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To cite this article: Mats Persson et al 2014 Phys. Med. Biol. 59 6709

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Energy-resolved CT imaging with a photon-counting silicon-strip detector

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Received 29 April 2014, revised 27 August 2014
Accepted for publication 3 September 2014
Published 20 October 2014

Abstract
Photon-counting detectors are promising candidates for use in the next generation of x-ray computed tomography (CT) scanners. Among the foreseen benefits are higher spatial resolution, better trade-off between noise and dose and energy discriminating capabilities.

Silicon is an attractive detector material because of its low cost, mature manufacturing process and high hole mobility. However, it is sometimes overlooked for CT applications because of its low absorption efficiency and high fraction of Compton scatter. The purpose of this work is to demonstrate that silicon is a feasible material for CT detectors by showing energy-resolved CT images acquired with an 80 kVp x-ray tube spectrum using a photon-counting silicon-strip detector with eight energy thresholds developed in our group.

We use a single detector module, consisting of a linear array of 50 0.5 × 0.4 mm detector elements, to image a phantom in a table-top lab setup. The phantom consists of a plastic cylinder with circular inserts containing water, fat and aqueous solutions of calcium, iodine and gadolinium, in different concentrations.

By using basis material decomposition we obtain water, calcium, iodine and gadolinium basis images and demonstrate that these basis images can be used to separate the different materials in the inserts. We also show results showing that the detector has potential for quantitative measurements of substance concentrations.

Keywords: photon counting, spectral CT, material decomposition, silicon-strip detector

(Some figures may appear in colour only in the online journal)
1. Introduction

Photon-counting detectors are attracting attention for use in the next generation of x-ray computed tomography (CT) scanners, promising several advantages over conventional energy integrating detectors such as better trade-off between noise and dose, improved spatial resolution and spectral imaging capabilities. In contrast to the dual energy CT systems commercially available today, dual source and kVp switching, photon-counting spectral CT eliminates the risk of misregistration due to patient motion between the energy images and can achieve very good spectral separation between the images without requiring heavy prefiltration. Also, using more than two energy levels with good energy separation is expected to be possible using photon-counting detectors whereas this is hard to achieve with multi-source or kVp switching systems. This enables new applications such as K-edge imaging, where the K-edge discontinuity of the attenuation curve of a high atomic number contrast agent, e.g. iodine or gadolinium, is used to separate out that contrast agent and measure its concentration in the image.

The most promising sensor materials for photon-counting medical x-ray detectors are cadmium telluride (CdTe), cadmium zinc telluride (CZT) and silicon. Since CT uses high x-ray energies (up to 140 keV) compared to other x-ray imaging modalities, most detector development projects for photon counting CT focus on the pixellated detectors made of CdTe and CZT, which are high-Z materials and therefore have high absorption efficiency at these energies (Shikhaliev 2008, Szeles et al 2008, Iwanczyk et al 2009, Overdick et al 2009, Kappler et al 2010, Taguchi and Iwanczyk 2013). However, these materials are expensive to manufacture and have several drawbacks. They have low charge carrier mobility, which causes problems at high count rates, when a second photon may arrive before the charge deposited by the first one has had time to be collected. This phenomenon is called pileup and it leads to lost counts and degraded energy resolution. Simulation studies of pileup have been made by Wang et al (2011) and Taguchi et al (2010). CdTe and CZT also suffer from charge trapping, meaning that charge carriers are trapped in lattice defects or impurities in the sensor material. This leads to incomplete charge collection and, more importantly, the trapped holes cause a buildup of positive charge in the sensor which can become large enough to counteract the external electric field and destroy the charge collection. This effect, which is called polarisation, causes the detected count rate to drop rapidly when the photon flux reaches above a certain level (Bale and Szeles 2008).

Another detrimental effect in CdTe/CZT is the high probability of K-fluorescence. The K-shell characteristic photons which may be emitted when a primary x-ray photon is photoabsorbed can travel far enough to deposit their energy in neighboring pixels, especially if the pixels have submillimeter size, thereby causing double counting (Shikhaliev et al 2009, Xu et al 2011).

Silicon, on the other hand, has a mature manufacturing process and is comparatively cheap. It has higher charge carrier mobility than CdTe/CZT, meaning that it can handle higher x-ray fluxes without suffering from pileup and it does not suffer from the problems with polarisation and K-escape. On the other hand, silicon has limitations that CdTe/CZT does not have. Because of its low atomic number, the absorption efficiency of silicon is low and the sensors must accordingly be very thick. A few centimeters of silicon is required to detect most of the incident photons, whereas only a few millimetres of CdTe/CZT are needed. Furthermore, the low atomic number means that a large fraction of the incident photons are Compton scattered instead of photoabsorbed, meaning that they deposit a small amount of energy in the original interaction location and move on in a different direction. They may then either leave the sensor volume or interact again at other locations, one or more times. The Compton interactions degrade the energy resolution since they do not supply much information about the energy of
the original photon and the secondary interactions of scattered photons cause double counting and loss of spatial resolution.

