Photon-counting, energy-resolving and super-resolution phase contrast X-ray imaging using an integrating detector.

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Abstract: This work demonstrates the use of a scientific-CMOS (sCMOS) energy-integrating detector as a photon-counting detector, thereby eliminating dark current and read-out noise issues, that simultaneously provides both energy resolution and sub-pixel spatial resolution for X-ray imaging. These capabilities are obtained by analyzing visible light photon clouds that result when X-ray photons produce fluorescence from a scintillator in front of the visible light sensor. Using low-fluence monochromatic X-ray projections to avoid overlapping photon clouds, the centroid of individual X-ray photon interactions was identified. This enabled a tripling of the spatial resolution of the detector to 6.71 ± 0.04 μm. By calculating the total charge deposited by this interaction, an energy resolution of 61.2 ± 0.1% at 17 keV was obtained. When combined with propagation-based phase contrast imaging and phase retrieval, a signal-to-noise ratio of up to 15 ± 3 was achieved for an X-ray fluence of less than 3 photons/mm².

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1. Introduction

Modern X-ray imaging is based on the attenuation and refraction of an X-ray wavefield as it propagates through a material, together with the detection of the resulting intensity distributions. An ideal X-ray imaging detector would be low cost, efficient, and have high spatial and energy resolution. This paper focuses on strategies for interpreting the information provided by the detection system, applying these towards improvements in spatial resolution, dose efficiency, and energy resolution. Specifically, we present an experimental method and a post-processing algorithm to achieve accurate, single-photon localization on an energy-integrating detector (EID). We demonstrate that this can be particularly beneficial for phase contrast X-ray microscopy.

To establish context, we first briefly outline the two main categories of digital detector available for X-ray imaging, namely EIDs (Sec. 1.1), and photon-counting detectors (PCDs, Sec. 1.2). We then very briefly review some fundamentals of X-ray phase contrast imaging (Sec. 1.3), together with techniques for photon-counting using EIDs (Sec. 1.4). Finally, in Sec. 1.5 we outline the specific contributions of the present paper.

1.1. Energy-integrating detectors and X-ray conversion

A common arrangement for an EID is the coupling of a light-conversion material to a visible-light sensor (Fig. 1). Their relatively low cost and simple design are ideal. Although the choice of sensor is important, the X-ray detection efficiency is dominated by the choice of conversion material [1]. There are many examples of EIDs without a scintillator, but these are typically
less efficient at detecting hard X-rays (>20 keV) unless they are made from materials with high atomic number [1].

![Schematic of a position sensitive X-ray detector](image)

**Fig. 1.** Schematic of a position sensitive X-ray detector, including the light-conversion material coupled to a visible-light sensor (typically CCD or CMOS). Locations where detection efficiency is affected are labeled as: (a) $\eta_{\text{Conversion}}$; (b) $\eta_{\text{Coupling}}$; and (c) $Q_{\text{Sensor}}$ (see text for definitions).

Scintillators (crystalline) and phosphors (amorphous) allow for the detection of X-rays by using the photoelectric and Compton effects to convert high-energy photons into free electrons. De-excitation of these free electrons results in the emission of a number ($N$) of UV-visible light photons. This emission is typically a multi-component, exponentially-decaying function of time, with fast and slow components. Sensors can efficiently convert these emitted photons into charges that can then be read out into an image. For visualizing incident X-rays, the most important properties associated with these X-ray conversion materials are: the proportionality of the scintillator signal to the incident X-ray energy, the conversion efficiency of X-rays to visible light photons, and how rapidly this conversion takes place.

Detector efficiency can be decomposed into four key processes that affect the resultant analog-to-digital (ADC) counts:

$$\eta_{\text{Total}}(E) = \eta_{\text{Stopping power}}(E) \eta_{\text{Conversion}}(E) \eta_{\text{Coupling}} Q_{\text{Sensor}}.$$  

(1)

Here, $\eta_{\text{Stopping power}}$ quantifies the probability that an X-ray photon will interact with the light-conversion material, $\eta_{\text{Conversion}}$ describes the efficiency of the X-ray conversion material as a ratio of the incident X-ray energy, $E_{\text{X-ray}}$, to outgoing visible-light energy, and $\eta_{\text{Coupling}}$ is the efficiency of visible-light transport to the sensor. This conversion is complicated since some interactions do not result in X-ray to UV-visible conversions, such as Auger emission and X-ray fluorescence [2]. As these effects are energy-dependent, $\eta_{\text{Conversion}}(E)$ is a function of energy, $E$, which is typically found to be linear to a good approximation [3]:

$$\eta_{\text{Conversion}}(E) \approx \frac{N_{\text{Photons}}E_g}{E_{\text{X-ray}}}.$$  

(2)

Here, $N_{\text{Photons}}$ is the number of photons emitted, which determines the number of photons detected at the sensor, and $E_g$ is the bandgap energy of the scintillator. Finally, the photoelectric effect converts visible light to electrons on the sensor, which in turn are read out in ADC counts by an analog-to-digital converter, with a conversion rate of $Q_{\text{Sensor}}$.

