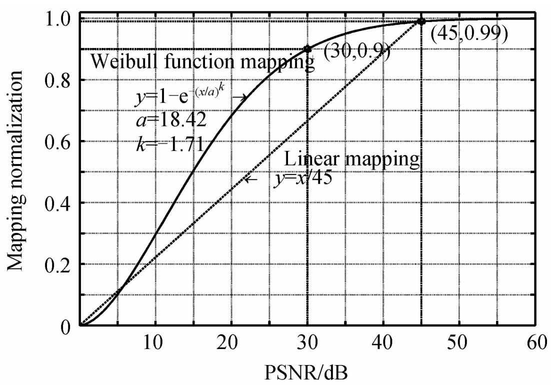

Fig. 3 Illustration of the principle of PSNR mapping normalization

$$y=1-\mathrm{e}^{-(x/a)^k},(a>0,k>0) \quad (6)$$

2.2 Normalized mutual information

Information theory, originally developed by C. Shannon, is becoming increasingly popular now in many fields, including the field of image quality and fidelity evaluation[18-20]. The image histogram carries important information about the distribution of intensities in an image. Considering the gray-level normalized histogram $\{\mathrm{hist}_i,\ i=0,1,2,\cdots\cdots,N_g-1\}$, where N_g is the number of gray levels in the image, the probability $p(i)$ of the gray level i in an image can be estimated by the corresponding normalized histogram hist_i. And hence, the Shannon entropy of the image is defined as

$$H(R)=-\sum_i p(i)\log_2 p(i) \quad (7)$$

Then, the Shannon entropy for a joint distribution between the actual image R and the simulated image S is defined as

$$H(R,S)=-\sum_{i,j} p(i,j)\log_2 p(i,j) \quad (8)$$

wherein $p(i,j)$ is the value of the joint probability distribution. The mutual information is a measure of the dependence between the two variables. Mutual information based on histograms differs from standard mutual information in that it accounts for the degree of overlay between the two images[21]. For two images R and S, the mutual information MI, which combines the marginal and the joint entropies (shown in Fig. 4), can be

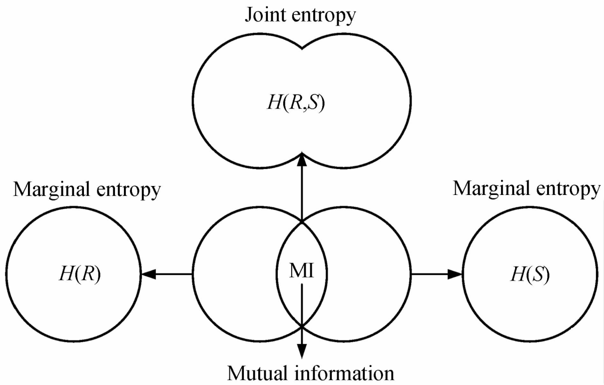

Fig. 4 Relationship between mutual information and entropies

defined as

$$\mathrm{MI}(R,S)=H(R)+H(S)-H(R,S) \quad (9)$$

For configuring the quality parameter definition, the normalized mutual information NMI can be expressed as

$$\mathrm{NMI}(R,S)=\frac{\mathrm{MI}(R,S)}{[H(R)+H(S)]/2}=2-\frac{2H(R,S)}{H(R)+H(S)} \quad (10)$$

After normalization, its dynamic range is [0, 1] and the best value 1 is achieved if and only if the two images are the same.

2.3 Structural similarity

The structural similarity (SSIM) metric, which is proved to be more consistent with human eye perception than traditional image quality metrics like PSNR and MSE, is introduced by Wang and Bovik *et al.*[22] for measuring the similarity between two images and is also popularly used in many other fields now[23-24]. The SSIM metric separates the similarity task into three components: luminance l, contrast c, and structure s, and then combines them together to yield an overall similarity scale. The technical details of the SSIM metric can be obtained from Wang *et al.*[22], and in this paper the luminance, contrast, and structure between the actual image R and the simulated image S are described as follows

$$l_{R,S}=\frac{2\mu_R\mu_S}{\mu_R^2+\mu_S^2} \quad (11)$$

$$c_{R,S}=\frac{2\sigma_R\sigma_S}{\sigma_R^2+\sigma_S^2} \quad (12)$$

$$s_{R,S}=\frac{\sigma_{RS}}{\sigma_R\sigma_S}=\frac{\mathrm{cov}(R,S)}{\sigma_R\sigma_S} \quad (13)$$

where μ and σ represent the mean value and the standard deviation of the image R or S. Combine Eq. (11)~(13), and then the structural similarity SSIM is defined as

$$\mathrm{SSIM}(R,S)=l(R,S)^\alpha\cdot c(R,S)^\beta\cdot s(R,S)^\gamma \quad (14)$$

where α,β and γ are positive constant parameters used to adjust the relative importance of the three components. The dynamic range of the SSIM value is [−1, 1] and the best value 1 is achieved if and only if the two images R and S are the same. Note that the classical SSIM metric is calculated on various divided windows of an image, however, in our work, it is calculated on the basis of the whole image.

