Perception Evaluation: A New Solar Image Quality Metric Based on the Multi-fractal Property of Texture Features

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Abstract The next generation of ground-based solar observations requires good image quality metrics for post facto processing techniques. Based on the assumption that texture features in solar images are multi-fractals and that they can be extracted by trained deep neural networks as feature maps, a new reduced-reference objective image quality metric, the perception evaluation, is proposed. The perception evaluation is defined as the cosine distance of the Gram matrix between feature maps extracted from high-resolution reference images and that from blurred images. We evaluate the performance of the perception evaluation using simulated blurred images and real observed images. The results show that with a high-resolution image as reference, the perception evaluation can give a robust estimate of the image quality for solar images in different scenarios.

Keywords Atmospheric seeing · Instrumental effects · Instrumentation and data management

1. Introduction

The resolution of ground-based telescopes is limited by many different factors such as: the quasi-static aberrations or the dynamic aberrations caused by atmospheric turbulence. The atmospheric turbulence induced aberration, termed “seeing”, prevents large aperture ground-based solar telescopes from achieving their theoretical angular resolution. For solar

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telescopes without adaptive optics (AO) systems (Thompson, 2000), to alleviate the atmospheric turbulence induced image degradation and achieve higher angular resolution, post facto image reconstruction techniques are widely used (Van Noort, Rouppe Van Der Voort, and Löfdahl, 2005; Mikurda and Von Der Lühe, 2006; Scharmer et al., 2010). A proper objective image quality metric (IQM) is required for these post facto image reconstruction techniques, because the IQM is used either as criterion for frame selection-based methods or as cost function for deconvolution algorithms. In recent decades, several IQMs have been proposed and they can be classified into: full-reference (FR), no-reference (NR), and reduced-reference (RR) metrics.

FR IQMs require high-resolution images as reference. The mean squared error (MSE) is the simplest FR IQM, which computes the average of the squared difference between the distorted and reference image. The structural similarity (SSIM) proposed by Wang et al. (2004) is widely used and it can give a similar result as that given by a human visual system. Root-mean-square contrast (RMS contrast) is the most commonly used IQM for image reconstruction (Denker et al., 2005, 2007; Danilovic et al., 2008). Because the granulation is uniform and isotropic, the FR IQMs have been successfully used for granulation images (Scharmer, 1989; Denker et al., 2005; Danilovic et al., 2008). Unfortunately, FR IQMs have several drawbacks, for example their performance strongly depends on the wavelength (Albregtsen and Lynne Hansen, 1977) and their sensitivity is related to the structural contents of the image (Deng et al., 2015).

The median filter-gradient similarity (MFGS) proposed by Deng et al. (2015) is an NR IQM, which does not need a reference image and is suitable to evaluate the quality of solar images directly. However, Popowicz et al. (2017) and Denker et al. (2018) showed that the MFGS is not completely independent of the structural contents or the spatial sampling rate of an image. This property would limit the performance of image reconstruction methods in different regions of the Sun.

In this article, we propose a new RR IQM, perception evaluation (PE). PE only requires one high-resolution image as reference and can evaluate the quality of blurred images with this reference image. The PE is based on the assumption that texture features in solar images are multi-fractals and that they should be similar for solar images obtained in the same wavelength. In this article, the multi-scale distribution of the multi-fractals is extracted using a trained deep neural network (DNN) (Yu, Schmid, and Victor, 2015; Motoyoshi et al., 2007). The difference of multi-fractal properties between high-resolution images and blurred images is then used to evaluate the image quality. We introduce the PE in Section 2. In Section 3, we evaluate the performance of the PE using simulated blurred images and real observed ones and in Section 4, we present our conclusions and discuss possible applications in the future.

