Tests of Solar X-Ray Image Reconstruction: Study of X-Ray Imaging Algorithms and Reconstruction Parameters (Postprint)

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Abstract

Imaging observations of solar X-ray bursts can reveal details of the energy release process and particle acceleration in flares. Most hard X-ray imagers make use of the modulation-based Fourier transform imaging method, an indirect imaging technique that requires algorithms to reconstruct and optimize images. During the last decade, a variety of algorithms have been developed and improved. However, it is difficult to quantitatively evaluate the image quality of different solutions without a true, reference image of observation. How to choose the values of imaging parameters for these algorithms to get the best performance is also an open question. In this study, we present a detailed test of the characteristics of these algorithms, imaging dynamic range and a crucial parameter for the CLEAN method, clean beam width factor (CBWF). We first used SDO/AIA EUV images to compute DEM maps and calculate thermal X-ray maps. Then these realistic sources and several types of simulated sources are used as the ground truth in the imaging simulations for both RHESSI and ASO-S/HXI. The different solutions are evaluated quantitatively by a number of means. The overall results suggest that EM, PIXON, and CLEAN are exceptional methods for sidelobe elimination, producing images with clear source details. Although MEM_{GE}, MEM_{NJIT}, VIS_{WV} and VIS_{CS} possess fast imaging processes and generate good images, they too possess associated imperfections unique to each method. The two forward fit algorithms, VF and FF, perform differently, and VF appears to be more robust and useful. We also demonstrated the imaging capability of HXI and available HXI algorithms. Furthermore, the effect of CBWF on image quality was investigated, and the optimal settings for both RHESSI and HXI were proposed.

Full Text

Preamble

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Abstract

Imaging observations of solar X-ray bursts can reveal details of the energy release process and particle acceleration in flares. Most hard X-ray imagers employ the modulation-based Fourier transform imaging method, an indirect imaging technique that requires algorithms to reconstruct and optimize images. During the last decade, a variety of algorithms have been developed and improved. However, it is difficult to quantitatively evaluate image quality without a true reference image. How to choose optimal imaging parameters for these algorithms also remains an open question. In this study, we present a detailed test of algorithm characteristics, imaging dynamic range, and a crucial parameter for the CLEAN method: the clean beam width factor (CBWF). We first used SDO/AIA EUV images to compute DEM maps and calculate thermal X-ray maps. These realistic sources and several types of simulated sources serve as ground truth in imaging simulations for both RHESSI and ASO-S/HXI. Different solutions are evaluated quantitatively through multiple metrics. The overall results suggest that EM, PIXON, and CLEAN are exceptional methods for sidelobe elimination, producing images with clear source details. Although MEM_{GE}, MEM_{NJIT}, VIS_{WV}, and VIS_{CS} possess fast imaging processes and generate good images, they each have associated imperfections. The two forward-fit algorithms, VF and FF, perform differently, with VF appearing more robust and useful. We also demonstrate the imaging capability of HXI and available HXI algorithms. Furthermore, we investigate the effect

of CBWF on image quality and propose optimal settings for both RHESSI and HXI.

Key words: techniques: image processing – Sun: flares – Sun: X-rays, gamma rays

1. Introduction

X-ray emissions in solar flares originate primarily from thermal and non-thermal bremsstrahlung (e.g., Brown et al. 1998; Holman et al. 2011). X-ray observations of solar flares, particularly X-ray imaging, provide a powerful tool for investigating magnetic reconnection mechanisms, particle acceleration, plasma heating, and energy transfer processes.

Most solar X-ray imagers employ an indirect Fourier-transform imaging technique. They modulate incident X-rays using a group of subcollimators, each consisting of a pair of grids installed on front and rear panels. Modulation profiles can be obtained in temporal space by rotating subcollimators with different pitches, or in spatial orientation by arranging combinations of subcollimators with different positioning angles, pitches, and phases. The Reuven Ramaty High Energy Solar Spectroscopic Imager (RHESSI, 2002–2018, Lin et al. 2002) represents a successful application of time modulation, spinning every 4 s to achieve full coverage of grid positioning angles.

Spatial modulation is often employed in comprehensive missions requiring stabilized platforms for direct optical imaging at other wavelengths, such as Yohkoh/Hard X-ray Telescope (HXT, Kosugi et al. 1991), the Spectrometer/Telescope for Imaging X-rays (STIX, Krucker et al. 2020) aboard Solar Orbiter, and the Hard X-ray Imager (HXI, Su et al. 2019, 2024; Zhang et al. 2019) aboard the ASO-S mission (Gan et al. 2019, 2023).

In recent years, NuSTAR (Harrison et al. 2013), designed for astrophysical observations, and FOXSI (Krucker et al. 2014), a rocket experiment, have utilized direct-focusing optics to achieve much higher sensitivity in hard X-ray imaging. However, application of this method in regular solar observations remains under development.