### 1.2. Photon-counting detectors for X-ray detection

Each pixel in a photon-counting detector has its own circuitry to read out the charge imparted by individual X-ray photons. Upon readout of the accumulated charge, the pulse height is used to verify that (i) it is not electronic noise and (ii) to discriminate the X-ray energy. Such pulse-height analysis is a common PCD feature [4]. PCDs differ from traditional EIDs that instead integrate...
the energy deposition due to incident photons over a set time period [4]. As distinct from EIDs, PCDs have no dark current or read noise and can provide energy resolution [5].

Prototype medical imaging PCDs have been paired with X-ray and computed tomography (CT) systems, showing promise with reported increases in contrast and decreases in noise [6,7]. However, Pourmorteza et al. (2016) reported that the visibility specific to each organ, in X-ray imaging of the human abdomen, had no statistical difference when compared to EIDs when imaging with PCDs [8].

Current PCD technology requires dense electronics as each pixel is typically connected to its own application-specific integrated circuit (ASIC). This limits the number of pixels per unit area, as well as causing issues with heat buildup due to the power requirements of low-noise amplifier electronics. This issue is compounded by the need for fast readout times to avoid pulse pileup [5].

In summary, PCDs have the potential to offer superior images due to their ability to resolve individual photons. Their ability to discriminate energies is ideal for techniques such as energy-discriminating CT [4]. Currently, the disadvantages associated with their design include large pixel sizes (>50 µm [4]), heat buildup, and high cost.

1.3. Phase contrast X-ray imaging

Attenuation and refraction arise from the complex refractive index of a material at a given energy, 
\[ n = 1 - \delta + i\beta \]. The real part, \( \delta \), relates to the refraction, and hence the phase imparted on a wavefield by a material, whereas \( \beta \) describes the attenuation. Conventional X-ray projections rely on differences in the attenuation coefficient, \( \mu(E) \propto \beta(E) \), between materials such as bone and soft tissue. This attenuation of a wavefield, with incident intensity \( I_0 \), is given by integrating through the sample in the direction of X-ray propagation, \( z \), to give the output intensity:

\[ I = I_0 \exp \left[ -\int \mu(E)dz \right]. \quad (3) \]

For soft tissues, and in the absence of contrast agents, X-ray attenuation provides relatively low contrast relative to techniques such as magnetic resonance imaging (MRI) or sonography.

An alternative to attenuation contrast is phase contrast imaging. Phase changes (\( \Delta \phi \)) are imparted on the X-ray wavefield as it passes through a sample of thickness \( T \). For a single material embedded in another, 
\[ \Delta \phi = \frac{2\pi}{\lambda} (\delta_{\text{Material}1} - \delta_{\text{Material}2}) T \] for a wavefield of wavelength \( \lambda \). These phase variations affect the intensity as described by the transport-of-intensity equation [9]:

\[ -k \frac{\partial I(x,y,z)}{\partial z} = \nabla_\perp \cdot [I(x,y,z)\nabla_\perp \phi(x,y,z)] , \quad (4) \]

where \( \nabla_\perp \) is the 2D gradient in the \( xy \) plane perpendicular to the optical axis, \( z \).

In recent decades, multiple phase contrast techniques have been developed that show that phase effects can provide much stronger contrast than attenuation alone [4]. For example, in propagation-based phase contrast imaging, Fresnel diffraction produces fringes at the boundaries between media [10]. Spatial resolution on the order of tens of microns is essential to resolve the fine fringes. Moreover, detection and subsequent utilization of the information encoded in these fringes can enable the radiation dose to be kept very low [11].

1.4. Photon-counting techniques using EIDs

Early work by Lumb & Holland (1988) showed that CCDs can successfully be used to isolate individual photon signals from background noise with up to 99.9% efficiency and with high energy resolution at X-ray energies of a few keV [12]. Gureyev et al. (2001) [13] and Mayo et al. (2002) [14] showed that high resolution phase contrast imaging can be performed using a CCD sensor in photon-counting mode, with clear fringe visibility using soft X-rays. In their work,
direct-detection photon-counting modes were based on the exclusion of events where charge was deposited over multiple pixels. They also achieved an energy resolution of \( \approx 40\% \) via the direct detection of incident X-rays. A challenge faced by these researchers was the low flux required to detect individual photons. Hence, their images exhibited relatively high shot noise despite long exposure times, typically on the order of minutes [14].