An effect that degrades the performance of both silicon and CdTe/CZT detectors is charge sharing. This happens in a pixellated detector when the deposited charge cloud from an interaction grows large enough while drifting through the sensor that it is registered in two or more neighboring pixels. This causes double counting and energy resolution degradation. The problem can be mitigated by including anticoincidence logic in the readout electronics, such as in the Medipix3 chip where the collected charge in several neighboring pixels is summed and registered in the pixel that received the largest amount of charge (Ballabriga et al 2013, Koenig et al 2013).

Various methods have been proposed to correct for count rate loss and spectral distortion caused by pileup, charge sharing and the other effects described above. Ding and Molloi (2012) and Cammin et al (2012) used measurements through slabs of attenuating materials with different thicknesses to calculate correction factors whereas Rink et al (2013) made calibration measurements by varying the x-ray tube current. However, any detector imperfections which cause some counts to be lost or leads to some photons being counted more than once leads to noisier measurements, and noise (in contrast to systematic errors) cannot be removed by corrections after the acquisition.

We are developing an energy-resolving photon-counting silicon-strip detector with eight energy bins for x-ray computed tomography (Bornefalk and Danielsson 2010, Xu et al 2013a, Liu et al 2014). To get a sufficiently large absorption path length, our detector is fabricated as a stack of flat modules, each module oriented with its edge pointing towards the x-ray source (figure 1). To reduce the count rate in each individual readout channel, each strip is subdivided into 16 depth segments. The diode array is made on a single silicon substrate, with nothing else than the electric field lines in the silicon separating the detector elements from each other.
so charge sharing may occur between neighboring strips and, to a lesser extent, between different depth segments in one strip. However, since charge cannot be shared between different wafers, charge sharing only blurs the image in one direction, whereas it would give two-dimensional blurring in a 2D pixellated detector.

We have previously published measurements on the detector demonstrating count rate linearity up to very high fluence rate, with only 1% lost counts at an incident photon fluence rate of 300 Mcps mm\(^{-2}\) (Xu et al 2013b), an RMS energy resolution for monochromatic radiation in the low fluence rate limit varying from 1.5 keV for 40 keV photons to 1.9 keV for 100 keV photons (Liu et al 2014) and a temperature stability of 0.1 keV threshold offset per K at 30 keV (Bornefalk et al 2013). The purpose of the present work is to demonstrate the feasibility of using this detector for spectral CT imaging by presenting material selective images acquired with a single detector module in a table-top laboratory setup. Because of space constraints in the current setup, the objects imaged here are around 10 cm in diameter, which is smaller than an adult human but a realistic size for some pediatric applications.

Spectral CT enables material selective imaging using a procedure called basis material decomposition (Alvarez and Macovski 1976) where the energy-dependent linear attenuation coefficient in each voxel of the reconstructed image is expressed as a linear combination of the linear attenuation coefficients of a number of predefined basis materials. For substances containing only low atomic numbers, such as human tissues, two basis materials are enough to a good approximation (Alvarez and Macovski 1976). If the imaged volume contains an element heavy enough to have a K-absorption edge in the energy range used in CT examinations, then that material must be added as a third basis function. K-edge imaging, i.e. basis material decomposition with a heavy element contrast agent such as iodine or gadolinium, can therefore be used to generate an image containing only the contrast agent.

Basis material decomposition can be done either in projection space or in image space. In projection-space basis material decomposition, the transmitted energy spectrum in each projection line is used to estimate the thicknesses of the different basis materials which the projection line has passed. The resulting basis projections are then taken as input to the reconstruction algorithm and one image per basis material is reconstructed. This method was introduced by Alvarez and Macovski (1976) and has been applied successfully to photon counting CT (Roessl and Proksa 2007, Schlomka et al 2008). In theory this method allows complete elimination of beam hardening artefacts, but it requires detailed knowledge of the x-ray tube spectrum and the detector characteristics (Bornefalk et al 2014). In image-space basis material decomposition, one image per energy bin is first reconstructed and the material composition of each reconstructed voxel is then estimated from the corresponding voxel value in the different bin images (Firsching et al 2006, Ronaldson et al 2012). In this work, we use image-space decomposition since the detailed calibration schemes necessary for projection-space decomposition are still under development.

2. Materials and methods

The detector module developed in our group consists of a diode array on a 0.5 mm thick silicon substrate (figure 1). The module is oriented with its edge directed towards the x-ray beam which gives the large absorption path length of 30 mm. One module contains 50 strips constituting the detector elements, each with a cross-section of 0.5 × 0.4 mm transverse to the beam direction. The readout electronics are contained in five application specific integrated circuits (ASICs), handling 160 readout channels each, which are bonded directly to the silicon substrate. The ASICs amplify and shape the current pulses from the diode array
and register each pulse in one of eight energy bins by comparing it with eight electronic
treshold levels. The bins are double-sided, i.e. the ASIC registers the photons with pulse
height between two neighboring thresholds in one bin. Detailed descriptions and charac-
terisation of the ASIC and diode array can be found in earlier publications (Xu et al 2013a,

Although the measurements presented here were made with a single detector module, we
will briefly describe how a full detector can be constructed from these modules. To obtain a
full CT detector, a large number (1500–2000) of detector modules must be stacked on top of
each other. To enable cooling and to give room for readout electronics, the stacking is made
in two different layers, one closer to and one further away from the x-ray source. In this way,
a fill factor of 100% can be achieved, meaning that there are no holes in the detector array
where x rays from the source can pass through. In practice, however, it is probably optimal to
put tungsten sheets between the modules for scatter rejection, giving a fill factor between 95%
and 100%.

