Tests of Solar X-Ray Image Reconstruction: A New Index for Assessing Image Quality postprint

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Abstract

Indirect X-ray modulation imaging has been adopted in a number of solar missions and provided reconstructed X-ray images of solar flares that are of great scientific importance. However, the assessment of the image quality of the reconstruction is still difficult, which is particularly useful for scheme design of X-ray imaging systems, testing and improvement of imaging algorithms, and scientific research of X-ray sources. Currently, there is no specified method to quantitatively evaluate the quality of X-ray image reconstruction and the point-spread function (PSF) of an X-ray imager. In this paper, we propose percentage proximity degree (PPD) by considering the imaging characteristics of X-ray image reconstruction and in particular, sidelobes and their effects on imaging quality. After testing a variety of imaging quality assessments in six aspects, we utilized the technique for order preference by similarity to ideal solution to the indices that meet the requirements. Then we develop the final quality index for X-ray image reconstruction, QuIX, which consists of the selected indices and the new PPD. QuIX performs well in a series of tests, including assessment of instrument PSF and simulation tests under different grid configurations, as well as imaging tests with RHESSI data. It is also a useful tool for testing of imaging algorithms, and determination of imaging parameters for both RHESSI and ASO-S/Hard X-ray Imager, such as field of view, beam width factor, and detector selection.

Full Text

2. Image Quality Assessment Indices

For the purpose of quantitatively and effectively describing the quality of reconstructed X-ray images, existing image quality assessment methods must be considered. Many of these constitute benchmarks in the image fusion and image reconstruction fields (Sara et al. 2019; Zhang et al. 2020). However, as previously noted, specialized methods must also be developed to effectively describe features commonly seen in reconstructed X-ray images, whether natural or artificial, such as sidelobes. In the following subsections, we present the generally adopted indices and develop a new index specifically for X-ray image reconstruction.

2.1. Existent Image Quality Assessment Indices

Image quality assessment methods can be grouped into two categories: full-reference and no-reference (Sara et al. 2019), based on the availability of reference images. Full-reference methods require at least one reference image to compute metrics, while no-reference approaches only calculate parameters from the image itself.

As summarized in Zhang et al. (2020), there are 12 evaluation metrics for assessing the quality of fused images, including both full-reference and no-reference metrics. Most of these metrics can be generally applied to other types of images, though a few are specially designed for fused images. Table 1 shows a quick look and simple division of existing image quality assessment indices from Zhang et al. (2020), along with some methods developed later such as information content weighted SSIM (IW-SSIM; Wang & Li 2011), multi-scale SSIM (MS-SSIM; Wang et al. 2003), feature similarity (FSIM; Zhang et al. 2011), and metrics constructed for images of natural scene statistics that correlate well with the human visual system such as visual information fidelity (Sheikh & Bovik 2006) and information fidelity criterion (Sheikh et al. 2005).

To evaluate reconstructed X-ray image quality, comparison between the reconstructed image and ground truth is needed, rather than evaluating the reconstructed image itself. Thus the no-reference approach does not apply to this work. The specifically designed indices in Table 1 are also improper for application here, since the emphasis on quality for reconstructed images differs from that for natural scene statistics images, and those indices designed for multiple image fusion are inapplicable to double-object cases. Therefore, eight indices are applicable in this study: RMSE, SSIM, CE, MI, PSNR, IW-SSIM, MS-SSIM, and FSIM. Note that these eight indices still require further testing to exclude improper or unstable evaluation for X-ray image reconstruction quality, which is provided in Section 2.3.

