A median-Gaussian filtering framework for Moiré pattern noise removal from X-ray microscopy image

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Abstract

Moiré pattern noise in Scanning Transmission X-ray Microscopy (STXM) imaging introduces significant errors in qualitative and quantitative image analysis. Due to the complex origin of the noise, it is difficult to avoid Moiré pattern noise during the image data acquisition stage. In this paper, we introduce a postprocessing method for filtering Moiré pattern noise from STXM images. This method includes a semi-automatic detection of the spectral peaks in the Fourier amplitude spectrum by using a local median filter, and elimination of the spectral noise peaks using a Gaussian notch filter. The proposed median-Gaussian filtering framework shows good results for STXM images with the size of power of two, if such parameters as threshold, sizes of the median and Gaussian filters, and size of the low frequency window, have been properly selected.

Keywords

STXM; Moiré pattern; Image processing; Median filter; Gaussian notch filter

1. Introduction

In the spectromicroscopy (SM) beamline at the Canadian Light Source (CLS) (Kaznatcheev et al., 2007), the Scanning Transmission X-ray Microscopy (STXM) technique is used to probe the composition of a variety of materials ranging from soft matter to hard materials. The monochromatic soft X-ray beam is focused by a Fresnel zone plate, forming a fine probe with a diameter about 30 nm. The sample is positioned at the zone plate focal point and scanned with synchronized detection of transmitted X-rays to form transmission images over a series of photon energies across the measured elemental edge(s). STXM routinely produces a large number of two-dimensional X-ray transmission images.

However, Moiré pattern noise has occasionally been observed in STXM images [Fig. 1(a)]. The STXM images with Moiré pattern noise will introduce significant errors in image analysis for chemical speciation and quantification of the specimen composition. The noise

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is presumably formed by the interference of a systemic noise with the raster scanning motion of the sample stage to form roughly parallel dark and bright stripes on the STXM images (Nováková et al., 2008). On the other hand, an STXM imaging process can be thought as a digital sampling process, and an image has spatial frequency components with a maximum spatial frequency. Based on Nyquist-Shannon-sampling-theorem, only those image signals with frequencies up to half of the sampling frequency can be reproduced faithfully. If the signal frequency exceeds this limit, *i.e.*, half of the sampling frequency, alias signals, whose spectrum are the faint peaks in the vicinity of the zero frequency as shown in Fig. 1(b), would appear in the lower frequency region. These aliased signals lead to artifact patterns known as Moiré patterns.

The Moiré pattern noise can be exacerbated at CLS STXM in the following situations: (1) when STXM signal to noise ratio is too low due to low transmission at specific photon energies; (2) when the photon energies are on the steep sides of an intense X-ray absorption peak; (3) when some of the beamline optics are mistuned so as to deteriorate the beam quality or beam feedback. Due to the complex origination of the noise, it is difficult to control during the data acquisition stage to avoid the Moiré pattern noise. As a result, we hope to develop an efficient post-processing method to remove the noise.

Noise with the Moiré pattern implies a periodic structure. Periodic noise is typically processed in an image by filtering in the Fourier domain of the image, because the spectrum of the purely periodic (sinusoid) noise would be a pair of conjugate impulses located at the conjugate frequencies of the sinusoid wave at the appropriate frequency location. As a result, periodic noise can be effectively removed by correcting the amplitude spectrum components altered by the noise, and two frequency filtering methods are currently available, *i.e.*, Wiener filtering and notch filtering. However, a Wiener filter requires an accurate noise model, which may be difficult to obtain in various practical cases, such as STXM scanning. In addition, a Wiener filter is also complicated in computation. As a consequence, notch filters are preferred by researchers in investigating the methods for periodic noise removal from an image.