Miyata et al. (2006) [15] developed a scintillator-deposited, back-illuminated CCD (SD-BICCD) and showed that sub-pixel resolution can be obtained when using this EID in photon-counting mode. By isolating photon clouds created by X-ray photons and thus locating the centroid of each photon cloud, they increased the effective resolution of a detector employing a CsI(Tl) scintillator. Their detector was cooled to \(-60^\circ\text{C}\) to minimize noise. Natively, their detector had a contrast transfer function (CTF) of \( \approx 0.2 \) at 100 \( \mu\text{m} \). With their charge-cloud analysis, the CTF became \( 0.91 \pm 0.06 \) at 100 \( \mu\text{m} \). With no test object with shorter length scales than 100 \( \mu\text{m} \), an estimate of the final spatial resolution based on the edge profile was 10 \( \pm 3 \) \( \mu\text{m} \). An energy resolution of 28.4\% at 22.1 keV was also achieved when using photon-counting techniques in combination with charge transfer inefficiency (CTI) corrections [15].

Similar charge-cloud-localization techniques are also used for sub-pixel resolution in gaseous detectors (e.g. [16]), solid state energy-integrating detectors (e.g. [17]), and in the visible-light technique of Super Resolution Single-Molecule Localization Microscopy (SMLM) (e.g. [18]). For example, in SMLM, highly sensitive cameras detect single fluorescence photons emitted randomly from excited molecules. Images are then reconstructed by locating the centroids of the photon clouds and then placing the centroid in the nearest pixel. Typically, these locations have higher accuracy than the pixel dimensions and therefore can be placed onto a finer grid, obtaining sub-pixel resolution. There are many algorithms available due to the widespread use of SMLM [19]. Some of the algorithms employed for SMLM are similar to that presented in this paper. These programs are designed for localizing stationary fluorophores with repeated emission and are therefore difficult to use for X-ray data, as explained in Sec. 2.1.

1.5. Outline of this work

The aim of this work is to show photon-counting, energy-resolving X-ray detection capabilities with super-resolution using an EID; with specific focus on improving phase contrast X-ray imaging. This is a similar approach to that taken in the work of Miyata et al. [15]. Whilst they used a custom-designed SD-BICCD cooled to \(-60^\circ\text{C}\), we employed a commercially available scientific-CMOS (sCMOS) detector, at room temperature, coupled via optical fibres to a light-conversion material. sCMOS detectors have much higher frame rates and lower electronic noise than CCD detectors. We developed a robust algorithm to analyze charge depositions (photon clouds) across multiple pixels. Here, we show that combining this technology with phase contrast X-ray imaging enables extremely high resolution imaging with very low radiation dose.

2. Experimental setup and photon cloud localization

The conversion from incident X-ray energy to ADC counts recorded by the sensor is described in Eq. (1). Part of the total efficiency is taken from the efficiency of coupling between the phosphor and the sensor. A fiber-optic coupling element (as described [20]) was chosen over a lens coupling as their efficiency can be up to an order of magnitude larger [20,21]. The transmittance in a tapered fiber-optic system is affected by the ratio of the taper. For these experiments, a 1:1 taper was used, which ideally would have perfect transmittance (100\%) but is often only as high as 80\% due to factors such as imperfect acceptance of light from the phosphor [22]. We employed a Hamamatsu X-ray detector (Model number C11440-52U) with a 10 \( \mu\text{m} \) thick Gadox (\( \text{Gd}_2\text{O}_2\text{S}:\text{Tb}^+ \)) phosphor and a pixel size of 6.5 \( \mu\text{m} \). The sCMOS sensor has an extremely low noise of 2.3 electrons RMS at 30 fps.
Given a system efficient enough to render X-ray interactions visible, we required a sufficiently low number of X-ray interactions in each exposure to isolate individual X-ray interactions. For the results in Secs. 3 and 4 below, 20 ms exposures were used with a low X-ray fluence on the order of 0.01 photons per pixel. Exposure times of 15 ms and 20 ms offered optimum energy resolution, as shown in Sec. 5. Highly coherent synchrotron radiation was used at beamline 20B2 of the SPring-8 synchrotron radiation facility, Japan, for phase contrast imaging experiments. Monochromatic radiation between 17 and 37 keV was used with an energy bandwidth of around $10^{-3}$. These energies were obtained using a double bounce Si(111) monochromator in the Bragg geometry. The photon flux was controlled by tuning the first crystal about the Bragg peak.