2.2. Development of Percentage Proximity Degree

We first consider sidelobes, one of the most crucial characteristics in X-ray image reconstruction that affect overall image quality, particularly in maps generated through back projection (BP) approaches. In principle, sidelobes should be minimized in both amount and strength to avoid generating or reduce artificial structures. The intensity of sidelobes is generally smaller than the peak intensity of the source itself, and the number of sidelobes usually increases with decreasing intensity threshold of the BP map. Thus we consider the number of pixels above a threshold of level p (%) of the maximum intensity of the map, denoted $N_{BP,cts>p}$, and take the ratio of $N_{BP,cts>p}$ to the total number of pixels N_0 of the map as A_{BP,cts}(p). The difference between A_s(p) and A_{BP}(p) (i.e., the blue area between the two black curves in Figure 1(c)) represents the contribution of sidelobes. Apparently, the value of PPD increases when the BP map has heavier sidelobes.

For the original X-ray source, the ratio is written as A_s(p). The difference between A_s(p) and A_{BP}(p) should be smaller at level p (%) for a BP map with better image quality. Thus it is reasonable to establish the proximity degree between the two ratios as functions of p to evaluate the contribution of sidelobes, which expresses image quality to a certain extent. Here we define the percentage proximity degree (PPD) as:

$$PPD = \int_a^b |A_{BP,cts}(p) - A_s(p)|dp$$

where a and b are the integral limits with default values of 1 and 100, respectively. Equation (2) describes the integral of the difference between the two ratio curves, which quantifies the sidelobe effect.

2.3. Testing Indices

It is necessary to select proper indices after introducing the eight quality assessment indices from Section 2.1 and the new PPD index from Section 2.2. For quantification and convenience, we assume that the reconstructed X-ray image should have specific features in six different aspects, which are listed below. Therefore, it is presumable that the image quality assessment indices should correctly respond to changes in those features.

The six test aspects are: 1. **Consistency**: Imaging quality should improve when the number of u–v pairs (grid configuration parameters) increases (though how u–v distributes is also important). 2. **Shape**: Imaging quality should worsen when the shape of the reconstructed image is more distorted. 3. **Size**: Imaging quality should deteriorate as the size difference between the reconstructed source and original source increases. 4. **Position**: Imaging quality should deteriorate as the position of the reconstructed source moves further from the original location. 5. **Number of sidelobes**: Imaging quality should deteriorate as more sidelobes appear in the reconstructed image. 6. **Orientation**: Imaging quality should show no obvious change when the reconstructed image is only rotated due to rotation of the imaging system.

Ideally, image quality should be better if the X-ray imager configures more types of grid pitches and position angles (i.e., more u–v points, more visibilities). We generate a series of images reconstructed from a simulated Gaussian source with $\sigma = 5$ using an increasing number of u–v points (from 11 to 45 pairs) to test the responses of the nine indices.

As a preview of this sequence, Figure 2 shows three samples with u–v points of 15, 25, and 45 pairs, corresponding to the three BP maps below each u–v map. Notably, sidelobes become fainter and smaller as the number of u–v points increases, and the calculated PPD (marked in the bottom panels of Figure 2) also decreases. The u–v configurations are chosen from the complete HXI grid configuration in Zhang et al. (2019) (all hollow u–v points in Figure 2).

After forward processing on the nine indices, all indices should increase with the increasing number of u–v pairs, as larger values correspond to better image quality. The results are gathered in Figure 3, where the consistency column shows index score trends. The other five columns present results for the remaining test aspects, with index scores changing across designed sample series featuring distorting shape, increasing size, changing source position from left to right, increasing sidelobes, and rotating orientation.

Based on the tendency curves for each index, we can judge whether it performs as expected. Cross marks and check marks in Figure 3 indicate which indices are beneficial for composing the final index and which would influence overall evaluation, respectively. Four candidates remain: PSNR, SSIM, RMSE, and PPD, which performed well without abnormal behaviors. Note that light cross marks on CE, IW-SSIM, and PPD indicate they showed slight or no response to source changes.

3. The Quality Index for X-Ray Image Reconstruction

The four indices selected in Section 2.3 have different response magnitudes for different aspects. For SSIM, larger values correspond to better image quality, ranging from 0 to 1. For RMSE, smaller values correspond to better image quality. The percentage proximity degree PPD ranges from a−1 to b−1. PSNR can theoretically reach infinity.