For indirect HXR imaging, algorithms are essential. X-ray photons passing through a modulation imager are recorded by detectors behind bi-grid subcollimators with different pitches, phases, and positioning angles. The transmittance of photons or measured counts in different modulation profiles contains information about various aspects of the sources (location, intensity, size, etc.). X-ray images are reconstructed from these data through imaging algorithms, making this imaging process an inverse problem of deducing source geometry from modulation profiles with limited data.

In general, two types of reconstruction methods exist: those based on visibilities and those based on patterns. Visibilities, which are Fourier components of spatial flux distribution converted from modulation profiles and calibrated

(Hurford et al. 2002; Hannah et al. 2008), represent the Fourier components of X-ray sources in the two-dimensional Fourier space known as the (u, v) plane. Patterns represent the responses of subcollimators to point sources at each location (x, y) in their field of view (FOV). Algorithms based on patterns compute source images directly from modulated counts.

More than ten image reconstruction algorithms have been developed for RHESSI software, frequently used for different scientific applications. Tests of these methods and brief summaries appear in Dennis & Tolbert (2019), Piana et al. (2022), and at https://hesperia.gsfc.nasa.gov/rhessi3/software/imaging-software/image-algorithm-summary/index.html. However, drawing solid conclusions from such tests is usually difficult for three reasons: (a) these methods serve different scientific purposes and applications; (b) no ground truth images exist for evaluation or comparison (except in imaging simulations); and (c) quantitative evaluation of reconstructed image quality is challenging.

In this paper, we test ten algorithms developed for RHESSI data analysis. To obtain ground truth images, we used Atmospheric Imaging Assembly (AIA, Lemen et al. 2012) data to derive thermal X-ray images through the differential emission measure (DEM) method (Cheung et al. 2015; Su et al. 2018; Li et al. 2022, hereafter DEM-X method). Studies have shown that accurate DEM results can produce soft X-ray images and estimate detailed density distributions along flaring loops for quantitative electron transport studies (Li et al. 2022). We compute reduced ^{2}, C-statistic (Cstat), and QuIX index (a new quantitative method named Quality Index of X-ray images that also accounts for sidelobe effects, Li et al. 2024) to estimate imaging quality. Using RHESSI data and software, we tested four cases: DEM-based simulation test, double sources, dynamic range test, and CLEAN beam width factor (CBWF) test. We also tested algorithms available for HXI with observational data, DEM-based simulation, and dynamic range simulation. Using the QuIX index, we further studied CBWF effects on imaging results and identified optimal default settings for both RHESSI and HXI. This work is important for improving our understanding of different imaging algorithms and useful for HXI algorithm development.

2. Imaging Algorithms

We present a brief introduction to the imaging algorithms tested in this work; for detailed descriptions, we refer readers to Piana et al. (2022).

The most straightforward image reconstruction method is Backprojection (BP, Mertz et al. 1986), where modulation profiles or visibilities are added linearly to produce a so-called dirty map. Sidelobes always appear in the dirty map due to instrumental effects from indirect imaging. Consequently, additional imaging algorithms have been developed to improve image quality.

CLEAN (Högbom 1974) is a widely used iterative algorithm in radio and hard X-ray imaging based on the assumption that an image can be well represented by a superposition of multiple point sources (Hurford et al. 2002). It begins with the dirty map as the initial image. The iterative process successively identifies the brightest points as CLEAN components and subtracts a fraction of the point-spread function (PSF) centered at the selected location from the dirty map. The process repeats over the remaining image (residual image), attempting to remove as many sidelobes as possible. The final CLEAN image results from CLEAN components convolved with a CLEAN beam of certain size, plus the final residual image. Different methods for adding back residual images were proposed in Dennis & Tolbert (2019).

Expectation Maximization (EM, Benvenuto et al. 2013) is a statistical iterative method that searches for the flux distribution maximizing the probability of observation under the constraint that pixel content must be positive. The STIX version of EM is now available (Massa et al. 2019).

Pixon (Metcalf et al. 1996) was originally developed for Yohkoh/HXT, from which RHESSI's version was derived. This approach uses fewer pixons to minimize degrees of freedom and maximize use of limited data, but requires longer reconstruction times.

The Forward-Fitting (FF) method (Aschwanden et al. 2002, 2004) is a parameterization modeling approach that posits the existence of one or more sources with specific shapes within an image. Source structures are typically quantified by circular Gaussians, elliptical Gaussians, or curved elliptical Gaussians (i.e., loop shapes). The imaging process determines best-fit parameters by comparing predicted modulation profiles from assumed sources with observed profiles. The Visibility Forward Fit (VF, Hurford et al. 2005; Hannah et al. 2008) algorithm also requires prior hypotheses regarding the number and shape of sources. Additionally, it allows greater flexibility in setting initial values for source flux, centroid location, width, and angle, or fixing them as constant parameters before fitting begins, which helps effectively constrain the imaging process. Flux, area, and other source parameters, along with their uncertainties, can be easily derived through the VF method (Dennis & Pernak 2009).