2.1. Data acquisition

We used a single detector module to image a phantom consisting of a PMMA cylinder, 90 mm
in diameter, with five cylindrical inserts consisting of polystyrene containers filled with dif-
f erent substances (figure 2). The phantom was mounted on rotation and translation stages and
illuminated with radiation from an x-ray tube (MXR-160HP/11, Comet Switzerland, Flamatt,
Switzerland). The source-to-isocenter distance was 45 cm and the source-to-detector distance
was approximately 95 cm. Since the detector module was too small to cover the entire field of
view, the phantom was translated in 11 steps through the field of view with a translation step
of 9.3 mm in between, corresponding to the width of 49 detector strips (19.6 mm) divided by
the magnification factor 2.1. See figure 3. Choosing a step of 49 pixel strips instead of 50 gave
slightly overlapping projection measurements so that gaps in the data were avoided. Even
though 180° would have been enough to get complete data, the phantom was rotated 360° at
each translation step in order to suppress artefacts (misalignment artefacts and ring artefacts
from channel inhomogeneity) by averaging the image over two half-rotations.
The tube voltage was set to 80 kV, the focal spot size to 1 mm and the tube current to 4 mA. No bowtie filter was used but the beam was filtered through a 2 mm thick flat Al filter in addition to the 0.8 mm Be inherent in the x-ray tube. To reduce scatter from the imaged object, a 2 cm wide and 3 mm high postcollimator slit was placed between the object and the detector. The rotation stage was rotating continuously during the acquisition and the rotation angle for each sample was measured using a rotary encoder triggered by a signal from the detector every time a sample was measured. 7601 angular samples were acquired for each translation position, covering 360°. Each of these was measured during 4.7 ms which gives an exposure time of 35.6 s and a current-time product of 4 mA· 35.6 s = 143 mAs for the irradiation that contributed to the image, although the actual dose to the phantom was higher in this experiment since no precollimator was used and since the object was exposed to x-rays during waiting time between the samples. Also note that the slight overlap between the translation positions increases the dose by a factor 50/49 = 1.02.

The energy thresholds were spread out in the range of x-ray energies used so that no energy bin would be close to photon starved, but they were not optimised in any other way. In practice, the thresholds are defined by setting comparator voltages, listed in Table 1, in the ASIC. The eight energy thresholds in keV can be calculated from these by using the

\[
T = \frac{U}{g} - m + \sqrt{\frac{\sigma_m^2}{g^2} + \frac{\sigma_g^2}{g^2} + 2\sigma_m\sigma_g}{\sigma_g}^{2} \]

where \(\sigma_m\) and \(\sigma_g\) are the standard deviations of \(m\) and \(g\) (not listed).

**Table 1.** Comparator voltages \(U\) and the corresponding energy thresholds \(T\) in keV, as well as the measured offset \(m\) and gain \(g\), measured on another detector module sample, which are used to calculate \(T\) from \(U\) for each threshold. Also given are the standard deviations of \(m\) and \(g\) and the resulting uncertainty in \(T\), calculated by error propagation:

\[
\sigma_T = \sqrt{\frac{\sigma_m^2}{g^2} + \frac{\sigma_g^2}{g^2} + 2\sigma_m\sigma_g}{\sigma_g}^{2} \]

\(\sigma_m\) and \(\sigma_g\) are estimated as the averages of the corresponding values of the other thresholds. We do not supply any error estimate for this threshold.

<table>
<thead>
<tr>
<th>Threshold</th>
<th>(U) (mV)</th>
<th>(m) (mV)</th>
<th>(\sigma_m) (mV)</th>
<th>(g) (mV keV(^{-1}))</th>
<th>(\sigma_g) (mV keV(^{-1}))</th>
<th>(T) (keV)</th>
<th>(\sigma_T) (keV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>35</td>
<td>8.3*</td>
<td>—</td>
<td>1.7*</td>
<td>—</td>
<td>16</td>
<td>—</td>
</tr>
<tr>
<td>2</td>
<td>41</td>
<td>3.3</td>
<td>3.7</td>
<td>1.7</td>
<td>0.073</td>
<td>22</td>
<td>2.0</td>
</tr>
<tr>
<td>3</td>
<td>47</td>
<td>7.0</td>
<td>3.8</td>
<td>1.7</td>
<td>0.065</td>
<td>24</td>
<td>2.1</td>
</tr>
<tr>
<td>4</td>
<td>53</td>
<td>6.1</td>
<td>3.4</td>
<td>1.7</td>
<td>0.078</td>
<td>27</td>
<td>2.0</td>
</tr>
<tr>
<td>5</td>
<td>59</td>
<td>7.6</td>
<td>4.1</td>
<td>1.7</td>
<td>0.063</td>
<td>30</td>
<td>2.0</td>
</tr>
<tr>
<td>6</td>
<td>71</td>
<td>9.8</td>
<td>3.2</td>
<td>1.7</td>
<td>0.053</td>
<td>35</td>
<td>1.9</td>
</tr>
<tr>
<td>7</td>
<td>88</td>
<td>13.6</td>
<td>3.0</td>
<td>1.7</td>
<td>0.055</td>
<td>44</td>
<td>1.6</td>
</tr>
<tr>
<td>8</td>
<td>118</td>
<td>10.9</td>
<td>3.4</td>
<td>1.7</td>
<td>0.050</td>
<td>64</td>
<td>2.3</td>
</tr>
</tbody>
</table>