2.4 Sample results

A simulation example is given here to illustrate the behavior of the image quality metrics above. Fig. 5 and Fig. 6 show the output images with their normalized histograms obtained from a real infrared camera and a virtual camera simulator, respectively. If the position of the target in the actual image do not perfectly accord with that in the simulated one, image registration is required before the calculation of the evaluation metrics. Table 1 shows the detailed numerical results of the NMI, PSNR and SSIM metrics for the actual and simulated outputs in Fig. 5 and Fig. 6.

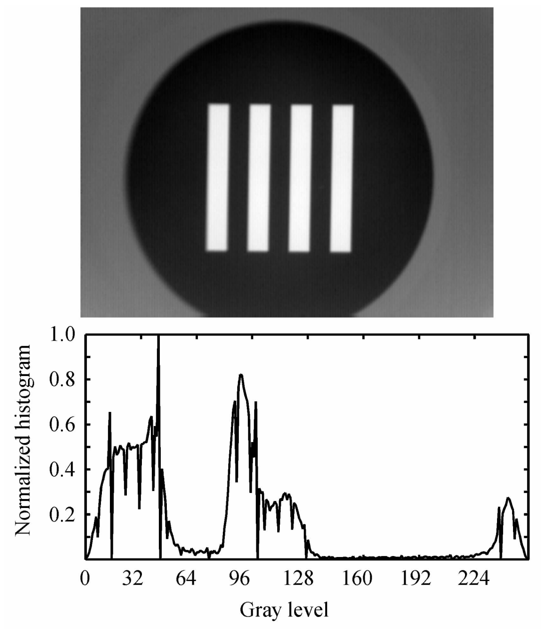

Fig. 5 Illustration of a captured image obtained from an actual camera

Table 1 Values of the Proposed Three Quality Metrics for the Simulation Example in Fig. 5 and Fig. 6

Metric	Original value		Normalization
NMI	Marginal entropy	6.871 2 6.468 2	0.220 8
	Joint entropy	11.867 1	
	MI	1.472 4	
PSNR	PSNR	21.072	0.716 0
SSIM	Liminance	0.997 7	0.933 0
	Contrast	0.999 8	
	Structure	0.935 4	

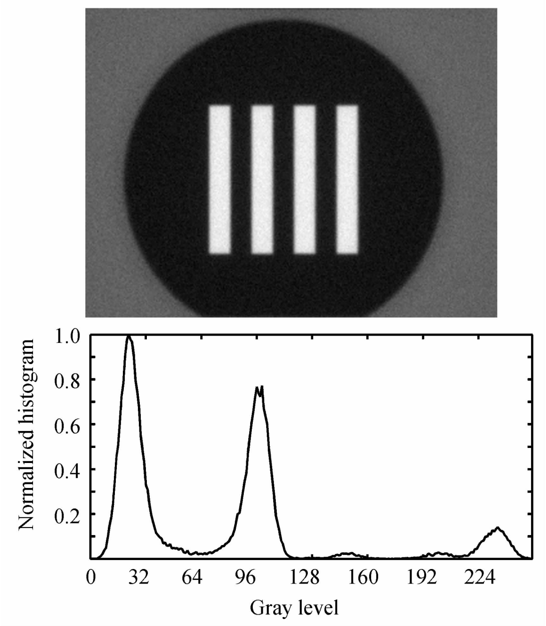

Fig. 6 Illustration of an image obtained from a virtual camera simulator

3 Fuzzy comprehensive evaluation metric

To make overall considerations, a fuzzy-logic-based theoretical framework is proposed here to quantitatively evaluate the fidelity of infrared camera simulators. A fuzzy feature set $F=\{f_1, f_2, f_3, f_4, f_5\}$ is defined here on the basis of the above evaluation metrics discussed in Section 1 and Section 2, the membership function of which is $K=\{k_1, k_2, k_3, k_4, k_5\}$. The detailed representation of each component in the fuzzy feature set is shown in Table 2. In fuzzy logic theory, the membership function represents the degree of truth as an extension of valuation. Here, the membership function K is used to characterize the importance of each component in the fuzzy feature set F, and it is assumed that $k_i \geqslant 0$ and $\sum_i k_i = 1, (i=1,2,\cdots,5)$. Accordingly, we get the comprehensive fidelity metric in this block