2. Perception Evaluation

2.1. The Principle of the Perception Evaluation

The texture feature is a description of the spatial arrangement of the gray scale in an image. The texture feature is usually used to describe the regularity or coarseness of an image (Guo, Zhao, and Pietikainen, 2012). Human beings can easily distinguish between images with different texture features, such as the rainforest or the desert in a black-and-white aerial photograph. For solar images, the texture features are almost everywhere. In different wavelengths, solar images are different and these images are composed of different texture features as shown in Figure 1.
Figure 1  The high-resolution images observed in different wavelengths. On the left is the Hα image obtained by the New Vacuum Solar telescope (NVST) and the prominent feature visible is a dark filament. On the right is the G-band image containing granulation, which is obtained by the Swedish 1-m Solar Telescope (SST). A skilled astronomer can easily tell the difference between these two figures according to their texture features.

Texture features in solar images may be self-similar and these images are usually called fractals (Jia, Dongmei, and Wang, 2014), such as the granulation. In other wavelengths, they are not self-similar in the whole spatial scale, which means they cannot be described by a spectrum with the same exponent. However, these images can be described by a continuous spectrum with different exponents in different scales. This property is usually called multifractal property (Turiel and Parga, 2001; Peng et al., 2016). If we assume multi-fractal properties of texture features on the solar images do not change between images observed in the same wavelength, with one high-resolution image as reference, we can easily discriminate images with different blur levels. The difference between texture features of high-resolution images and that of blurred images is a good tracer for image quality. Can we model that difference to evaluate image quality?

Modeling directly the difference of multi-fractal properties is hard, because texture features are complex and they are different for solar images in different wavelengths. Many different image quality metrics based on texture features are proposed, such as: the image gray scale statistics (Nth order joint histograms) introduced by Julesz (1962) and models based on other statistical measurements (Heeger and Bergen, 1995; Portilla and Simoncelli, 2000). Because the DNN is complex enough to directly learn texture features, parametric texture feature models based on DNN features are widely used (Gatys, Ecker, and Bethge, 2015b; Liu, Gousseau, and Xia, 2016). In this article, we will use a trained convolutional neural network (CNN) to extract the multi-fractal properties of texture features. We will discuss our algorithm in the following section.

2.2. Algorithm of the Perception Evaluation

CNN is a kind of DNN, which includes many convolutional layers. A convolutional layer has $K$ channels. A different channel means the input signal will be convolved with a different trainable convolutional kernel. The output of each convolutional layer is called feature map. After a convolutional layer, an image with $M \times N$ pixels will become a 3D feature map with a size of $M \times N \times K$, where $K$ is the channel number. Visualization of feature maps shows that these describe images in a multi-scale way (Zeiler and Fergus, 2013), which makes it adequate to model multi-fractal properties of texture features on solar images.
The structure of the VGG16, which extracts multi-fractal properties from texture features of the input image. A red block represents a convolutional layer with 64 channels and kernel size of $3 \times 3$. An orange block represents a convolutional layer with 128 channels and kernel size of $3 \times 3$. A green block and a blue block represent a convolutional layer with 512 channels and kernel size of $3 \times 3$. There is a pooling layer of $2 \times 2$ between blocks with different color. Feature 1, Feature 2, Feature 3, and Feature 4 are feature maps of the convolutional layer.

Table 1 Parameters for Monte-Carlo simulations. The turbulence profile used in this article is the ESO 35 turbulence profile (Sarazin et al., 2013).

| Parameter                          | Value                                                                 |
|------------------------------------|----------------------------------------------------------------------|
| Telescope diameter                 | 980 mm (Gregorian type) for Hα (656.281 nm)                          |
|                                    | 1000 mm (Schupmann type) for G-Band (430.5 nm)                       |
| Atmospheric turbulence profile      | ESO 35 turbulence profile                                            |
| Fried parameter ($D/r_0$)          | 1 to 20 with step of 1                                               |
| Outer scale and inner scale        | 10 m and 0.1 cm                                                      |
| Pixel scale                        | 0.136 arcsec for Hα                                                  |
|                                    | 0.041 arcsec for G-Band                                              |
| Exposure time                      | 20 ms for Hα                                                         |
|                                    | 4 ms for G-Band                                                      |

The Visual Geometry Group (VGG), which is a CNN with many small convolution kernels and several convolutional layers proposed by the Visual Geometry Group of the University of Oxford (Pfister et al., 2014), is used in this article. Considering texture features of solar images are complex and may have different multi-fractal properties, we use VGG16 to model multi-fractal properties of texture features. The VGG16 is a VGG with 12 convolutional layers and four pooling layers as shown in Figure 2. In the first several convolutional layers, feature maps from VGG16 have rich details. The deeper the convolutional layer is, the feature maps are more abstract and contain larger scale texture features (Gatys, Ecker, and Bethge, 2015a). According to our experience, we select feature maps: Feature 1, Feature 2, Feature 3, and Feature 4 from the trained VGG16 as candidate feature maps, as shown in Figure 2.