2.1. Photon cloud detection

Once low-fluence images were acquired, the next step required the segmentation of the incident photon clouds from the noise in each image. A histogram of the ADC counts across the resultant images did not show any clear peaks. Therefore, there were no obvious threshold levels to enable

![Fig. 2](image-url). The main steps in the algorithm developed to localize X-ray interactions. Starting with an original image (a), a threshold of 10 counts is applied to form the binary image in (b). An open (erosion-dilation) operation is then applied giving (c), where smaller noise structures have been eliminated. Finally, (d) shows the localizations overlaid on the original image. Images were collected at an X-ray energy of 37 keV with an exposure time of 20 ms.
us to isolate photon clouds from the electronic noise. This presented an interesting challenge of devising an algorithm to localize the photon occurrences in an image. This is a similar problem to that encountered in SMLM, where multiple fluorescent emissions from a fluorophore are detected over an extended area and then localized. However, as mentioned in Sec. 1.4, we present an algorithm customized for the low-fluence X-ray data. The main steps are outlined in Fig. 2. First, all images had the average dark current subtracted. The resulting images revealed the desired photon clouds due to individual X-ray photons (see Sec. 1.1). However, also seen are smaller structures due to thermal excitations and read-out noise. A low threshold value, 10% of the maximum ADC, was used to convert this to a binary problem [Fig. 2(b)]. Binary morphological operations were then used to sort the resultant structures by their size and shape. The operation of erosion-dilation (open) was used, with a structuring element of 2 \times 2 found to be optimum. This produced results such as seen in Fig. 2(c), where only the shapes that extend over several pixels remained (i.e. the photon clouds). Finally, we see the center of each binary object (photon cloud) overlaid on the original image in Fig. 2(d). Our code was written in Python, using the SciPy module “ndimage” for morphological operations [23].

The algorithm incorrectly categorized some regions of noisy pixels as photons (false detections) whilst others were indistinguishable from the noise although they could be seen by eye (missed photons). To assess the accuracy and efficiency of our photon identification we used the definitions:

\[
\text{Accuracy} = \frac{N_{\text{Photons found}}}{N_{\text{Photons found}} + N_{\text{False detections}}}, \quad \text{Efficiency} = \frac{N_{\text{Photons found}}}{N_{\text{Photons found}} + N_{\text{Missed photons}}}. \tag{5}
\]

After testing five regions (100 \times 100 pixels) using this algorithm, an efficiency of 89 \pm 2\% and an accuracy of 99 \pm 1\% were obtained. False detections and missed photons were verified by human observation.

3. Super-resolution via photon cloud localization

Integrating detectors traditionally record a signal that is the convolution of the original stimulus with the point-spread function (PSF) of the system, which reduces the spatial resolution of the system. The dominant contributors to the PSF are the angular spread of visible light from the phosphor, the spread of charge at the sensor, and the penumbral blurring due to the finite source size. However, the centroids of each photon cloud can be calculated to length scales smaller than the pixel size. Localizing the centroids of photon clouds will, in principle, remove blurring caused by all of these sources except for penumbral blurring, thereby significantly increasing the spatial resolution. In hutch 3 of SPring-8 beamline BL20B2, the penumbral blurring effect is approximately a few microns, due partly to the finite source size, finite object-to-detector distance, and vibration of the monochromator crystals.

Each photon cloud can be well approximated by a 2D Gaussian function since there should not be any asymmetry in the point spread function of the chosen detector. To determine the centroids of each photon cloud, we applied least-squares fitting for each cloud with a 2D Gaussian with peak intensity \(I_0\), width \(\sigma\), and centroid co-ordinates \((x_0, y_0)\):

\[
I(x, y) = I_0 \exp \left[ -\left( \frac{(x - x_0)^2}{2\sigma^2} + \frac{(y - y_0)^2}{2\sigma^2} \right) \right]. \tag{6}
\]

With centroid co-ordinates obtained for each localization, we placed a single count per photon, fitted into the nearest whole pixel of the same size as the original image. To set up finer grids, we divided up the original grid by a magnification factor \(m\) for each axis, up to a limit where the uncertainty in locating the photon cloud center \((\xi_{x_0, y_0} = \sqrt{\xi_{x_0}^2 + \xi_{y_0}^2})\) is larger than \(1/m\) pixels. When constructing images, the mean signal \((\mu_{\text{signal}})\) must be taken into account as it will be
reduced by a factor of $m^2$. With these considerations, images with each axis magnified up to $m = 4$ were constructed. To construct an image, the morphological and curve-fitting operations must be applied to many low X-ray fluence images (on the order of $10^3$). Our full Python algorithm is freely available online [24].