The purpose of a notch filter is to exclude “bad” components from an image by removing the isolated noise or distortion frequencies. Because the purely periodic noise has a very narrow bandwidth with high magnitude leading to a sharp peak in the Fourier amplitude spectrum, it is easy to localize the spectral component of the noise in the frequency domain by simply using the thresholding technique, then correcting the noise using a notch filter. However, in most cases the Moiré pattern noise in STXM images is not purely periodic. As we noticed in Fig. 1(a), the noise has spatial distortions throughout the image, and in Fig. 1(b), there are two faint star-like components in the Fourier amplitude spectrum of an STXM image. This fact implies, as Gonzalez and Woods indicated (2001), there must be more than one sinusoidal pattern in the noise, leading the Moiré pattern noise to quasi-periodic. In addition, there are some other peaks in high-frequency area which are even visually unrecognizable. This can cause two problems. Firstly, the Moiré pattern noise in a CLS STXM image does not contain easily detectable sharp peaks in the frequency domain, because the noise is not purely periodic. As a consequence, a peak detection scheme by simply using thresholding of the Fourier amplitude spectrum is not suitable for this situation

(Aizenberg and Butakoff, 2002b). Secondly, correcting only the spectral peak is not sufficient for suppressing the Moiré pattern noise in an STXM image, since the noise is quasi-periodic, and all spectral components in an area around the spectral peak, not just the spectral peak itself, are affected by the noise.

Based on above-mentioned facts, and previous work done by Aizenberg and Butakoff (2002b), we propose a filtering framework for Moiré pattern noise removal from STXM images by using a semi-automatic spectral noise detector and a spectral Gaussian notch filter used by Aizenberg and Butakoff (2008). The spectral noise detector was revised from an impulsive noise detection algorithm in spatial domain using the median filter (Aizenberg et al., 2002a). In this paper, we investigate the feasibility to apply this median-Gaussian filtering framework to remove the Moiré pattern noise from STXM images. We will describe the procedure to implement the spectral noise peak detection and image filtering, and report the achievable power for Moiré pattern noise removal from STXM images by using the proposed filtering framework.

2. Median-Gaussian notch filtering algorithm

2.1. Detection of the spectral peaks of Moiré pattern noise

As mentioned in Section 1, we will consider a spectral filtering for the Moiré pattern noise removal in the Fourier amplitude spectrum of a noised image, which can be described by the following formula:

$$H(k, l) = \left| \sum_{n=0}^{N_1-1} \sum_{m=0}^{M_1-1} h(m, n) e^{-i2\pi((km/M_1) + (ln/N_1))} \right| \quad (1)$$

where $h(m, n)$ is the $M_1 \times N_1$ sized image whose spectrum is calculated. $H(k, l)$ is the amplitude of the spectral (k, l) th coefficient.

From the amplitude spectra in Fig. 1(b), we can see that the bright white spots, which represent the peaks, look very similar to the impulses. As a result, our peak detection algorithm can be based on a consideration that those peaks be impulses. Because the median filter is the most common and useful impulsive noise filter (Astola and Kuosmanen, 1997; MathWorks, 2011), and a median itself can be used for the detection of impulses, a criterion for impulsive noise detection in spatial domain on an image has been introduced (Aizenberg et al., 2002a). This criterion is based on the comparison of the current signal value to a local median value. We can extend this idea to spectral peak detection in the Fourier amplitude spectrum, which includes the following two steps:

1. Define a low-frequency area

Since the low-frequency coefficients [see Fig. 1(b) in the middle] contribute to the signal energy, we want all the spectral coefficients to be preserved from any changes in this area. For simple implementation, we define the area of preservation as a rectangle with a size of $M \times N$ around the zero

frequency coefficient $H(0, 0)$. The area is denoted as A_{LF} , where all the spectral coefficients have to be preserved.

2. Localize a spectral peak

The (k, l) th spectral coefficient H_{kl} is a peak, if the following inequality holds:

$$\frac{H_{kl}}{\text{MED}_{K \times L}(H_{kl})} \geq T \quad (k, l) \notin A_{LF} \quad (2)$$

where $\text{MED}_{K \times L}(H_{kl})$ is a local median in a $K \times L$ window around the (k, l) th spectral coefficient H_{kl} . T is a threshold value pre-defined by the user. Obviously, larger T leads to a more careful peak detection, and fewer peaks will be detected.