To evaluate the representative ability of these feature maps, we generate several short exposure point spread functions (PSF) with different $D/r_0$ ($D$ stands for the size of the telescope and $r_0$ stands for the coherent length of the atmospheric turbulence) as shown in Table 1 through Monte Carlo simulations (Jia et al., 2015b; Basden et al., 2018). Then we convolve high-resolution solar images with these PSFs to generate blurred images as shown in Figure 3. We extract multi-fractal properties from these blurred images by VGG16 and use Feature 1, Feature 2, Feature 3, and Feature 4 to reconstruct these images as shown in Figure 4. These reconstructed images show that feature maps from different layers can reflect multi-fractal properties in different scales. Because image quality metric should be
only relevant to the blur level, we need to transform feature maps to a quantity that is not relevant to the image size or the structural content.

The Gram matrix calculates the correlation between two variables without subtracting their mean values. The Gram matrix can reflect the difference between two variables and is normally used for kernel generation for classical machine learning tasks (Hofmann, Scholkopf, and Smola, 2008). In recent years, the Gram matrix of feature maps is used in image style transfer to reflect the style difference between two images (Johnson, Alahi, and
Feifei, 2016) as shown in Equation 1,

\[ G_{ij} = \sum_k F_{ik} F_{jk}. \]  

(1)

In this equation, \( F_{ik} \) and \( F_{jk} \) are the 2-dimensional feature maps in a particular layer. To evaluate the image quality, the Gram matrix has the following advantages (Gatys, Ecker, and Bethge, 2015a):

i) The size of the Gram matrix depends only on the number of feature maps instead of the image size.

ii) The Gram matrix is only related to texture features of an image, not its structural content.

Thanks to the above advantages, we will use the Gram matrix to represent the multi-fractal properties of texture features. In real applications, the Gram matrix of the reference image and that of blurred images will be obtained separately by the VGG16. Then we will calculate the cosine distance (Ustyuzhaninov et al., 2018) between these two matrices to evaluate the image quality,

\[ L_{\text{quality}} = \sum_i \sum_j \frac{G_{ij} \cdot G_{ij}^{\text{ref}}}{|G_{ij}| |G_{ij}^{\text{ref}}|}, \]  

(2)

where \( G_{ij} \) and \( G_{ij}^{\text{ref}} \) are the Gram matrices of the blurred image and that of the reference image, \( L_{\text{quality}} \) is the PE. According to our experience, the Gram matrix of Feature 4 is best in representing the multi-fractal properties of texture features, because it concentrates the response from previous layers and contains the largest amount of information, i.e. it has better expressive ability compared to other feature maps. In VGG16, the size of Feature 4 is \( M' \times N' \times 512 \), where \( M' \) and \( N' \) are the size of the input signal. In the following sections, we will only use the Gram matrix of Feature 4 to calculate the PE.

3. Performance Evaluation

3.1. Sample Data

There are two data sets used in this article: G-band data from the SST (Scharmer et al., 2002) (430.5 nm with pixel scale of 0.041 arcsec and exposure time of 4 ms) and H\( \alpha \) data from the NVST (Liu et al., 2014) (655.32 nm with pixel scale of 0.136 arcsec and exposure time of 20 ms.). The SST data are reconstructed with phase diversity and corrected to the theoretical telescope and detector magnitude transfer function (MTF). The NVST data are reconstructed by speckle reconstruction (Li et al., 2015). All these data are near the diffraction limit and used as reference images in this article. At the same time, we generate many short exposure PSFs through Monte Carlo simulations (Basden et al., 2018). The parameters in Monte Carlo simulations are set according to Table 1 and we will use an accurate atmospheric turbulence phase screen generation method as discussed in Jia et al. (2015a,b). These simulated short exposure PSFs will be convolved with reference images to generate simulated blurred images.
3.2. Performance of the Perception Evaluation