Maximum Entropy Method (MEM) algorithms maximize information entropy while minimizing a measure of goodness-of-fit (usually reduced ^{2}) and maintaining correct flux values (Schmahl et al. 2007). MEM_{NJIT} was developed at the New Jersey Institute of Technology. It sometimes produces images with multiple unrealistically small sources and exhibits super-resolution phenomena (Dennis & Pernak 2009). MEM_{GE} (Massa et al. 2020) optimizes this problem while maintaining MEM_{NJIT}'s advantages.

UV_{Smooth} (Massone et al. 2009) involves spline interpolation at spatial frequencies. It proceeds by smoothing observed visibilities in the spatial frequency plane to broaden the available set of Fourier components used in Fourier inversion that leads to the final image.

VIS_{CS} (Felix et al. 2017) is a compressed sensing image reconstruction method. It assumes solar flares can be represented by a linear combination of a few scaled and rotated two-dimensional Gaussian distributions. VIS_{CS} strives to generate realistic images aligning with measurements, thereby frequently obtaining favorable Cstat outcomes.

VIS_{WV} (Duval-Poo et al. 2018) is another compressed sensing method utilizing finite isotropic wavelets. It considers X-ray sources to be either isotropic or having slowly varying shapes, without relying on prior knowledge of specific shapes compared to VIS_{CS}.

3.1. Evaluations of Reconstructed Images

In this work, we consider three metrics to evaluate reconstructed image quality: Cstat (Cash 1979), reduced ^{2}, and QuIX (Li et al. 2024).

Generally, smaller Cstat and ^{2} values indicate better image quality. However, they cannot reflect all image aspects in some cases. QuIX (Li et al. 2024) is a new method developed to quantitatively evaluate X-ray imaging quality. It is a composite parameter containing three indices: root mean square error (RMSE), structural similarity index measure (SSIM), and percentage proximity degree (PPD). An important feature of X-ray imaging is the presence of sidelobes and artifacts. PPD is a parameter specifically designed to measure sidelobe extent, accounting for the number of pixels above a threshold of the maximum map value.

SSIM and RMSE measure source structure, including shape, size, position, and orientation. Li et al. (2024) evaluated multiple existing image quality assessment methods for different grid settings and source structures, selecting the most representative ones: SSIM and RMSE. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS, Hwang & Yoon 1981) was then used to order samples based on a decision matrix formed by the three indices, weighting them to formulate QuIX.

QuIX values can only be obtained by simultaneously inputting reconstructed images and model images (ground truth). QuIX ranges from 0 to 1, where higher values indicate better imaging quality. A QuIX of 1 means the two images are identical.

To avoid possible contributions from non-thermal bremsstrahlung and saturated extreme ultraviolet (EUV) images, we selected two B-class flares that occurred on 2010 October 29 and 2011 January 2. Both flares show loop-shaped SXR sources in time intervals close to GOES peak times. We deliberately avoided the hard X-ray peak so that X-ray emission during the selected decay phase intervals is mostly thermal. RHESSI detected no enhanced emission above 25 keV, and the attenuator state was A0 (highest sensitivity at low-energy X-rays) during both flares. Figure 1 [Figure 1: see original paper] depicts the light curves of the two events and the time intervals used in this study.

3.2. Observations

Figures 2 and 3 show RHESSI images reconstructed by all algorithms and 131 Å images from Solar Dynamics Observatory (SDO)/AIA. We used detectors 3–6, 8, 9 with an image size of 129 × 129 pixels and pixel size of 1 . The CLEAN process followed the approach described in Dennis & Tolbert (2019). Maximum iterations were set to 2000, CLEAN_{{{beam}}*{{width}}*}{factor} (CBWF) to 2.0, and scaled_{resid} was used for the CLEAN_{{{regress}}*{{combine}}*}{method}. Other parameters used RHESSI defaults.

The X-ray source in the first flare (Figure 2 [Figure 2: see original paper]) appears as a narrow loop. Most algorithms produce generally consistent results, but the FF image is clearly different, displaying a source with incorrect loop orientation and size despite using a seven-parameter loop model. The VF image exhibits a tendency for breaking up and discontinuity in loops presented by different sources. The lengths from different algorithms are relatively consistent, while considerable variation exists in loop widths, likely attributable to inadequate measurement of the smallest source dimensions, similar to Dennis & Pernak (2009).

The CLEAN image shows a wider loop-shaped source than the input source (possibly corresponding to the CBWF and detectors used). PIXON, EM, MEM_{GE}, and VIS_{WV} images present more or less consistent results. The loop source width in the MEM_{NJIT} image is small and similar to that in the AIA 131 Å image, showcasing its superior ability to image narrow sources, as demonstrated in Dennis & Pernak (2009), Warmuth & Mann (2013), and Dennis & Tolbert (2019). The VIS_{CS} image shows a wide loop with two bright sources near the loop top. The UV_{Smooth} image is also a wide loop with obvious sidelobes, exactly as depicted in Massone et al. (2009). Although the VF image shows a nice loop structure, the loop shape differs from observation, primarily because irregular loop shapes cannot be reconstructed with the loop models used in the current VF method.