For our experiment, we used an exposure time of 20 ms per frame, with a similar readout time. Figure 3 shows a conventional (high fluence) energy-integrated image [Fig. 3(a)] and photon-counted images [Figs. 3(b) and 3(c)], with Fig. 3(c) having each axis magnified by a factor of 4. The images show the boundary of a 250 µm thick tungsten plate. An immediate observation is the difference in the boundary sharpness, which will be discussed below. Also observed is a difference in signal-to-noise ratio (SNR) between Figs. 3(a) and 3(b), which will be discussed in Sec. 4.

![Fig. 3. Tungsten edge imaged at 37 keV in (a) energy-integrating mode and (b) photon-counting mode, reconstructed using the method outlined in Sec. 2.1, with the grid size the same as the original image ($m = 1$). (c) Photon-counting data with the grid size upsampled by $m = 4$. It can be seen that as the pixel size decreases, and the resolution increases, there are fewer photons per pixel so the relative photon noise increases. All image palettes are scaled individually for ease of viewing. Quantitative profiles are provided in Fig. 4.](image)

An alternative method of suppressing the effect of the detector PSF is by deconvolving the image collected in integration mode using a measured PSF. However, accurately measuring the PSF is not easy and is sensitive to image noise [1]. Deconvolution can be performed as a Fourier-space operation. Modeling the PSF as a Gaussian for example, its Fourier transform will be Gaussian with reciprocal width. Deconvolution then amplifies signals at high spatial frequencies. Although this will sharpen the image, it also amplifies high-frequency noise. Conversely, use of the centroid-fitting method performed here will not amplify noise but will reduce the width of the effective point spread function. To test this, we measured the edge-spread function (ESF) of the 250 µm thick tungsten blade in Fig. 3. Figure 4(a) shows ESFs for the energy-integrating (EI) and photon-counting (PC) image reconstructions with $m = 1, 2, 3, 4$, where $m = 4$ reduces the effective pixel size from 6.5 µm to 1.6 µm. Note an increase in the sharpness of the interface between the EI and PC data, and a continued increase in sharpness with higher PC magnifications; although there is not a considerable improvement between $m = 3$ and $m = 4$. This coincides with the mean signal being spread over $m^2$ pixels, thus increasing noise with increasing magnification (see Fig. 3).

The one-dimensional derivative of the ESF ($\partial I/\partial x$) gives the one-dimensional PSF [see Fig. 4(b)]. Upon fitting these PSFs with a Pearson VII function [25] (typically used for PSF fitting [20]), we can determine the full width half maximum (FWHM) of each PSF. Figure 4(c) shows the decreases in the width of the PSF as we go from energy-resolving to photon-counting with $m = 4$. We have increased the spatial resolution of the system, with the PSF FWHM decreasing from $21.2 \pm 0.2$ µm with energy-integration detection to $6.71 \pm 0.04$ µm with photon counting.
Fig. 4. (a) Row-averaged edge-spread functions of the tungsten blade in Fig. 3. Energy-integrating image and photon-counting image reconstructions with axis magnification $m = 1, 2, 3, 4$ are shown. (b) Point-spread functions computed from (a). (c) FWHMs of point spread functions as a function of $m$, as well as the energy-integrating image (EI) PSF. Error bars reduce in (c) as we increase the number of pixel ‘bins’ to deposit a count.

Hence, the maximum resolution is approximately equal to the pixel size in our case, with possible improvements potentially limited by penumbral blurring and curve fitting accuracy.

The slightly lower contrast in the energy-integrating data [Fig. 4(a)] results from the broad PSF tails [Fig. 4(b)]. The energy-integrating PSF shows non-zero counts arising hundreds of pixels away from the tungsten edge, which most likely results from scattering of visible light within the detector. This can seriously affect quantitative imaging as each pixel can be contaminated with signals emanating from across the entire field-of-view. Photon localization prevents this problem. The photon-counting results in Fig. 4(a) also show a slight increase in counts adjacent to the tungsten edge that is not seen in the EI profile. This effect may result from forward scattering from the tungsten edge, which is lost in the EI data as a result of blurring by the PSF.

4. Low-fluence X-ray image quality

Like most imaging detectors, sCMOS cameras produce images that contain dark current and read noise. Dark current is associated with the random liberation of electrons due to thermal energy, with standard deviation, $\sigma_{\text{Dark}}$. Read-out noise is added to the signal as electrons in each pixel well are read out and converted to ADC counts with standard deviation, $\sigma_{\text{Read}}$. Detection of the electromagnetic radiation results in noise with a Poisson distribution, $\sigma_{\text{Poisson}}$. The standard deviation of the total noise, $\sigma_{\text{Total}}$, is proportional to the sum in quadrature of these three uncorrelated noise sources [26]:

$$\sigma_{\text{Total}}^2 = \sigma_{\text{Poisson}}^2 + \sigma_{\text{Dark}}^2 + \sigma_{\text{Read}}^2.$$  

For an indirect detector (i.e., one that converts X-ray to visible light before detection via a phosphor or scintillator), $\sigma_{\text{Poisson}}$ will be comprised of noise sources from each of the photon conversion, coupling and collection stages [see Eq. (11) in [22]]. Photon counting eliminates both the dark current and read noise. At low radiation doses, these can be the dominant sources of noise. Hence eliminating the detector noise via photon counting is important for low dose imaging applications.