According to Popowicz et al. (2017), the MFGS proposed by Deng et al. (2015), is robust in real applications and considered as a candidate solar image quality metric. In real applications, Denker et al. (2018) have proposed a modified implementation of the MFGS to evaluate image sequences obtained with the High-resolution Fast Imager (HiFI) at the 1.5-meter GREGOR solar telescope (von der Lühe et al., 2001; Volkmer et al., 2010; Schmidt et al., 2012) and have revealed the field and structure dependency of the MFGS. In this article we select the MFGS for comparison. According to our requirements, we use the Scharr filter from opencv2 (Zelinsky, 2009) to calculate the horizontal and vertical gradients of an image and add their magnitude as the MFGS to achieve higher effectiveness.

Firstly, we use G-band SST data as shown in Figure 5 to test the PE. Areas X1, X2, with a size of 12 × 12 arcsec, are used as reference images. We extract 100 images with a size of 300 × 300 pixels (12 × 12 arcsec) from the W area (750 × 950 pixels) in Figure 5 in steps of 50 pixels (around 2 arcsec; these images have overlapping regions). Then we convolve these images with simulated short exposure PSFs \((D/r_0)\) from 1 to 20 to generate simulated blurred images. In the right panel of Figure 5 we show the simulated blurred images with different degradation levels. These simulated short exposure images are evaluated using the PE and the MFGS, respectively. The results are shown in Figure 6. We can find that the PE is more sensitive to different levels of blur than the MFGS, because the error bar is much smaller for the former. Besides, we can also find that different reference images will not change the trend of the PE, which indicates that the PE is robust as concerns reference images.

Secondly, we use the Hα data from the NVST to test the PE. As shown in Figure 7, we extract two reference images X1 and X2 with a size of 41 × 41 arcsec from the Hα data as reference images. Then we extract small images with a size of 300 × 300 pixels (41 × 41 arcsec) from the W area (1024 × 1024 pixels) in Figure 7 in steps of 50 pixels (6.8 arcsec) and convolve these images with simulated PSF to generate simulated blurred images. The PE and the MFGS are used to evaluate the quality of these images and the results are shown in Figure 8. We can find that the PE still maintains discriminative power for different degrees of image degradation and is more sensitive than the MFGS.

![Figure 5](image-url)  
**Figure 5** Left panel is the G-band image. X1 and X2 are the selected standard map areas, W is the area to be evaluated. The right panels show a patch degradation effect.
Figure 6  Comparison between the PE and the MFGS using the G-band images. The left and central figures are box plots of the experimental results of the PE using X1 and X2 as reference images. The right figure is a box plot of the experimental results of the MFGS. The standard error of the PE is much smaller than that of the MFGS and the PE plot is almost the same with different reference images. It is a box plot figure. The size of the box shows the lower quartile and higher quartile of all the data, while the minimum and maximum of all the data is shown by the error bar. All the box plot figures in this article are plotted in the same way.

Figure 7  The Hα data obtained by the NVST that we use to test the PE and the MFGS. The regions marked with X1 and X2 are reference images and we extract small images from the region marked with W.

Figure 8  Comparison between the PE and the MFGS using Hα images. The left and central figures are box plots of the experimental results of the PE using X1 and X2 as reference images. The right figure is a box plot of the experimental results of the MFGS. The PE decreases monotonically, when D/r₀ is small. The standard error of the PE is much smaller than that of the MFGS. The trend of the PE plot is almost the same with different reference images.

Thirdly, we use the PE to evaluate the image quality of real observed data. These real observational images are extracted from the NVST Hα observation data on 1 April 2018.
There are 150 frames of real observation data that have a size of 1024 × 1024 pixels. We use high-resolution images X1 and X2 shown in Figure 7 as reference images. One frame of the observed images and its PE values in different sections are shown in Figure 9. We find that the PE can reflect a spatial variation of the image quality and the variation trend is almost the same for PE with different reference images, which shows that the PE is robust as concerns reference images.