Figure 3 [Figure 3: see original paper] shows another example of a larger loop with more scattered emissions. The situation is similar to the first flare. FF exhibits the same problems, with Cstat and reduced ^{2} values of 6.625 and 18.881 respectively, while other algorithms are all below 2.6, as shown in Table 1 .

3.3. DEM-X Images from AIA DEM Maps

Comparing and evaluating images from different algorithms is challenging when true source properties are unknown. Most simulation studies use input images combining assumed sources with simple shapes. However, ground truth is usually missing in observational cases. To address this and use more realistic HXR sources as input images, we computed low-energy thermal X-ray images from EUV observations by SDO/AIA.

First, we obtain DEM maps of thermal plasma from SDO/AIA data. EUV images from six AIA channels (94, 131, 171, 193, 211, and 335 Å) are processed to level 1.5 using the standard AIA procedure aia_{prep}.pro. We average AIA images during RHESSI integration time and rebin the images by 2×2 pixels, resulting in a pixel size of 1.2 . Second, we calculate thermal bremsstrahlung X-ray maps in the 4–10 keV and 15–20 keV ranges from DEM maps using f_{vth}.pro provided by Solar SoftWare (SSW). These SXR maps are then compared with RHESSI and HXI imaging results and used in imaging simulations for algorithm testing.

The calculated DEM-X 4–10 keV images appear in the top left of Figures 4 and 5. Consistency between DEM-X images and those from RHESSI is generally good, though detailed structural differences exist as expected. Indirect imaging from limited modulation profiles or visibilities cannot reconstruct all details, and its dynamic range cannot compete with direct imaging.

The DEM-X image for HXI testing was obtained in the 15–20 keV range because HXI's starting imaging energy is about 15 keV (Su et al. 2024), much higher than RHESSI's 3 keV. The possibility of non-thermal emission contributions is also higher, making comparison with thermal X-ray images difficult. Thermal emission in 15–20 keV often originates from hot plasma at temperatures exceeding 20 MK (or hot plasma with lower temperatures but high emission measure), which is beyond AIA's most sensitive temperature range. However, such test results remain useful.

4. Imaging Simulation with RHESSI Software

Using RHESSI software's simulation mode (Schwartz et al. 2002), we tested ten imaging algorithms in four cases: (1) test with input sources from AIA-based 4–10 keV images; (2) test of flux ratios for double Gaussian sources with equal fluxes; (3) test of imaging dynamic range with double Gaussian sources of different fluxes; and (4) test of CLEAN beam size with single Gaussian sources of different sizes. We implemented the simulation process following https://hesperia.gsfc.nasa.gov/rhessi3/software/simulation-software/index.html.

4.1. Case 1: Simulation with Realistic Sources

In this simulation test, we adopted the same pointing and imaging center as the observations. Pixel size was set to 1.2 (same as rebinned AIA maps), and imaging FOV to 120×120 . Other parameters remained consistent.

Figure 4 [Figure 4: see original paper] shows simulation results based on the 4–10 keV DEM-X image of the 2010 October 29 flare, in good agreement with those directly reconstructed from observations in Figure 2. The incorrect FF image remains unchanged. MEM_{NJIT} makes the closest super-resolution approximation to the model. EM, PIXON, and MEM_{GE} perform well. The VIS_{CS} source shape is not quite consistent with the input image, and other algorithms present relatively wide loops. According to quantitative imaging quality results (Table 2 (a)), including QuIX, Cstat, and ^{2}, the best two results are from PIXON and EM, while the (relatively) worst two are from FF and UV_{Smooth}.

Simulation results for the 2011 January 2 flare also agree well with observations (except for the FF image in Figure 3). The AIA DEM-X 4–10 keV source in this case is a loop wide at the top and narrow at the legs. All methods except FF produce loop-shaped sources, though some images show clear sidelobes. According to quantitative results in Table 2(b), the best two results are again from PIXON and EM, same as the first case. All three indices suggest the relatively poor three images are from FF, MEM_{NJIT}, and UV_{Smooth}. MEM_{NJIT} does not perform as well as in Table 2(a), probably due to its super-resolution effect, resulting in smaller source size and different flux distribution along the loop compared to the source.

In Table 2, Cstat, ^{2}, and QuIX are consistent in most cases. Cstat appears to overestimate VIS_{CS} performance, while QuIX overestimates FF performance (Table 2(a)). Overall, QuIX effectively supplements ^{2} and Cstat, particularly in assessing sidelobes. Using all three parameters together helps verify image quality and provides comprehensive evaluation of imaging results.

4.2. Case 2: Double Sources with Equal Fluxes

In this test, we evaluate algorithm performance using double Gaussian sources with the same flux but different sizes. Accurate flux ratios of the two sources in reconstructed images are important for HXR imaging spectroscopy investigations and understanding particle acceleration/transport processes.