2.2. Gaussian notch filtering

The Gaussian notch filtering scheme is based on the peak detection described in Section 2.1. The key point is that this filter corrects not only the spectral coefficient of interest, but all the amplitude spectrum coefficients within the filter window. Mathematically, the Gaussian notch filtering used here can be described as following:

$$\tilde{H}_{kl}^{IJ} = \begin{cases} H_{kl}^{IJ} \circ G_{IJ}, & \text{if (2) holds} \\ H_{kl}^{IJ}, & \text{otherwise} \end{cases} \quad (3)$$

where H_{kl}^{IJ} is a group of the amplitude spectrum coefficients, selected by an $I \times J$ window around the (k, l) th spectral coefficient H_{kl} . $\tilde{H}_{kl}^{IJ}$ is a group of the amplitude spectrum coefficients after the filtering described by Eq. (3). The “ $\circ$ ” sign represents elementwise multiplication of two $I \times J$ matrices. G_{IJ} is the Gaussian notch filter.

A standard Gaussian notch filter defines a Gaussian surface covering a pair of conjugate peaks (Gonzalez and Woods, 2001). However, filtering using such a surface is computationally intensive. In the presence of multiple pairs of noise peaks, the filtering takes a very long time. In this paper, we use a Gaussian notch filter modified from the standard one, which is defined as follow (Aizenberg and Butakoff, 2008):

$$G_{IJ}(u, v) = 1 - C e^{-a(u^2 + v^2)} \\ u = -\text{floor}\left(\frac{I}{2}\right), -\text{floor}\left(\frac{I}{2}\right) + 1, \dots, \text{floor}\left(\frac{I}{2}\right) - 1, \text{floor}\left(\frac{I}{2}\right) \\ v = -\text{floor}\left(\frac{J}{2}\right) - \text{floor}\left(\frac{J}{2}\right) + 1, \dots, \text{floor}\left(\frac{J}{2}\right) - 1, \text{floor}\left(\frac{J}{2}\right) \quad (4)$$

where $\text{floor}(\blacksquare)$ is an operation to round the element within the bracket to the nearest integers less than or equal to that element. $0 < C \leq 1$ is the scaling coefficient along z direction and $a > 0$ is the scaling coefficient along x and y direction. Eq. (4) defines a Gaussian surface, with

a single peak in the center of the surface. The magnitude and the width of this single Gaussian peak are determined via C and a respectively.

In summary, there are six groups of adjustable parameters in the proposed median-Gaussian filtering framework. These parameters are: size of the low frequency window (A_{LF}) $M \times N$, size of the median filter $K \times L$, the threshold value T , size of the Gaussian notch filter $I \times J$, and two scaling factors C and a , among which K , L , I , J , M and N must be odd numbers. For simple implementation, we choose $K = L = I = J$, $M = N$, $C = 1$ and $a = 0.01$. The proposed filtering framework has been programmed using Matlab. Fig. 2 is a block diagram of the filtering framework.

3. Results

To evaluate the performance of the filter, we used 13 images collected from SM beamline without noticeable Moiré Pattern Noise [see Fig. 3(a) for an example]. These images were artificially corrupted by adding the same Moiré Pattern noise in the spatial domain [see Fig. 3(b) for an example]. Then, we filtered the noised images using the median-Gaussian filter (MGF) proposed in this paper [see Fig. 3(c) for an example], the Point Fourier-domain median filter (PMF) (Aizenberg and Butakoff, 2002b) [see Fig. 3(d) for an example], and the median filter (MF) (Al Hudhud and Turner, 2005) [see Fig. 3(e) for an example]. While there is no noticeable remaining noise in both MGF and MF filtering results, the result for PMF in Fig. 3(e) still contains noticeable noise. To quantify the efficacy of each filter for noise removal, we calculated the Peak Signal-to-Noise Ratio (PSNR) for these 13 images and plotted the results in Fig. 4. It is shown that both MGF and MF work comparatively well, and better than PMF.