*Note:* the asterisk indicates that no measurement is available for the lowest threshold and the listed \(m\) and \(g\) values are estimated as the averages of the corresponding values of the other thresholds. We do not supply any error estimate for this threshold.
formula $T = (U - m)/g$ where $U$ is the comparator voltage, $m$ is the threshold offset in mV and $g$ is the gain in mV keV$^{-1}$. $g$ and $m$ vary slightly among different detector channels (each channel corresponding to one depth segment of a strip in figure 1) and vary to a larger extent depending on which ASIC the channel is connected to. To find out the threshold levels in keV with high precision, it is therefore necessary to calibrate each channel with a beam containing known energies, e.g. a monochromatic synchrotron beam. We do not have access to such calibration data for the detector module used here but for another, identical module, $g$ and $m$ were measured at a synchrotron for 91 detector channels. This measurement was made in the same way as described by Liu et al (2014) with the differences that beam energies of 40, 80 and 100 keV were used (for the highest threshold, only 80 and 100 keV) and that a linear term in $x$ was added to equation (2) in that publication to improve the curve fitting accuracy. These parameters, if applied to the module used here, give the energy thresholds listed in table 1. Since the 91 channels used to calculate the standard deviations in table 1 are connected to different ASICs and we expect the variation between detector module samples to be similar to the variation between ASICs, $\sigma_T$ in table 1 can be taken as a measure of the uncertainty of the threshold location of the module used in this study.

In order to reduce the level of ring artefacts stemming from the threshold variations in the detector, the detector was calibrated by measuring the transmission through a wedge-shaped calibration phantom made of polyoxymethylene (POM). The wedge was oriented with one vertical side facing the detector and the slanted side facing the x-ray tube, so that the rays from the source to each of the detector elements would measure the same POM thickness (neglecting the small path length difference caused by the fan shape of the beam) and by translating the phantom vertically this thickness was varied between 9.8 mm and 98 mm in 10 steps of 9.8 mm (figure 4). For each thickness, 1200 samples of 4.7 ms each were acquired giving in total 5.6 s exposure time. In addition, an air scan was made with the same parameters. These measurements was used as described in section 2.2.

In order to demonstrate the value of basis material decomposition in a setting closer to the clinical one, we also imaged a meat slice (a lamb chop, including a slice of the spine). First a nonenhanced image was acquired, then approximately 0.4 ml iodinated contrast agent (undiluted Visipaque, 300 mg I ml$^{-1}$, or 2.36 mmol I ml$^{-1}$) was injected into the spinal canal and a second image acquisition was made. In this way, we tried to mimic a CT myelography examination, where iodinated contrast agent is injected into the spinal canal in order to visualise the spinal cord. The imaging procedure was the same as for the PMMA phantom, although this time the detector had to step through 14 positions to get a large enough field of view.
2.2. Signal normalisation and reconstruction

Before further processing, the counts were summed over the 16 depth segments, both in the calibration and image measurements. These 16 depth segments together will be referred to here as a ‘detector element’.

Since the different detector elements have slightly different response, the registered data contains inhomogeneities which would cause ring artefacts in the image if left uncorrected. The calibration data obtained from scans of the wedge-shaped calibration phantom was therefore used to correct the data in order to make the response of different detector elements as similar as possible. Before image reconstruction, each measured count number $N$ should be transformed into a log-normalised projection $p = -\ln(N/N_{\text{air}})$ and by measuring $N_{\text{air}}$ for each detector element individually, one can to some extent avoid that the inhomogeneities in $N$ propagate to inhomogeneities in $p$. However, to further reduce the inhomogeneity between detector elements, we have used a more sophisticated calibration scheme:

(a) For each energy bin $i$ and phantom thickness $j$, including the air scan $j = 0$, an average log-normalised count value was calculated as

$$p_{ij}^{\text{calib,av}} = -\ln\left(\frac{1}{M} \sum_k N_{ijk}^{\text{calib}}\right)$$

where $N_{ijk}^{\text{calib}}$ is the average number of counts per sample interval in the calibration measurement, for energy bin $i$, phantom thickness $j$ and detector element $k$ and where $M$ is the number of detector elements. (Note that this gives $p_{i0}^{\text{calib,av}} = 0$ by definition.)