As shown in Figure 8 [Figure 8: see original paper] of Felix et al. (2017), simulated detector count statistics can impact image morphologies. Here, we used two different signal-to-noise ratios (SNRs) by changing background intensity and statistical counts per detector during simulation. To ensure consistency between simulation and observation, we employed the snr_{value} defined in the RHESSI program to specify SNR and provide approximate SNR values in Table 3 .

Figure 6 [Figure 6: see original paper] displays the test result for SNR = 30, roughly comparable to observational SNR in Figure 2, effectively illustrating source sizes and fluxes. In this case, the left source (Source 1) is slightly larger than the right one (Source 2), with Gaussian full width at half maximum (FWHM) values of 11.8 and 7.1 respectively. The UV_{Smooth} image has obvious sidelobes, similar to previous results. VIS_{WV} exhibits nonexistent structures at the imaging area edge. The PIXON image shows an additional weak source to the upper left of Source 1.

Source parameters are presented in Table 3, where sizes and fluxes of the two sources are obtained within the 5% contour level. Flux ratios of Source 1 and

Source 2 are consistent within 17% of the assumption of 1 for all methods except FF, which shows nearly half the flux ratio. The proportion of background flux is calculated from source flux and total flux, Pbk. As shown in Table 3, forward-fit images have the lowest background. CLEAN and VIS_{CS} also have low background, followed by PIXON, MEM_{NJIT}, and EM. MEM_{GE}, VIS_{WV}, and UV_{Smooth} have the strongest backgrounds. Emissions below 5% around the source are considered background here, which may result in smaller source flux and correspondingly larger background. Sidelobes close to sources may contribute to source flux, resulting in larger source flux.

The VF image fails to accurately obtain the sizes of the two sources, with Source 1 smaller and brighter than Source 2, opposite to the model. Both FF sources are smaller than in the model. Overall, deviation in size ratio between images and model is significant, while flux ratio remains acceptable for most methods.

For the test with SNR = 5 (Figure 7 [Figure 7: see original paper]), overall image quality clearly decreases and sidelobes increase, impacting the topological morphology of one of the two main sources. Quantitatively, the larger source (Source 1) mixes with surrounding background, resulting in higher flux ratio, and total background flux Pbk noticeably increases. VIS_{CS}'s Pbk remains low across different SNRs, ranking just below VF and FF, confirming VIS_{CS}'s accurate and robust photometry (Felix et al. 2017).

Source 1 sizes are larger than in the SNR = 30 case (except for FF), while Source 2 sizes are less affected by SNR. No significant differences appear in Cstat for most methods. However, ^{2} significantly decreases, which cannot represent decreasing image quality. QuIX decreases for all methods except VF and FF, successfully reflecting decreased image quality. SNR considerably impacts flux measurements. VF algorithm uncertainties show errors significantly increase when SNR is 5. Although all algorithms are affected by SNR = 5 to some extent, they generally maintain good robustness. Changes in SNR do not significantly alter conclusions about algorithm performance.

4.3. Case 3: Imaging Dynamic Range

RHESSI's design goal is achieving a 100:1 dynamic range with sufficient observational counts (Hurford et al. 2002). In practical observations, dynamic range is influenced by various conditions, producing varying outcomes. Nonetheless, 10:1 is typically achievable (Piana et al. 2022). To test algorithm imaging dynamic ranges, we simulated double-source scenarios where both sources have the same size but different intensities.

First, we investigated imaging dynamic range using simulated double Gaussian sources with the same FWHM (8.2) but varying fluxes. The flux ratio R_{12} of the weak source (Source 1) to the strong source (Source 2) ranges from 0.1 to 0.9, with no background added in simulations. Figure 8 [Figure 8: see original paper] shows examples of models with different R_{12} (left column) and corresponding images from three algorithms (right three columns). For R_{12} = 0.2, the weak source is not clearly visible in the EM image but appears more pronounced in MEM_{GE} and UV_{Smooth} images.

To compare flux ratio R_{12} of two sources in imaging results, we first used the 5% contour of maximum intensity to obtain each source's flux. However, when the weaker source is below the 5% threshold, this approach limits identification of weaker sources. The second method searched for the strongest intensity around the known source position to represent peak intensity. Table 4 shows results from both methods, presenting R_{12} for models and images. Most algorithms exhibit R_{12} smaller than the model, as expected.

In Table 4, FF deviates from the model, reflecting substandard flux allocation, with flux ratios notably smaller than in the model. When model $R_{12} = 0.1$, EM and UV_{Smooth} cannot identify the weak source. At $R_{12} = 0.2$, EM remains unsatisfactory, possibly due to super-resolution effects. EM results improve with increasing R_{12} and become comparable to other algorithms. Weak sources in all MEM_{GE} images are relatively weaker than the model, barely identifiable at $R_{12} = 0.1$. MEM_{NJIT} consistently outperforms MEM_{GE} in R_{12}, as expected, since it is considered excellent for determining component fluxes (Schmahl et al. 2007).