Besides, we also evaluate the PE with 150 continuous frames of images. The results are shown in movie 1, included as supplementary material, and Figure 10. We find that the PE can reflect the temporal variation of the atmospheric turbulence. With different reference images, the absolute value of the PE is different. The difference of the absolute value of the PE is caused by a different amount of texture features in different reference images. In real applications, we will use one high-resolution image as reference, which means only that the relative variation is important. From Figure 10, we find that the variation trend of the PE is the same when the reference image is different, which indicates the effectiveness of our method.

We further explore the stability of the PE with the same figure and different rotation angles. We calculate the PE of a speckle reconstructed Hα image (600 × 600 pixels) from the NVST with eight different rotation angles. The reference image is the first one in Figure 11 and as shown in this figure, the difference of the PE values between different images is very small, regardless of the rotation angle.

### 3.3. Limitation of the Perception Evaluation

We use simulated blurred images with different sizes and different blur properties (different coherent lengths) to further test the robustness of the PE and the MFGS. We extract 100 images from the W region of Figure 5 and Figure 7 and convolve these images with PSFs of different coherent lengths to generate simulated blurred images. For the PE, we use the same image as reference for different wavelengths (X1 and X2 regions in Figure 5 and Figure 7). We evaluate the PE and MFGS of these images; the results are shown in Figure 12 and

![Figure 9](image_url)  
**Figure 9** The value of the PE in different sections of real observed data. The *left panel* is the PE with X1 as reference and the *right panel* is the PE with X2 as reference. This image is also obtained by the NVST on 1 April 2018.
Figure 10. Variation of the mean PE in different frames of real observed Hα data. Lines with different color stand for the PE values with different reference images (blue for X1 and orange for X2). As shown in this figure, the absolute value of the PE is different when the reference images are different, which may be caused by a different amount of texture features in the reference images. However, the reference image is large enough to contain all the texture features, because we can find that the PE has the same trend when reference images are different.

Figure 11. Images with different rotation angles and their PE values. The PE values are almost the same for the same images with different rotation angles.

Figure 13. We can find that the MFGS and the PE are both sensitive to sampling and image scale. The PE is more sensitive to the image size, because it reflects the statistical property of texture features. To keep evaluation results robust, the PE requires a lot of texture features from images with larger size. Higher resolution and more pixels in the science camera of future solar telescopes will reduce the limitation of the PE in real applications. Otherwise particular attention should be paid when using the PE to evaluate image quality. According to our experiences, images with at least $150 \times 150$ pixels are adequate to be evaluated by the PE.

4. Conclusion

Based on the assumption that texture features in the solar image are multi-fractal, we propose a new RR IQMs, the PE. The PE only needs one high-resolution image to evaluate the
image quality of blurred images. We test the performance of the PE with simulated blurred images and real observed data and find that the PE is robust to image content and rotation angle. However, we also find that the PE is sensitive to the image size. In real applications, we recommend to use the PE to evaluate the quality of images which should have at least $150 \times 150$ pixels.

Because the PE is robust and only related to texture features of the solar image, we can use it to evaluate the quality of solar images of any wavelength, if we have a high-resolution image as reference. The PE will be beneficial to frame selection-based image restoration methods because better frames can be selected. The PE can also be directly used as cost function to increase the performance of deconvolution algorithms. Furthermore, the PE can even be used to evaluate the image quality of any astronomical images with texture features, such as nebulae, supernova remnants and galaxies, which would boost the development of post facto methods in the astronomical community.

**Figure 12** The values of the PE and the MFGS for G-Band images with different sizes. The top, middle, and bottom figures are the PE and MFGS values using the same reference images and blurred images of $50 \times 50$, $150 \times 150$, and $250 \times 250$ pixels, respectively.
Figure 13 The values of the PE and the MFGS for Hα images with different sizes. The top, middle, and bottom figures are the PE and MFGS values using the same reference images and blurred images of 50 × 50, 150 × 150, and 250 × 250 pixels, respectively.

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