(b) Then, for each energy bin $i$ and detector element $k$, a relationship

$$\ln N = a_k p^2 + b_k p + c_k$$

was fitted using unweighted least squares to the data points $(N_{ijk}^{\text{calib}}, p_{ij}^{\text{calib,av}})$ for $j = 0, 1, ..., 10$ where $j = 0$ is the air scan.

(c) Finally, the fitted model (2) was used to transform the registered count numbers in the real imaging data to log-normalised count values $p$. More precisely, for each energy bin and $i$ and detector element $k$ and for every sample interval $l$ in the image acquisition, the registered count numbers in that sample interval $N_{ilk}$ was inserted into (2) together with the calibration coefficients $a_k, b_k$ and $c_k$ fitted in the previous step and (2) was solved for $p$, yielding $p_{ilk}$.

This calibration method reduces image inhomogeneities by mapping each count value $N$ to the log-normalised count value $p$ which would have been obtained from the average counts over all detector elements if they had all received the same illumination. The method is similar to the previously described signal-to-thickness calibration method (Persson and Bornefalk 2012) with the difference that the calibration reference here is derived from the average count number over all detector elements instead of thickness measurements of the phantom, which would have had to be done accurately in order not to introduce errors.

To reduce the effects of drift over time, scans of the calibration wedge were made both before and after the image data acquisition and the average of the fitted parameters $a$, $b$ and $c$ over these two measurements were used for the calibration curve. The total time for the image
acquisition and the two calibration scans was 34–40 min, limited by the stage rotation speed and, for the calibration measurements, by data readout speed.

The projection data was rebinned to a parallel-beam geometry using linear interpolation and an exponential average of the projection data from the first and the last half-rotation was calculated as

\[ p_{\text{average}} = -\ln \left( \frac{1}{2} e^{-p_1} + \frac{1}{2} e^{-p_2} \right) \]

where \( p_1 \) and \( p_2 \) are the log-normalised projection values for the same projection line measured in the first 180° and last 180°, respectively. The images were then reconstructed from \( p_{\text{average}} \), separately for each energy bin, using filtered backprojection implemented as \texttt{iradon} in MATLAB (MathWorks, Natick, MA, USA) on a 700 × 700 pixel grid using a Hann filter. In the meat image, where higher resolution was desired, the sinogram was upsampled by a factor 10 in the detector direction using linear interpolation before the reconstruction, which was made on a 7000 × 7000 pixel grid.

Since the calibration method described above does not remove the ring artefacts completely, these were further suppressed by image postprocessing as described in appendix A.

### 2.3. Material decomposition

From the eight reconstructed energy bin images, material-selective images were produced by image-space basis material decomposition, in a similar way as done earlier by Firsching et al. (2006) and Ronaldson et al. (2012). Let \( \mu \) denote the eight-dimensional vector of effective linear attenuation coefficients in each energy bin, i.e. the pixel values in each of the eight reconstructed images, and assume that a number of basis materials, with known linear attenuation coefficient vectors \( m_1, \ldots, m_m \), have been chosen. In practice, each such basis vector \( m_i \) can be computed as the average of \( \mu \) over a region of interest (ROI) in a reconstructed image. Furthermore let \( a \) be the \( m \)-dimensional vector of densities of the different basis materials, normalised to a unitless quantity in such a way that a component \( a_i \) being equal to 1 corresponds to the same density as that of the basis material. The relationship between \( \mu \) and \( a \) is nonlinear, because of the exponential form of x-ray attenuation, but since the exponential function can be approximated by a linear function, the relationship can be assumed to be approximately linear:

\[ \mu = Ma \]  

where \( M = (m_1, m_2, \ldots, m_m) \) is a matrix built up from the basis material linear attenuation coefficient vectors.

Since the number of bins exceeds the number of basis materials in this case, equation (3) must be solved in the least squares sense, which gives an estimate \( \hat{a} \) of \( a \) as

\[ \hat{a} = (M^T M)^{-1} M^T \mu \]  

where \( T \) denotes transpose. The different noise level in different bins could be taken into account by using a weighted least squares solution instead, but we have not done so here.

Equation (4) maps the \( \mu \) vector at each pixel in the image to a set of estimated basis coefficients. Another way to view equation (4) is that each row of the matrix \( (M^T M)^{-1} M^T \) is a set of weight factors that, when used to weight the bin images together and under the assumption that (3) holds exactly, produces a material-specific image where one basis material is visible and all combinations of the others are cancelled out. In reality (3) is just an approximation of the true nonlinear relationship and furthermore \( \mu \) is dependent on the surrounding material due to beam hardening, so the resulting images will only be approximately material-specific.
3. Results