Weak sources and sidelobes mix together in UV_{Smooth} images, resulting in larger intensities in weak sources and higher flux ratios compared to the model. At $R_{12} = 0.9$, some algorithms show slightly higher flux ratios than the model, possibly for similar reasons. Overall, VF is closest to the model, primarily because both method and model exclude background flux and the number of sources is known. Other algorithms perform almost equally well in most cases.

The dynamic range of distinguishable sources can reach 10:1 in this simulation. However, various backgrounds in actual observations introduce more uncertainties.

We also tested imaging dynamic range with two point sources, where R_{12} varies from 0.1 to 0.9. Notably, no background was incorporated into these simulations. The same statistically low-level condition comparable to a B-class flare was employed as in previous tests. Figure 9 [Figure 9: see original paper] shows examples of models with different R_{12} (left column) and corresponding images from three algorithms (right three columns).

Table 5 presents flux ratios and peak intensity ratios, yielding broadly comparable results. However, at $R_{12} = 0.1$, all methods except VF significantly underestimate the weak source flux. FF even fails to identify the weaker source. Peak intensity results are slightly better, but only UV_{Smooth} and CLEAN produce ratios consistent with the model within 20%. Conversely, at $R_{12} = 0.9$, the 5% contour threshold effect becomes pronounced, and flux ratio is more consistent with model R_{12}. Peak intensity ratios from VF, UV_{Smooth}, and FF are clearly different from input. For instance, VF should theoretically increase continuously with input ratio, but actual results exhibit erratic fluctuations instead.

Overall, most methods produce good results for source fluxes. VF provides the most accurate source flux estimates. FF does not provide consistent results with input. Differences among algorithms at various R_{12} values are relatively minor, and most methods achieve a 10:1 dynamic range (the weak source can be identified at the 5% contour).

4.4. Case 4: CLEAN Beam Size

The CLEAN algorithm has several parameters: maximum iterations, method for combining clean component map and residual map, CLEAN_{{{beam}}{{width}}}{factor} (CBWF), etc. Among these, CBWF is an important free parameter affecting CLEAN beam size, source sizes, and imaging quality.

According to RHESSI software definition, the width (σ) of the Gaussian source convolved with CLEAN components relates to the resolution of selected detectors (R), their weights (w), and CBWF. When the default CBWF = 1 is used for imaging, sources often appear larger than those produced by other methods. Larger CBWF narrows the width of convolving Gaussian sources and produces smaller source sizes. Better imaging can be obtained by adjusting CBWF in many cases.

Dennis & Tolbert (2019) performed imaging using CBWF values of 1, 2, and 10. Resulting Cstat remained unchanged, while reduced ^{2} improved significantly as CBWF increased. However, at CBWF = 10, the image approached the CLEAN component map, with sources appearing noticeably dispersed and fragmented. Kontar et al. (2010) found in a particular event that using 1.7 for CLEAN produced images comparable to other algorithms, but the universally appropriate value remains unknown. Here we simulated a series of single Gaussian sources with different widths to find the best default setting for CBWF.

For each width, we used different CBWF values (bin size 0.1) and detector combinations for imaging. All images were compared with the model to obtain QuIX imaging quality. Figure 10 [Figure 10: see original paper] shows some examples of models and images, revealing that reconstructed image quality depends not only on CBWF setting but also on source sizes and detector resolution (detector combinations). Small CBWF can indeed produce better images for large sources, but for small sources, images are better with larger CBWF.

Figure 11 [Figure 11: see original paper] shows QuIX imaging quality results for RHESSI. Brighter color indicates better quality. The abscissa is CBWF, and the ordinate represents source size (Gaussian FWHM). Figures 11(a)–(e) present results with different starting detectors, showing roughly the same trend. For a given detector combination, larger sources require smaller CBWF to produce good images, and vice versa. From this perspective, the best CBWF is variable.

Using simulated sources provides the advantage of knowing actual source sizes. In Figure 11(f), we selected the finest starting grids with approximately suitable resolution for each source size and found the best CBWF value for all detector combinations (brightest region) is around 2.0–2.4. The smallest source requires large CBWF for an extremely narrow CLEAN beam to produce images more consistent with the model. Excluding the smallest source result and calculating the average best CBWF for FWHM 3.53 –37.7 yields about 2.20. Considering that sparse grid resolution is not sensitive to continuous source size changes, we anticipate error exceeding the bin size of 0.1. Combining bin size with standard deviation of optimal CBWF values results in an error of 0.326.

Simply stated, when appropriate detectors are selected, a fixed CBWF of 2.2 is sufficient. Therefore, we suggest a value of 2.2 as the default CBWF for RHESSI. However, to obtain the best image, one can further adjust detector range and CBWF according to source properties.