Therefore, a composite indicator must be constructed to ensure accurate and valid response, allowing reasonable measurement of imaging quality. Note that PSNR is defined by RMSE as:

$$PSNR = 20\log_{10}\left(\frac{MAX_I}{RMSE}\right)$$

where MAX_I is the maximum intensity of the map. PSNR and RMSE are strongly correlated according to this equation and their tendency curves in Figure 3. Hence, we exclude PSNR from the index candidates.

Different grid configurations of an X-ray imager could result in different reconstructed maps from the same X-ray source. The best score of each evaluating index may be distributed across different maps. For instance, the image with the least sidelobes generates the best PPD, while the image that best fits the source shape generates the best SSIM. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS; Hwang & Yoon 1981) is therefore necessary to properly rank the quality of all reconstructed images.

The TOPSIS method orders samples according to distance between each sample and the optimal solution, which consists of the best score of each index across all samples. The sample with the shortest distance from the optimal solution is ranked highest, even though it may not contain all optimum scores. The TOPSIS method mainly includes: (i) data processing (forward processing and standardization), (ii) computing extremum solutions (optimal and worst solutions), (iii) computing Euclidean distances from extremum solutions (distances from optimal and worst solutions are d_i^+ and d_i^-, respectively), and (iv) sorting samples by final scores calculated from these distances.

Given an X-ray source and a series of reconstructed image samples, relative image quality can be assessed by computing scores via the TOPSIS method. The optimal and worst solutions both derive from this sample series itself.

When assessing the quality of a single reconstructed image (such as evaluation of instrument PSF), or when comparing image quality among different series, the worst solution can be set as the theoretically lowest value of the three indices (i.e., $RMSE^- = 0$, $SSIM^- = 0$, $PPD^- = 0$). Similarly, the optimal solution is set to theoretically highest values ($RMSE^+ = 1$, $SSIM^+ = 1$, $PPD^+ = 1$). Scores calculated this way are regarded as absolute scores, which can generally describe image qualities across different occasions. Consequently, the final quality index for X-ray image reconstruction (QuIX) using the TOPSIS method has been established, containing three indices: RMSE, SSIM, and PPD.

4. Test Results

The performance of the QuIX index should be tested in the six aspects from Section 2.3 using a series of samples with corresponding features. All calculated relative QuIX scores respond correctly for each aspect, as shown in Figure 4. This basic ideal test reflects that QuIX functions well in representing map changes across these six aspects.

QuIX is also efficient for testing PSF or imaging of loop sources under different grid configurations, which can help design X-ray imager imaging systems. We rearrange the HXI grid configuration by reducing position angles (Test 1) and reducing pitch widths (Test 2), then reconstruct images from three different configurations using the VIS_{BP} algorithm. Note that the total number of u–v pairs remains the same as HXI. We use a point source and simple loop source to reconstruct images through each grid configuration. Results are shown in Figure 5, with calculated QuIX scores marked in each panel. Both test cases generate worse image quality than the HXI configuration due to substantial sidelobe artifacts at certain angles or radii (as shown in Massone et al. 2009). QuIX scores for maps generated by the HXI configuration are all higher (better) than those in the two test cases, meaning QuIX correctly reflects reconstructed image quality. For the point source, the QuIX score of HXI is only slightly higher than Test 1 but shows a larger difference with Test 2. The reason is that Test 1's pitch width remains the same as HXI to obtain comparable resolution for a centrosymmetric source, although Test 1 has fewer position angles than HXI. This explanation is confirmed by QuIX score discrepancies for loop source imaging, which requires more position angles and pitch widths to reconstruct a resolvable image.

5. Applications

Test results suggest QuIX can evaluate different grid configurations of X-ray imagers and presumably any modulated imaging system such as radio telescopes utilizing aperture synthesis (e.g., Kellermann & Moran 2001). This section presents several practical QuIX applications related to X-ray imaging processes.