$$\text{Fidelity}=\sum_i k_i f_i (i=1,2,\cdots,5) \tag{15}$$

Different values for K can be defined to be fit for different simulation mission situations. We can set a larger k (k_1, k_2) for a simulation mission emphasized on system performance evaluation or set a larger k ($k_3 - k_5$) for a simulation mission emphasized on image quality evaluation. A larger value of Fidelity means that the simulated image is more similar to the real one and it will achieve the best value 1 if the camera simulator perfectly agrees with the real camera. In order to simplify the expression and obtain a demonstration of this fidelity evaluation framework, we set $k_i = 1/5$, $(i=1,2,\cdots,5)$ and $c\alpha = c\beta = \alpha = \beta = \gamma = 1$ here and finally get the result of Fidelity=0.767 8 for the sample in Section 2.4.

Together, the feature set $F=\{f_1, f_2, f_3, f_4, f_5\}$ represents the evaluation results for the typical character parameters of a single simulator, and the weight set $K=\{k_1, k_2, k_3, k_4, k_5\}$ can be adjusted to adapt to different simulation mission situations. Finally, the value of the Fidelity can be used to make a comparison between different simulators developed in the same simulation mission

Table 2 Representation of each metric component in the fuzzy feature set

Type	Metrics	Representation
System performance	f_1: MTF curve similarity	System resolution level
	f_2: SiTF curve similarity	Response characteristics Noise level Saturation level
Image quality	f_3: PSNR	Signal-to-noise ratio
	F_4: NMI	Overlapping part
	f_5: SSIM	Luminance Contrast Structure

situations. All of them play important roles in this evaluation framework above.

4 Discussion

In general, the diversity of the evaluation parameters and the uniqueness of the evaluation result are both the most important and critical features of the fidelity evaluation framework which is discussed above. In this case, reasonable parameter selection for the feature set F can ensure the reliability and the validity of this evaluation system, and furthermore, the final evaluation result also depends on the accuracy and scientificity of the weight set K. Each element of the feature set F, i. e. , each evaluation parameter, represents a typical characteristic of the imaging system, and these metrics for the quality characteristics are all well known in some of the fields except the one of the fidelity evaluation. As has been stated, the application of multi-parameters evaluation makes the evaluation system become more scientific and comprehensive, and the application of the final evaluation result makes it easier to compare the fidelity between different camera simulators.

Certainly, there are still several unsolved problems in our evaluation framework, and further studies as follows will be carried out to make it perfect in the future.

1) A more representative target pattern, which should have more perfect performance than that of the simple four-bar target pattern available now, needs to be developed to use in the chain of output image quality assessment.

2) For a specific simulation application, reliable empirical values for the adjustable weight coefficients like α, β, γ, and k in the evaluation framework need to be obtained from a quantity of experimental results.

3) A horizontal comparison between the fidelity evaluation results from different camera simulators can be made to demonstrate the effect of quantitative characterization for our fidelity evaluation system. But at present, there are no conditions for us to make such comparisons because we can only acquire related data from one infrared camera simulator which is developed by our group.

5 Conclusion

In this work, we have investigated the current status of infrared simulator fidelity evaluation systems and proposed a fuzzy-logic-based, multi-scale, quantitative theoretical fidelity evaluation framework. This framework is different from any other evaluation system, which makes overall evaluation and takes both the system performance curves and the output image qualities into consideration. Due to including multiple adjustable weight coefficients like α, β, γ, and k in the evaluation framework, it can determine the optimal weight coefficient set for a specific simulation mission and theoretically it will have better mission flexibility than other methods. In a specific simulation mission situation, it is easy to make a comparison between the fidelity evaluation results from different camera simulators.

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基于模糊逻辑的红外相机模拟器定量化仿真度评价框架

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摘　要:针对红外相机模拟器仿真度量化评价体系的现状,提出了一种基于模糊逻辑和模糊集思想的全新的理论框架.该框架是一种客观的、多尺度的评价体系,涉及到模糊逻辑、曲线相似度评价、图像质量评估以及信息论等多个交叉领域.和现有的单一尺度的评价方法相比,这种多尺度的仿真度评价分析系统综合考虑了成像系统的主要性能特性参量和系统输出图像的质量,具有更好的任务适应性,可以方便地量化和比较具有相同或相似需求的相机模拟器的仿真度结果.

关键词:成像系统;红外相机模拟器;仿真度评价;图像质量准则