3.1. Material identification

To show the ability of our detector to discriminate between different materials, we imaged the cylindrical phantom with the five inserts filled with water, vegetabilic (rapeseed) oil, packed gypsum powder (which represents bone since it contains calcium), iodinated contrast agent (53 mg I ml$^{-1}$, or 0.42 mmol I ml$^{-1}$, diluted Visipaque) and gadolinium contrast agent (79 mg ml$^{-1}$, or 0.5 mmol ml$^{-1}$, Dotarem), as shown in figure 5(a). Also shown in the figure are the circular ROIs placed in each insert, with radii a few pixels less than that of the inserts so that the transition region at the border is excluded. In figure 5(b) the effective linear attenuation coefficient is plotted as a function of the bin number, measured from the ROIs. A four-material decomposition was made by the method described in section 2.3 using the average attenuation coefficient vectors in the water, calcium, gadolinium and iodine ROIs as basis materials and the resulting iodine, gadolinium and calcium images are shown in figures 6(a)–(c). To demonstrate a possible approach for reducing the artefacts in these material images, an additional ROI was added at the border of the calcium insert (ROI 6 in figure 5(a)), by manually selecting an area with strong artefacts in figures 6(a)–(b). The gadolinium and iodine images resulting from this decomposition are shown in figures 6(d)–(e).

The material images in figures 6(c)–(e) were used to create a color overlay for the flat-weighted image (figure 5(a)) as follows: the material images were low-pass filtered with a gaussian kernel with $\sigma = 10$ pixels, thresholded, low-pass filtered again with a gaussian kernel with $\sigma = 5$ pixels to get smoother boundaries and then turned into an RGB image by letting the red component be the iodine image, the green component be the calcium image and the

Figure 5. (a) Flat-weighted image of the cylindrical PMMA phantom with water, calcium, gadolinium, iodine and oil. Also shown are the ROIs used for measuring the energy-dependent linear attenuation coefficient for the different materials. A separate ROI was used for the border of the calcium insert, where the energy dependence of the reconstructed values is slightly different compared to the central parts of the insert, presumably due to beam hardening. (b) Measured linear attenuation coefficient in each energy bin, as measured in the ROIs. The dashed lines are the estimated threshold positions listed in table 1.
blue component be the gadolinium image, all normalised to assume values between 0 and 1. This RGB image was turned into a colour overlay for the flat-weighted image by converting it to the hue-saturation-value (HSV) colour scale, keeping the hue component but setting the saturation component equal to the value component (to make regions containing neither of the three materials gray) and then replacing the value component by the flat-weighted image. The result is shown in figure 6(f).
3.1.1. Material quantification. To demonstrate the potential of the method employed here for quantifying materials, we imaged the phantom with the five inserts filled with water, gadolinium contrast agent (79 mg Gd ml⁻¹, or 0.5 mmol Gd ml⁻¹), iodine contrast agent (32 mg I ml⁻¹, corresponding to 0.25 mmol I ml⁻¹ and 16 mg I ml⁻¹, corresponding to 0.13 mmol I ml⁻¹) and a mixture of both contrast agents (12 mg I ml⁻¹ and 20 mg Gd ml⁻¹, corresponding to 95 µmol I ml⁻¹ and 0.13 mmol Gd ml⁻¹). A flat-weighted image of this phantom is shown in figure 7 together with the circular ROIs used for the measurement. Like in figure 5(a), the radii of the ROIs where chosen to cover as much as possible of the inserts without touching the transition region between the insert and the PMMA. The water, gadolinium and 32 mg ml⁻¹ iodine inserts were used as basis functions in a three-material basis decomposition as described in section 2.3. Two of the resulting basis images, the ones for iodine and gadolinium, are shown in figure 8. The iodine and gadolinium concentrations in ROIs 4 and 5, measured as the corresponding basis coefficients scaled so that the averages over the 79 mg Gd ml⁻¹ and 32 mg I ml⁻¹ inserts agree with the nominal concentrations, are listed in table 2.

3.1.2. Imaging of a meat slice. Figure 9 shows reconstructed images of the lamb chop, with and without iodine injected into the spinal canal. To avoid using any prior information about where the iodine is located in this image, the attenuation curves measured in the first image of the PMMA phantom (figure 5(b)) were applied to make an iodine basis image (figure 9(c)) of the meat. The water, calcium, iodine and calcium border basis functions were used, but the gadolinium basis function was not included since gadolinium is known not to be present in this image. An iodine mask was created from this image by low-pass filtering, with a gaussian kernel with σ = 10 pixels and thresholding. This mask was then transformed into a colour overlay for the flat-weighted image in a similar way as for figure 6(f). The result is shown in figure 9(d).

4. Discussion

As shown in figure 5(b), the attenuation coefficient of the different substances in the image differ not only in magnitude but also in terms of energy dependence. The fact that the attenuation
of iodine is markedly high in energy bin 6–8 while that of gadolinium is high in bin 8 agrees with the locations of the K-edges of those elements (33 keV and 50 keV, respectively). It may seem surprising that the reconstructed effective attenuation coefficient drops towards the lowest energy bins, despite the fact that the linear attenuation coefficient is a decreasing function of energy in the absence of K-edges. However, this behaviour can be explained by noting that the photon energy registered by the detector does not always equal the true energy of each photon. In the lowest energy bins, a large fraction of the primary photons have been attenuated away during the passage through the object and so the counts in these bins are likely to be dominated by charge sharing and Compton scatter events, i.e. interaction events where only a fraction of the photon energy is registered. Many counts in the lower energy bins therefore come from photons with much higher energies where the attenuation coefficient is relatively low.