5.1. Evaluation of Imaging Algorithms

Imaging algorithms play important roles in solar X-ray burst studies. During the RHESSI mission, over 10 imaging algorithms were developed (see the RHESSI website) for different scientific applications. Therefore, evaluating imaging results from different algorithms is important for understanding each algorithm's advantages and limitations. Here we demonstrate QuIX application rather than attempting a full algorithm test.

We use double Gaussian sources with $\sigma = 2$ and equal flux separated by 20 to simulate double footpoint sources frequently seen in flare observations and simulation studies (e.g., Fletcher & Hudson 2002; Saint-Hilaire et al. 2008; Kong et al. 2022). The RHESSI simulating image routine (with real aspect data) generates reconstructed images from algorithms CLEAN (Högbom 1974; Schwarz 1978), EM (Benvenuto et al. 2013), PIXON (Puetter 1995; Metcalf et al. 1996), Forward Fit (Aschwanden et al. 2002, 2004), MEM_{NJIT} (Schmahl et al. 2007), MEM_{GE} (Massa et al. 2020), UV_{smooth} (Massone et al. 2009), VIS_{FWDFIT} (Hurford et al. 2005), VIS_{WV} (Duval-Poo et al. 2018), and VIS_{CS} (Felix et al. 2017).

Simulated sources and images generated by the 11 imaging algorithms are shown in Figure 6 in descending QuIX score order. The EM map has the largest QuIX value and is closest to the model. Differences among EM, MEM_{NJIT}, MEM_{GE}, and PIXON scores are not significant, and they produce similar imaging results. As expected, the BP algorithm only produces basic source structure with the worst imaging quality. Although UV_{smooth} exhibits two Gaussian source morphology, it also produces more sidelobes than other methods except BP. Both Forward Fit and VIS_{FWDFIT} generate source pairs differing in size and intensity, resulting in lower QuIX values. The VIS_{CS} image shows distorted structures, while VIS_{WV} sources are relatively large with slight sidelobes. These QuIX scores provide quantitative results consistent with visual judgment.

For comparison, we also calculated SSIM for each algorithm's imaging results (Figure 7). The SSIM trend is roughly consistent with QuIX, except for the order of PIXON, MEM_{GE}, and MEM_{NJIT}. Examining these three algorithms reveals that PIXON images show slightly wider structure deviating from Gaussian source width, and QuIX can effectively quantify imaging quality in this test. Note that the PPD index in QuIX mainly focuses on sidelobes by design, making QuIX potentially more sensitive to sidelobes than other indices. Detailed algorithm tests appear in Yu et al. (2025).

To exemplify QuIX application in practical scenarios, we evaluate imaging results from actual X-ray observations. Since true X-ray images are usually unavailable, we use soft X-ray emission in low-energy bands (3–12 keV), mainly from thermal bremsstrahlung, as a reference. We derive soft X-ray images from EUV observations (Su et al. 2018), such as Atmospheric Imaging Assembly (AIA; Lemen et al. 2012) observations, as the ground truth.

We select a RHESSI flare event on 2010 December 2 near location [−820 , 480] (Figure 8(a)). Focusing on soft X-rays reduces possible non-thermal component contributions. Figures 8(b) and 8(c) show the 4–10 keV image calculated from differential emission measure (DEM) maps (e.g., Cheung et al. 2015; Su et al. 2018; Li et al. 2022) derived from AIA images (henceforth DEM-X), and the reconstructed RHESSI CLEAN map (using detectors 3–6, 8, 9F) in the same energy range, respectively. The calculated DEM-X source may not be a fully precise estimation of the real source because observed 4–10 keV photons may contain non-thermal emission contributions in some cases (e.g., Li et al. 2022), and DEM calculations have limitations (Su et al. 2018), making accurate DEM maps difficult to obtain. However, it provides a realistic source as simulation ground truth, which is usually absent in practical cases.