A high SNR is desirable for both qualitative and quantitative image analysis. SNR is defined by the ratio of the mean of the signal, $\mu_{\text{Signal}}$, to the standard deviation of the total noise:

$$\text{SNR} = \frac{\mu_{\text{Signal}}}{\sigma_{\text{Total}}}.$$  

Rose [1] demonstrated that if an SNR is 5 or greater then the object will be conspicuous.
Poisson noise is present whenever a system detects $N$ quanta and increases as $\sigma_{\text{Poisson}} = \sqrt{N}$. Given a signal consisting of $N$ quanta, we represent Eq. (8) as $\text{SNR} = \frac{N}{\sqrt{N}} = \sqrt{N}$ [1]. Hence, increasing $N$ will improve the SNR. We can acquire a limited number of photons in a single image, since incident photon clouds will gradually overlap as we increase the source flux, thereby losing the ability to localize the position of each on the detector. Therefore, the addition of multiple images (on the order of thousands) with a low fluence of $\approx 10^3$ photons in a captured $2048 \times 2048$ frame ($\approx 2$ photons in a $10 \times 10$ pixels region of interest) was the chosen method.

To directly compare the photon fluence (photons/µm$^2$) between the PC and EI modes at 37 keV, the EI ADC counts were divided by the average number of counts measured for 37 keV photon clouds ($\text{ADC}_{\text{Total}}$). Figures 5(a) and 5(b) show phase contrast X-ray images of a polymethyl methacrylate (PMMA) cylinder using PC and EI, respectively, at similar radiation exposures. Despite having almost identical photon statistics, we note the significantly higher noise in the PC image despite having removed the electronic noise. This is because the detector PSF has acted as a blurring function and smoothed the Poisson noise in the energy-integrating image.

Fig. 5. Panels (a) and (b) show images of a PMMA rod from photon-counting ($m = 1$) and energy-integrating modes, respectively. The X-ray energy was 37 keV and the object-to-detector distance was 0.65 m. The aggregate X-ray photon-counting image fluence was $20.7 \pm 0.3$ photons/pixel, whilst that of the energy-integrating image was $19.2 \pm 0.2$ photons/pixel. The yellow boxes indicate the location of the line profiles in (c), where we observe phase contrast fringes at the edges of a PMMA rod, averaged over 140 pixel columns to reduce noise. The SNR versus the aggregate photons per pixel for each reconstruction is shown in (d) (PC) and (e) (EI), with the black curve indicating the expected Poisson curve for the given number of photons. This SNR was calculated for a region of air, indicated by the red boxes in (a) and (b).
Adding multiple PC or EI images together increases the aggregate photons per pixel. This allows us to plot the SNR for a region of air (indicated by red boxes) as a function of X-ray fluence to see how each method compares to each other and to pure Poisson statistics. The photon counting plot [Fig. 5(d)] fits well to the Poisson curve, fitting it to the form $\text{SNR} = f^n$, where $f$ is the X-ray fluence in photons/µm$^2$. We find that $n = 0.46 \pm 0.02$ which is slightly less than $n_{\text{Poisson}} = 0.5$. This could be due to both the accuracy of the localization algorithm being less than 100%, as well as defects in the detector adding structural noise. The corresponding plot for energy-integrating images is shown in Fig. 5(e). In energy integration, we do not measure counts of quanta $N$, so we would not expect adherence to a curve given by pure Poisson statistics. However, we observe an SNR well above that predicted by pure Poisson statistics (black line).

Fig. 6. Panels (a) and (b) show the result of applying phase retrieval to propagation based phase contrast images of Fig. 5 using Eq. (9). (a) (PC) and (b) (EI). (c) Resultant SNR as a function of X-ray fluence for a region of PMMA (red boxes) after phase retrieval, for both photon-counting and energy-integrating images. (d) Factor by which SNR has increased upon using the phase retrieval algorithm of Paganin et al. [28], when compared to that without phase retrieval (SNR gain), as a function of X-ray fluence. Also shown is the average SNR gain for both PC and EI data.
This shows a clear trade-off between spatial resolution and noise, as discussed by Gureyev et al. [27].