To clarify how the Compton interactions in the detector affects the measured energy distribution, we have simulated a deposited energy spectrum in the silicon-strip detector using
a simple model. The number of interacting photons at each energy was calculated from a simulated x-ray tube spectrum and the detection efficiency determined by the linear attenuation coefficient of silicon and the length of the detector in the beam direction. For each incident photon energy, the ratio between photoelectric and Compton interacting photons was calculated from the relative cross-sections of these two effects. The Compton events were assumed to deposit a random energy derived from the Klein–Nishina cross-section while the photoelectric events were assumed to get a very narrow Gaussian energy distribution caused by Fano noise. For details about the simulation model, see Bornefalk and Danielsson (2010) sections 3.2–3.3. The result, in figure 10, shows that Compton and photoelectric events are well separated, with Compton events below 19 keV and photoelectric events above 19 keV. Therefore, the Compton interactions do not destroy the energy information contained in the photoelectric part of the spectrum.

There are additional effects degrading the energy resolution that are not taken into account in figure 10. First, some of the Compton interacting photons may deposit more energy, either by Compton scattering or by the photoelectric effect, in one or more additional locations before leaving the detector. Such secondary interactions can be expected to give a deposited spectrum similar to the one in figure 10 but shifted slightly towards lower energies since some of the photon energy was lost in the first interaction. Second, charge sharing shifts the spectrum towards lower energies since some events are registered as lower-energy events in two adjacent detector
elements and this means that charge-shared events may be confused with true low-energy photons by the detector. Furthermore, at high count rates pileup may further distort the spectrum (Taguchi et al. 2010, Wang et al. 2011). A detailed investigation of the impact of these effects on image quality for the silicon-strip detector used here remains to be done.

Image-based basis material decomposition, which is the method employed here, is a linear postprocessing method and therefore unable to compensate for the nonlinear beam hardening effect and this causes the image artefacts apparent in the basis images in figures 6 and 8. These artefacts are most pronounced near the most highly attenuating inserts, where the exponential x-ray attenuation cannot be approximated well by a linear model.

One way of mitigating these artefacts, which is demonstrated here, is to introduce one or more additional basis materials. Since the iodine and gadolinium images in figures 6(a)–(b) exhibit especially strong artefacts near the border of the calcium insert we introduced an additional ROI in this region and the attenuation curve of this ROI (see figure 5(b)) turns out to be different from the average attenuation curve in the calcium insert, because of the incompleteness of the linear model. Adding this ROI as a fifth basis material gives iodine and gadolinium images with considerably less artefacts but also increased noise, as can be seen in figures 6(d)–(e). We do not display the calcium image resulting from this decomposition, because the calcium border would be cancelled out in such an image leaving only part of the insert visible. This problem can be solved by either adding the two calcium basis images together, or by just using the calcium image resulting from four-material decomposition together with the other material images from the five-material decomposition, as we do here in figure 6(f).

For routine clinical use, however, it is not practical to manually select ROIs where artefacts are prominent. Instead, the preferable way of removing these artefacts and ensuring that homogeneous regions in the imaged object become homogeneous in the basis decomposed image is to use projection-based basis material decomposition, involving an accurate forward model for the x-ray transmission. In theory, this should enable bias-free recovery of the basis coefficients at any point in the image volume even in the presence of Compton scatter or charge sharing, as long as those effects are included in the forward model. However, the drawback of projection-based basis material decomposition is that it is highly sensitive to errors in the forward model and therefore requires accurate calibration (Bornefalk et al. 2014) and high

Figure 10. Simulated deposited energy spectrum in the silicon detector when illuminated by an 80 kVp beam filtered by 0.8 mm Be, 2 mm Al and 90 m PMMA. The large peak at the low end of the energy spectrum consists of Compton interactions, while the part above the minimum at 19 keV consists of photoelectric events. Charge sharing and secondary interactions of Compton scattered photons have not been taken into account here.
stability of the detector response over time in order to avoid having to calibrate too frequently. Developing a sufficiently accurate forward model for the silicon-strip detector used here is an important topic for future work.

The measurements of iodine and gadolinium concentrations (see figures 7 and 8 and table 2) give the nominal values (0 mg ml\(^{-1}\) Gd and I in ROI 1, 79 mg Gd ml\(^{-1}\) in ROI 2, 32 mg I ml\(^{-1}\) in ROI 3) in ROIs 1-3, since those ROIs were used for the calculation of the matrix \((M^T M)^{-1} M^T\) used to transform the measured \(\mu\) into basis coefficients. The measurements in ROIs 4 and 5, however, can be used to determine how well the basis decomposition method employed here can be used to quantify concentrations of contrast agents (table 2). In ROI 4, with a nominal concentration of 16 mg ml\(^{-1}\) iodine and no gadolinium, the measured values are 16 mg I ml\(^{-1}\) and \(-1.4\) mg Gd ml\(^{-1}\), whereas the corresponding values in ROI 5 are nominally 12 mg I ml\(^{-1}\) and 20 mg Gd ml\(^{-1}\) and measured 11 mg I ml\(^{-1}\) and 17 mg Gd ml\(^{-1}\).