Simulation results—reconstructed images from 11 algorithms using the RHESSI simulation routine—are displayed in Figure 8. Absolute QuIX scores are calculated for each imaging result and marked in each panel of Figure 8(d) in descending order. Predictably, the BP image shows the worst result due to heavy sidelobes directly generated by linear BP processes (Hurford et al. 2002). VIS_{FWDFIT} produces the highest QuIX value, reconstructing by fitting a loop source function with several parameters. However, VIS_{FWDFIT} results may largely depend on initial source parameters. Additionally, both Forward Fit and VIS_{FWDFIT} have fitting method problems. More DEM-X tests appear in Yu et al. (2025). MEM_{NJIT} produces the second-best imaging result, visually the closest to the DEM-X source. Overall, QuIX scores properly assess imaging algorithm performance.

We did not explore more imaging results using different algorithm parameter settings, which may change source sizes/width/shape and affect QuIX values. The next section presents effects of imaging parameters on image quality that can be revealed by QuIX tests. However, detailed parameter study is beyond this work's scope.

To show differences between QuIX and its components, we compared QuIX with SSIM values for 11 algorithm imaging results (Figure 9). Algorithms are sorted by ascending QuIX values, while corresponding SSIM values do not show monotonic trend, whereas Forward Fit, VIS_{WV}, and MEM_{GE} show decreasing SSIM values as QuIX increases. Visually inspecting these three algorithms suggests QuIX values are more consistent with quality improvement trends.

5.2. Investigation of the Effect of Imaging Parameters

Imaging parameter choices significantly affect results, yet determining optimal settings for different instruments remains difficult. QuIX may help such studies. Here we demonstrate QuIX application in determining imaging parameters by testing CLEAN beamwidth factor (BWF) and imaging field of view (FOV) effects on image quality.

We use the DEM-X source from Section 5.1 as simulation input for CLEAN, EM, and MEM_{GE} algorithms with different imaging FOVs starting from 20 . Image qualities are displayed by QuIX and SSIM in Figure 10. All three algorithms produce unsatisfactory results with small FOV, corresponding to small QuIX and SSIM values, as expected for a relatively large source requiring adequate FOV. As FOV increases, both QuIX and SSIM rapidly reach maximum. Although both metrics show slight decreases with further FOV increases, overall diminution is minimal. One reason is that increased FOV introduces more zero-intensity pixels, increasing basis number and reducing image differences. Another reason is that all three algorithms produce no obvious sidelobes.

Test results in Figure 10 further demonstrate the importance of selecting appropriate imaging FOV. In practical X-ray imaging research, small FOV is desired whenever possible to see finer structures without significant sidelobes, while imaging quality, source size, and imaging grids constrain the minimum FOV. For the DEM-X source test, which is thin in width and moderate in length, Figure 10 reveals recommended imaging FOV for similar-sized sources: 180 $\times$ 180 for CLEAN and 140 $\times$ 140 (i.e., 3–4 times the source size) for EM and MEM_{GE}. Overall, after FOV reaches 100 $\times$ 100 (usually related to the coarsest grids used for imaging), QuIX values for all three algorithms exhibit only slight variations.

CLEAN beamwidth factor (CBWF) is another important parameter directly affecting CLEAN imaging results because it determines the FWHM of the Gaussian CLEAN beam (Hurford et al. 2002) that convolves with CLEAN components for the final image (larger CBWF corresponds to smaller FWHM). However, determining the optimal factor value is controversial and lacks robust evaluation approaches (Kontar et al. 2010; Piana et al. 2022). Figure 11 shows QuIX application in evaluating cleaned images with different CBWF. Here we only present CBWF's effect and corresponding changes in reconstructed images and QuIX values. More comprehensive CBWF tests appear in Yu et al. (2025).

These tests show two examples of QuIX index application for investigating imaging parameters in X-ray image reconstruction.

5.3. Application in the Test of HXI Imaging

HXI has 91 subcollimators/detectors for imaging (Zhang et al. 2019), and several imaging algorithms have been developed (Su et al. 2019). Grid pitch widths and HXI collimator length determine X-ray image spatial resolution. HXI detectors D1–D8 correspond to 3.1 resolution, D9–D18 to 4.5 , D19–D28 to 6.5 , D29–D38 to 9.3 , D39–D48 to 13.4 , D49–D58 to 19.3 , D59–D68 to 29.6 , etc.