In Fig. 5, we see how phase gradients in the X-ray wavefield manifest as interference fringes between media because of the highly spatially coherent source and large object-to-detector distances used in these experiments. This can be seen at the PMMA–air interface line profiles in Fig. 5(c). The phase contrast fringes increase the visibility of the object. Phase retrieval algorithms can be used to recover the attenuation contrast image or the projected thickness of the materials in the object. The algorithm of Paganin et al. [28], and extensions thereof [29,30], provide a highly noise robust solution [31] using:

\[ I(x, y, z = 0) = \mathcal{F}^{-1}\left[ \frac{\mathcal{F}[I(x, y, z = z_0)]/I_0}{1 + z_0(\delta/\mu)(k_x^2 + k_y^2)} \right]. \] (9)

Here, \( \mathcal{F} \) denotes Fourier transformation with respect to \( x \) and \( y \), \( \mathcal{F}^{-1} \) denotes the corresponding inverse Fourier transformation, \( (k_x, k_y) \) are Fourier coordinates corresponding to \( (x, y) \), and \( z_0 \) is the object-to-detector distance needed for propagation-based phase contrast to develop.

Equation (9) filters an image \( I(x, y, z_0) \) in Fourier space using a mask scaled by components of a material’s complex refractive index (\( \delta \) and \( \mu \)) and propagation distance, \( z_0 \).

This filter’s noise suppression properties have been shown to provide significant gain in SNR [11,28–33]. Using \( \delta \) and \( \mu \) values for PMMA at 37 keV, obtained from the NIST database [34], phase retrieval was applied to each X-ray image for both photon-counting and energy-integrating data-sets [see Figs. 6(a) and 6(b)]. Visually, we see large SNR increases compared to Fig. 5. Figure 6(c) shows SNR as a function of X-ray fluence for a region of PMMA (red box) that has near-constant intensity after phase retrieval has been applied. Smoothing by the phase retrieval algorithm strongly increases the SNR for the PC images, even at low X-ray fluence. Conversely, the SNR is less affected in the EI images since the PSF has already smoothed much noise. The gain in SNR is roughly four times higher with photon-counting images than with energy integration [see Fig. 6(d)]. At a fluence of just 0.12 ± 0.01 photons/pixel, an SNR of 15 ± 3 is achieved. This is a significant result for low dose X-ray imaging in terms of the previously mentioned Rose criterion [35].

5. Energy resolution

As discussed in Sec. 1.1, the total ADC counts resultant from a single incident X-ray increases as its energy increases, with relevant conversion efficiencies \( \eta_{Conversion}(E) \), \( \eta_{Coupling} \) and \( \eta_{Sensor} \). Distributions of the total ADC counts (ADC\text{Total}) from X-ray interactions at several energies can be plotted to determine properties of energy efficiency and energy resolution. We do this by analyzing large data sets containing the fitting parameters of >100,000 resultant photon clouds for energies 17, 22, 27 and 32 keV, with a fixed exposure time of 20 ms for all. ADC\text{Total} is calculated from the sum of ADC counts inside the incident photon cloud region (7 × 7 pixels). This was chosen over integration using the Gaussian fitting parameters of the photon cloud since the low number of pixels per photon cloud (fitting points) makes it difficult to accurately fit the tails of the photon cloud. Figure 7(a) shows the distributions of ADC counts for the energies stated above. We see an increase in the mean ADC\text{Total} (\overline{ADC\text{Total}}) per photon cloud with increasing energy, as predicted by Eq. (1). To determine the total efficiency \( \eta_{Total}(E) \) we write:

\[ \overline{ADC\text{Total}} = E_{X-ray}\eta_{Total}(E). \] (10)

Equation (10) allows us to track \( \eta_{Total}(E) \) as a function of \( E \). This trend is shown in Fig. 7(c), where we observe a decrease in \( \eta_{Total}(E) \) with increasing energy. Between the energies of 17 and 32 keV, a decrease of 16 % ± 2 % is observed. This can be explained by the average interaction
Fig. 7. (a) Normalized ADC<sub>Total</sub> distributions for incident X-ray energies of 17, 22, 27 and 32 keV. (b) Energy resolutions given by Eq. (11), where lower values indicates better energy resolution. (c) Efficiency for each distribution. Exposure time for a single image was 20 ms. (d) Energy resolution as a function of exposure time for an X-ray energy of 37 keV. Error bars in (b) and (c) are smaller than the symbols.