5.1. HXI Observations

HXI has observed flares for about two years, accumulating substantial observational data. Although preliminary calibration results for HXI grids (G3–G10 groups) were released with HXI software, calibration of the finest grids (G1–G2 groups) for high-resolution imaging at low energies is ongoing, requiring more data on compact flares. Furthermore, HXI visibility calibration still requires additional work (Su et al. 2024). Currently, five imaging algorithms are available for HXI: pattern-based HXI_{BP}, HXI_{CLEAN}, and Forward Fit, plus visibility-based HXI_{{{VIS}}{{BP}}} and HXI{{{VIS}}{{CLEAN}}}. Additionally, a machine learning-based algorithm, HXI{DLA} (Xia et al. 2024), is under development for practical use. In the following test, we reconstructed HXI images with basic calibration accounting for actual slit width and grid shadowing effects.

Figure 12 [Figure 12: see original paper] displays reconstruction results for a GOES M1.7 class flare observed by HXI on 2023 November 5. Images are reconstructed from grid groups G2–G10 in 35–50 keV. Sources in the HXI_{CLEAN} image correspond well with AIA 1700 Å bright sources in Figure 12(f). Forward Fit recognizes the upper two sources as one large source, and the VIS_{CLEAN} image also identifies them as an extended source with centroid between the two bright spots. In Forward Fit, we assumed four Gaussian sources according to HXI_{CLEAN} images but found the fourth source identified by FF is a faint source to the right, also seen in Figure 12(b). For the current stage, the HXI_{CLEAN} algorithm is recommended for scientific analysis.

5.2. DEM-X Test for HXI

In Figure 13 [Figure 13: see original paper], we employed the AIA DEM-X method to test HXI imaging algorithms. Here we used M5.0 flare data observed by HXI around 21:32:40 UT on 2023 March 5. As mentioned in Section 3.3, AIA DEM calculation may not be accurate for thermal plasma above 20 MK due to AIA's low temperature response. Additionally, possible non-thermal emission contributions may cause differences between reconstructed images and DEM-X images in 15–20 keV (Figures 13(a), (c)).

We used the DEM-X image as simulation input for algorithm testing. Figures 12(d)–(h) display images from different algorithms. HXI_{CLEAN} returns the best result, with a major source and two weak sources (indicated by two magenta arrows), consistent with the input model. For HXI_{{{VIS}}*{{BP}}} and HXI*{{{VIS}}_{{CLEAN}}}, we did not use G1–G3 groups, resulting in ~9.3 resolution and failure to identify the two weak sources.

5.3. Imaging Dynamic Range

In the following simulation, we tested HXI dynamic range with two footpoint sources similar to Figure 8, assessing its ability to identify weak sources. We used two source types: Gaussian sources with FWHM = 4.7 and point sources. Both tests were conducted under high SNR and low background conditions.

Results for Gaussian sources are presented in Figure 14 [Figure 14: see original paper], where two sidelobe sources are clearly visible. In Figure 14(c), with R = 20, the weak source flux is already less than that of sidelobes, and the calculated flux ratio between the two sources at the 5% contour is nearly 207:1. (Note that we did not add a residual map in this study, which may improve flux ratio. Adding a residual map to the cleaned map is another important study topic.) Without additional observational evidence, confirming a true source among sidelobes is challenging. When R = 30, the weak source is completely unresolved. Therefore, HXI dynamic range is similar to RHESSI's, approximately within 10–20:1 (for imaging with G2–G10).

Results for two point sources are shown in Figure 15 [Figure 15: see original paper] and Table 6 . The faint source is barely visible at R = 45:1 and barely discernible at 50:1. Total flux ratio R (5% contour) and peak flux ratio suggest HXI can achieve a dynamic range of 50:1 in extreme cases (for imaging with G2–G10).

5.4. CLEAN Beam Size Test

In the HXI_{CLEAN} procedure, CLEAN beam width (σ) is determined by the finest resolution of selected grids and CBWF_{HXI}, where CBWF_{HXI} definition differs slightly from RHESSI's. Using the same method as Section 4.4, we obtained CBWF_{HXI} test results (Figure 16 [Figure 16: see original paper]). Excluding the smallest source, we obtain an average value of 2.49 $\pm$ 0.231, or roughly 2.5. This value will be used as the default setting for CBWF in the next HXI analysis software version (V1.50 beta).

6.1. Forward Fit Methods

Parametric imaging schemes FF and VF differ from other algorithms in two aspects: they require prior assumptions on source shapes and numbers, and they perform parameter fitting to obtain best-fit parameters and images. Therefore, they are considered very useful for obtaining source parameters. However, we encountered problems in our tests. FF cannot correctly restore loop source size and orientation. In Table 4, flux ratios of the two sources are not as good as those from other methods. In the VF image in Figure 2, the narrow loop source tends to split into multiple sources but effectively reproduces narrow source characteristics, similar to findings in Dennis & Tolbert (2019). Two sources are occasionally identified as one large source, as in Figure 4 of Volpara et al. (2022). Adding restrictions such as source location and flux could produce better images. VF source flux ratio in Table 4 is similar to the model due to location constraints. However, when two sources have the same flux but different areas, the sizes of the two sources in imaging results may not be retrieved correctly.