Reconstructed images change with different detector combinations and imaging algorithms. Sources may be over-resolved when ground truth sources have larger scale structures than the finest grids' spatial resolution. Therefore, both imaging algorithm selection and detector choice are noteworthy.

We use simulated double Gaussian sources ($\sigma = 2$) from Figure 12(b0) as ground truth, with the right source flux twice the left source flux. Image size is 129 $\times$ 129 . Figure 12(a) shows QuIX values from five imaging algorithms with detectors ranging from D19 (6.5) to D91. QuIX scores reflect image qualities in Figures 12(b1)–(b5) corresponding to each algorithm. CLEAN, Forward Fit, and VIS_{CLEAN} perform best. Changing detectors for different finest resolutions (Figure 12(c)) shows optimal imaging settings are CLEAN with detectors starting from D1, or VIS_{CLEAN} with detectors starting from D9. In this test, image quality is better when finer grids are used due to small ($\sigma = 2$) Gaussian sources. Narrow source detailed structures cannot be reconstructed using only coarse grids. Conversely, using fine grids with resolution smaller than the source may cause over-resolution. Forward Fit shows relatively stable trends compared to VIS_{CLEAN} and CLEAN when changing finest detectors because this method can obtain best-fit source parameters when correct source numbers and shapes are given. Moreover, we did not change CBWF (default 1.7) when detector range changes, meaning CLEAN images can be further improved.

BP and VIS_{BP} maps have the lowest QuIX values as expected due to heavy sidelobes. Practically, we should roughly estimate reasonable source size before selecting detector ranges. Fine grids are more easily affected by non-ideal factors (e.g., internal shadowing, distortions), making them unreliable for imaging before grid calibration completion (Su et al. 2024). Currently, detectors starting from D19 or D29 are recommended for most imaging cases.

6. Summary and Discussion

This paper develops a new synthesis index, QuIX, to evaluate reconstructed X-ray image quality. QuIX contains SSIM, RMSE, and the percentage proximity degree PPD, specifically designed considering X-ray image reconstruction characteristics. We established an X-ray imaging quality evaluation scheme by systematically testing various quality assessment indices across six aspects and utilizing the TOPSIS method for selected indices. Operational procedures were developed for both the new index and overall evaluation scheme. Tests of DEM-based soft X-ray source imaging demonstrate that QuIX is useful for selecting appropriate imaging algorithms, parameters, and detectors.

To improve QuIX reliability, we set adjustable parameters for further optimization. The integral limits (a and b in Equation (2)) of PPD determine the pixel value range considered. Weights of the three indices—RMSE, SSIM, and PPD—can be adjusted for different emphases. As suggested in Wang et al. (2003), we also set a variable to partially utilize the SSIM index: the region of imaging interest, which equals the whole FOV by default. The specially designed QuIX in this work is not conclusive or definitive; further testing and refinement are needed. For example, Figure 8 shows the FF image source clearly differs from the DEM-X image yet receives higher QuIX score than CLEAN. Section 5.2 shows grainy structures within the reconstructed loop for CBWF = 3.8 with highest QuIX (possibly related to fixed detectors used in the test). Further optimizations can make QuIX focus more on reconstructed image shape similarity.

QuIX establishment is significant for X-ray imaging system design and optimization (where different designs' instrument PSF can be quantitatively tested) and reconstruction algorithm testing through imaging simulations. For practical X-ray observational studies, reference images are usually unavailable, severely limiting QuIX application. In such cases, we can use methods measuring distortion level between reconstructed images and observed signals to evaluate X-ray imaging quality, such as C-statistic and reduced ^2 (e.g., Dennis & Tolbert 2019; Massa et al. 2022), though they do not measure structural similarity or sidelobe amount.

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Note: Figure translations are in progress. See original paper for figures.