Depth between an X-ray photon and the scintillator increasing with energy. This, in turn, affects the number of emitted visible-light photons and hence the efficiency [36], as per Eq. (2). Over small energy ranges, we may ignore the energy dependence of $\eta_{\text{Total}}(E)$. We can then approximate the energy resolution as

$$\frac{\Delta E}{E} = \frac{\Delta \text{ADC}_{\text{Total}}}{\text{ADC}_{\text{Total}}}.$$  (11)

Here, $\text{ADC}_{\text{Total}}$ is the mean and $\Delta \text{ADC}_{\text{Total}}$ is the FWHM, for a distribution of ADC<sub>Total</sub> in a single data set. Figure 7(b) shows the measured energy resolution as a function of X-ray energy.

The distributions in Fig. 7(a) contain small, secondary peaks for ADC<sub>Total</sub>&lt;60. A likely explanation is that these ADC<sub>Total</sub> values are sourced from noise being included within image reconstructions. As mentioned in Sec. 2.1, the localization algorithm has an accuracy of (99±1)%.

By integrating from 0&lt;ADC<sub>Total</sub>&lt;60 to obtain the number of photons (data points) in the side hump and overall photons in the distribution, we can calculate to see if $A_{<60}/A_{\text{Total}} \approx (1 \pm 1)\%$. 

For the distributions in Fig. 7(a), this ratio equates to $(2 \pm 1)\%$, which falls within uncertainties. This indicates that some of the noise is being fitted and incorporated into the images. The advantage to this information is that, although the algorithm presented in Sec. 2.1 does have $1 \pm 1\%$ false detection rate, energy distribution plots can be used to easily identify the photon clouds that are in fact noise and filter the data points that do not meet a minimum ADC$_{\text{Total}}$.

The Gadox phosphor employed here has a primary decay time of $\approx 1$ ms and long decay components that cause an afterglow of $\approx 1\%$ at 3 ms [37]. This compares with typical exposure times used in scientific X-ray imaging. Therefore, we would not expect to see a uniform ADC$_{\text{Total}}$ for each resultant photon cloud as a function of exposure time, and this is potentially a significant contributor to the breadth observed in the distributions in Fig. 7(a), together with the associated poor energy resolution. By again using Eq. (11) to calculate energy resolution given the ADC$_{\text{Total}}$ and FWHM ($\Delta$ADC$_{\text{Total}}$), for data sets of varying exposure time, we obtain Fig. 7(d). Here, we see the energy resolution differ on the order of one percent, with an optimum in the region of 10-20 ms. However, since the difference is quite small, exposure times below the optimum, such as 5 ms or less, will not significantly impact energy resolution. This would allow for faster acquisition times, for which sCMOS sensors are well-suited. Development of scintillation materials with faster decays, such as Siemens ultra-fast ceramic (UFC) [38], could also decrease acquisition time. This is an important point concerning future work on our photon-counting method, as it could eliminate its major drawback of relatively long total acquisition time.

Recent developments in high frame rate, direct conversion CMOS sensors (see [39–41]) could significantly increase the sensitivity to individual photons and enable higher throughput imaging with better energy resolution than we have shown here. Such advances could therefore greatly increase the number of applications of the developments presented herein.

6. Conclusion

We demonstrated the ability of an sCMOS detector to operate as a photon-counting detector with super-resolution, energy resolving capabilities, and high SNR achievable when combined with phase contrast X-ray imaging. Utilizing low-fluence X-ray radiation and short exposure times, resultant photon clouds from individual X-ray interactions were localized on a fiber-optic-coupled sCMOS detector using a Gadox phosphor. A robust localization algorithm with an accuracy of $(99 \pm 1)\%$ was outlined for localizing and constructing images from such data. Python code implementing this algorithm is available online [24]. The immediate application of this method is to reducing the PSF width of X-ray imaging systems. After applying this process, we improved the spatial resolution of the system studied from $21.2 \pm 0.2 \, \mu\text{m}$ to $6.71 \pm 0.04 \, \mu\text{m}$. While on the order of $10^3$ frames were required to produce a single resultant projection, there will be many X-ray imaging applications where super-resolution at or below the micron scale is valued above temporal resolution. One such example would be large field-of-view microscopy. Removal of the detector-associated PSF is also seen to prevent the effect of counts bleeding across the sensor. This increases contrast and is important for experiments requiring a consistent and quantitative spatially-independent detector response. By tracking SNR as a function of X-ray fluence, it was found that the reduction in the width of the effective PSF increased the Poisson noise in the image. However, phase-retrieval methods reduced this Poisson noise significantly, achieving an SNR of $15 \pm 3$ at only $2.7 \pm 0.2$ photons mm$^{-2}$. A limitation of this work was the relatively long exposure times of the order of tens of seconds and the minimum energy resolution of $61.2\% \pm 0.1\%$ at 17 keV. Continuing advances in energy-integrating detector technology are expected to significantly reduce these limitations in future studies and increase the applicability of our findings.
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Disclosures
The authors declare no conflicts of interest.

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