Fig. 5 shows the result using the proposed median-Gaussian filtering framework to filter the noised image in Fig. 1(a). The parameter settings are as follows: $T = 7.5$ as the threshold value, the scaling factor for the Gaussian filter $a = 0.1$, $K = L = I = J = 11$ as the sizes of both the median and Gaussian filters, and $M = N = 11$ as the size of low frequency A_{LF} window. These parameter settings were obtained based on trial and error, and they will be referred to in the following as “standard parameter setting”. As we can see from Fig. 5, the noise has been effectively removed. In addition, the image intensity at each pixel was not distorted, which means the spectroscopic property of the image was not changed. We tested the filtering framework on additional 10 noised images collected from STXM in CLS using the standard parameter setting, and obtained good results from all those filtering operations.

To test the performance of the peak detector described in Section 2.1, we have used an image without the noise [Fig. 6(a)] based on the standard parameter setting to detect the peaks. As expected, no peak was localized in the Fourier amplitude spectrum using the standard parameter setting. We also tried to decrease the threshold value and no false peak detection was reported until $T = 4$. Fig. 6(b) shows a result image of over-filtering resulted from a false peak detection when $T = 4$.

The impact of the threshold value T to filtering results is shown in Fig. 7. Fig. 7(a) is the original STXM image with the Moiré pattern noise from CLS. This noised image was

processed using the standard parameter setting, and the resulting image is shown in Fig. 7(b). Furthermore, we also processed the original noised image by setting $T=5$ and $T=10$ respectively, with the other parameters kept the same the standard parameter setting. The resulting images are shown in Fig. 7(c) and (d), from which we can see that $T=5$ gives an over-filtered image, because some fundamental components of the signal has been filtered out from the original image. In contrast, $T=10$ generates an under-filtered image with the noise still existing. This makes sense because, based on Eq. (2), more spectral coefficients will be detected as the peaks with a smaller threshold value. Obviously, if any of these spectral coefficients is not a real spectral peak, over-filtering will result.

Fig. 8(a) and (b) shows the filtering results by varying the size of the median and Gaussian filters, whereas other parameters are still the same as the standard parameter setting. The size of the median and Gaussian filters defines the size of an area around a spectral noise peak, within which the Gaussian filtering will be performed. When the filter size is 7×7 , i.e., the size of the area is 7×7 , the image was under-filtered. This is due to the fact that, different from a purely periodic image, all spectral components of an STXM image with Moiré pattern noise in an area close to the spectral peak will be affected by the noise. As a result, if the filter size is too small, the median value selected from the area around the spectral noise peak will be larger. This will further cause the ratio $H_{kl}/\text{MED}_{K \times L}(H_{kl})$ in Eq. (2) smaller, and less spectral noise peaks will be picked out in response to a pre-defined threshold value T based on Eq. (2), leading to under-filtering. On the contrary, when the size of the filters is 15×15 , the image was over-filtered because some of signal spectrum will be selected by Eq. (2) as noise due to a false larger ratio of $H_{kl}/\text{MED}_{K \times L}(H_{kl})$.

For the images with more complicated noise patterns as shown in Fig. 9(a), we reduced the filter size to 9×9 , and threshold to $T=6$, in consideration that the noise here is less “periodic” than in previous noised images, and signal to noise ratio is lower. As we can see from the filtered images in Fig. 9(b), most noise structures have been removed. As a comparison, the image filtered using the standard parameter setting is also shown in Fig. 9(c), in which there is still noticeable noise remaining.

4. Discussion

The fundamental idea of the peak detector is based on the consideration that the ratio $H_{kl}/\text{MED}_{K \times L}(H_{kl})$ should be close to 1 for the spectrum without a spectral peak. If a spectral coefficient H_{kl} is much larger than a local median, this H_{kl} would be considered a spectral peak. As a consequence, the lower estimation of T would be: $T > 1$. On the other hand, the choice of a proper value of T is not a problem for each particular type of images. Our trials show that the spectral peak detector is not very sensitive to the changes of the threshold value T , which means we can try to find a proper threshold value by changing T with a step size as large as 0.5. The threshold value T is the main parameter of the peak detection algorithm, because it determines the strength of the detection and affects the number of the spectral coefficients detected as peaks. A larger T leads to more careful detection, and smaller number of the spectral peaks will be detected. For an image with the complicated noise pattern [Fig. 9(a)], smaller T should be used, because this kind of noise can cause very weakly marked peaks in frequency domain or no distinguishable peaks at all. However, an

unreasonably small T results in a false detection of the spectral peaks and over-filtering, leading to a loss of the image signal. Under this circumstance, some non-uniform noise as shown in Fig. 6(b) and Fig. 7(c) will be generated.