These problems highlight that increasing source number and complexity leads to greater imaging uncertainties. The current FF version is limited in setting source shape and number, while VF allows additional restrictions for each source to optimize images. In practical imaging, constraints can come from other algorithm images. Therefore, VF appears to be a better choice than FF for RHESSI data imaging.

6.2. Conclusions

A good, robust algorithm must effectively reconstruct images from limited data and accurately determine source flux, position, shape, and ideally detailed structures without producing non-physical results such as super-resolution effects and sidelobes. However, constraints of indirect X-ray imaging, including limited subcollimators/visibilities and limited imaging dynamic range, pose challenges for all algorithms.

Quantitative comparisons between reconstructed images from different algorithms and input images (ground truth) are important for understanding each algorithm's advantages and limitations. In this work, we used three evaluation indices— ^{2}, Cstat, and the new X-ray imaging quality evaluation parameter QuIX—to analyze all RHESSI algorithms in four imaging simulation cases: realistic source, double sources, imaging dynamic range, and CLEAN beam size. We also tested ASO-S/HXI algorithms with observational data and simulated sources for better understanding of HXI imaging capability. Additionally, we determined appropriate default CBWF settings for both RHESSI and HXI based on simulations of single sources with different sizes, significantly improving imaging results compared to the original default CBWF = 1. However, the best CBWF value also depends on source structures, sizes, and detector selection. Users are encouraged to adjust CBWF as needed.

Most algorithms perform well overall. The EM algorithm remains reliable in most tests, with good intuitive comparison between images and model and good quantitative description. EM does not need extra parameters. Drawbacks include slight information loss due to super-resolution effects and time-consuming imaging. CLEAN and PIXON achieve similarly high-quality images compared to EM. CLEAN requires proper parameter settings for best results, which can be complicated or tricky when optimal settings are unknown (for example, methods for adding back residual maps). PIXON simultaneously provides accurate image photometry (e.g., Aschwanden et al. 2004; Dennis & Pernak 2009) and excellent source morphology details, though sidelobes occasionally occur. Another deficiency is the time-consuming imaging process.

MEM_{NJIT} sources often break up, as noted in many studies. Its super-resolution effect can produce good images for small sources but may bring non-physical results for large sources. Massa et al. (2020) confirmed Maximum Entropy algorithm super-resolution properties using STIX simulation data. As an improved MEM_{NJIT} version, MEM_{GE} sources rarely break up. In our RHESSI tests, MEM_{GE} effectively balanced super-resolution effects with actual source size, though sidelobes are complicated in some cases.

VIS_{WV} and VIS_{CS} perform equally, slightly worse than EM. VIS_{WV} central source shape is good, with noise or sidelobes often appearing at imaging FOV edges (Figures 5 and 6). VIS_{CS} has a cleaner background, but source shape occasionally deviates. For example, the loop is recognized as footpoints in Figure 2. Robust photometry results are consistent with Felix et al. (2017).

UV_{Smooth} results are not as good as other algorithms except FF and VF. In almost every test, we observe sidelobes around sources, and source size is larger than input. However, the newly developed STIX team version of UV_{Smooth} has been optimized in this aspect (Perracchione et al. 2021).

Unlike other algorithms, FF and VF require prior assumptions about source number and shape. VF performs better than FF, allowing more parameter settings to constrain imaging results. Before using FF and VF, it is better to first examine images from other algorithms, as they provide more source information for setting initial parameters.

Overall, our study differs from Dennis & Tolbert (2019) by testing sources of varying sizes and shapes, including realistic sources estimated from AIA DEM maps. A narrower source does not necessarily imply better imaging quality. Non-physical super-resolution effects can cause information loss for larger sources, as observed with EM and MEM_{NJIT}. Detector resolution remains a more crucial parameter. According to test results, EM and PIXON provide overall best imaging quality. CLEAN, VIS_{CS}, VIS_{WV}, and MEM_{GE} also perform well in source structure reconstruction. MEM_{NJIT} can produce good results when SNR is high. VF, CLEAN, PIXON, and MEM_{NJIT} provide relatively good estimates of individual source total flux and can be used for imaging spectroscopy.

Based on our CBWF tests, we recommend a default setting of CBWF = 2.2 for RHESSI to replace the original default CBWF of 1. For HXI, we suggest a default setting of CBWF = 2.5 (with a slightly different CBWF definition). Note that these best values are obtained under specific test conditions—images made with selected detector sets providing resolution comparable to single Gaussian source size. Readers may still need to explore optimal CBWF and detector selection combinations (see Figures 11 and 16) for imaging different sizes/shapes/numbers of sources with observational data.

It should also be noted that poor imaging quality does not necessarily mean algorithms are meaningless or useless. Comparing and contrasting results from different algorithms helps verify their accuracy and reliability. Through testing various algorithms, we expound their characteristics, advantages, disadvantages, application conditions, and parameters affecting images. These results provide valuable guidance to users and support ongoing HXI algorithm development.

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