The size of the low frequency window A_{LF} depends on the type of image to be processed. For STXM images as shown in this paper, we chose 11×11 . A_{LF} can be determined on a trial and error basis, or through visualization of the spectrum in order for A_{LF} to cover the low frequency component (useful image information) and keep the noise components outside.

In this paper, we chose C in Eq. (4) equal to 1. However, using $C = 1$, the Fourier amplitude spectrum of the filtered image becomes 0 at the frequency positions where spectral noise peaks occur. By doing this, depending on the image, artifacts of a quasi-periodic nature may be generated. If C would have been set appropriately, for example, C is chosen in a way that the peak central pixel and the surrounding pixels acquire values in the range of the local median, the artifacts would be negligible in most cases.

5. Conclusion

A median-Gaussian filtering framework for Moiré pattern noise removal from STXM images has been proposed and tested in this paper. The method provides a semi-automatic approach to detect the spectral components corresponding to the noise, and corrects the spectral distortion in areas caused by the noise. Satisfactory results have been observed in STXM images. Meanwhile, we expect the proposed filtering framework can also be successfully used to remove the noise of the same pattern from the images obtained from other beamlines than just an X-ray microscopic beamline. However, current implementation of the median-Gaussian filtering framework needs to set several parameters by user on a trial and error basis, and these parameters can be different for different types of image. Although the trial-and-error way works well for proving of principle, which is the aim of this paper, we expect to develop a fully automated method in the future if the filtering algorithm will be used routinely for STXM and other images. The fully automatic method will free user from choosing these parameters manually, so that an optimized estimation of the parameters can be achieved for different types of image to utilize the full power of the filtering framework proposed in this paper.

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Fig. 1.

(a) STXM image of carbon nanotube with the Moiré pattern noise; (b) the central part of the Fourier amplitude spectrum of (a). The image was magnified for better visibility of two star-like spectral components around the center. The noticeable peaks in the higher frequency domain have been manually marked.

Fig. 2.
Block diagram of the median-Gaussian filtering framework.

Fig. 3. Filtering a sample image from the test set: (a) clean image: graphene flakes; (b) clean image corrupted by Moiré pattern noise; (c) the corrupted image filtered by MGF. PSNR = 33.76; (d) the corrupted image filtered by PMF. PSNR = 23.80; (e) the corrupted image filtered by MF. PSNR = 33.05.

Fig. 4.
Comparison of the PSNR for the different filtering techniques on a set of 13 images.

Fig. 5.
(a) The filtering result of Fig. 1(a) using the standard parameter setting; (b) the amplitude spectrum of the filtered image in (a).

Fig. 6.

(a) An STXM image of ZnS/ZnO nano-structure without noise. Image courtesy of Zhiqiang Wang, the University of Western Ontario, Canada. (b) The filtered image based on the false peak detection using the standard parameter setting except $T=4$.

Fig. 7.

The impact of the threshold value to the median-Gaussian filtering framework. (a) The original STXM image of SiO nanowires with the Moiré pattern noise from CLS; (b) the filtering result using the standard parameter setting; (c) the filtering result using the standard parameter setting except $T=5$; (d) the filtering result using the standard parameter setting except $T=10$.

Fig. 8.
The impact of the sizes of the filters to the median-Gaussian filtering framework using the standard parameter setting except: (a) $K = L = I = J = 7 \times 7$; (b) $K = L = I = J = 15 \times 15$.

Fig. 9.

(a) STXM image of bacteria with complex Moiré pattern noise. Image courtesy of Neil Telling, Keele University, UK. (b) Filtered image with $K = L = I = J = 9 \times 9$, and threshold value $T = 6$. (c) Filtered image using standard parameter setting.