Considering the artefacts that are apparent in the basis images of figure 8, this slight deviation from the nominal values is not surprising. Another possible explanation for the discrepancy could be that the true concentrations of the mixtures deviate from the nominal values.

These results show that, as one would expect from the linear forward model (3), the silicon-strip detector can be used to identify iodine and gadolinium, regardless of whether they appear in separate parts of the image or in a mixture. The results also show that the detector has potential for quantifying contrast agent concentrations, even though the accuracy of the quantification is limited by artefacts since image-space decomposition is used.

The meat images in figure 9 were made using only a cut-out slice of the spine, i.e. the spinal canal was open in both ends. These images therefore differ from a real myelography CT image in that the iodine solution was not confined inside the spinal canal but could diffuse down through the spinal cord tissue. The iodine visible in figure 9 may be contrast agent deposited on the surface of the spinal cord. Nonetheless, these images illustrate how material-selective CT imaging can be used to visualise the distribution of an iodinated contrast agent which cannot be separated from bone in an ordinary CT image. As can be seen by comparing the nonenhanced and contrast-enhanced images (figures 9(a)–(b)), the iodine is located in a ring-shaped region within the spinal canal and part of this region, where the signal-to-noise ratio is large enough, is correctly identified in the iodine image. Note that the weights used to produce the iodine image were calculated from measurements in the image of the PMMA phantom with inserts with known content (figure 5). This shows that the method used here can separate iodine from calcium in situations where there is no available prior information about which regions in the image contain which materials.

In this study, an 80 kVp x-ray spectrum was used. This is among the lower tube voltages used in clinical CT and was selected to agree with the small phantom size. Since the fraction of photons which are Compton scattered in the silicon detector increases with increasing tube voltage, it is an important topic for future investigations to evaluate the image quality for higher kVp. Also, the contrast agent concentrations in figure 5 were chosen to show up as approximately isoattenuating with the gypsum powder, which represents bone, and these are high concentrations for clinical CT, so an interesting topic for further study would be to investigate the detectability of very low contrast agent concentrations. Other topics for further research are implementing projection-based basis material decomposition as described above and evaluating image quality for larger phantom sizes.

5. Conclusion

Our results show that the photon-counting silicon-strip detector developed in our group can be used to acquire material-decomposed CT images with an 80 kVp x-ray tube spectrum.
and thereby to separate calcium, iodine and gadolinium. Furthermore, the work indicates the potential for quantitative imaging with this detector.

Acknowledgments

This study was financed by the Erling-Persson family foundation (Familjen Erling-Perssons stiftelse), the Swiss National Science Foundation and the China Scholarship Council. The authors are shareholders of Prismatic Sensors AB.

Appendix A. Postprocessing to further reduce ring artefacts

In this section the postprocessing method used to further reduce the ring artefacts will be outlined. Note that the measured values in table 2 were measured in images without postprocessing applied, in order to avoid any bias resulting from the ring artefact suppression algorithm.

Each of the basis images shown in figures 6 and 8 were corrected as follows: First the image was transformed into polar coordinates by resampling it on a grid with 1000 points in the radial direction (from the center to one side of the image) and 2000 points in the angular direction. Then the inserts were segmented out and subtracted to give a ‘background-only’ polar image, which was subsequently convolved with a one-dimensional gaussian kernel ($\sigma = 200$ pixels) in the angular direction. Denoting the convolved polar image by $I_c$, a ring artefact correction mask $M$ was calculated as

$$M(r, \theta) = \begin{cases} 
    \frac{\langle (I(r, \theta) - I_m) \rangle + I_m}{\langle I(r, \theta) \rangle + I_m} & \text{for } r < r_c \\
    1 & \text{otherwise}
\end{cases}$$

(A.1)

Here $r$ and $\theta$ are polar coordinates, $r_c$ is a constant cutoff radius chosen such that the most prominent ring artefacts are confined to the region $r < r_c$, $\langle \cdot \rangle_\theta$ denotes average over the angular direction and $I_m$ is the average pixel value in the insert with highest intensity in the image.

In order to avoid erasing slow radial variations in image intensity, a detrended mask was then calculated by first convolving $\langle M(r, \theta) \rangle_\theta$ with a one-dimensional gaussian kernel with $\sigma = 100$ pixels, denoted $K(r)$, whereby the outer edge of the pixel array was padded with the last pixel value and the edge towards the center was padded with the average of the first 100 pixels.

![Figure A1](image)

Figure A1. The gadolinium image in figure 6(e) before (a) and after (b) postprocessing to reduce ring artefacts.
pixel values to counter the effect of rapid fluctuations near the center. The detrended mask $M_d$ was then calculated as

$$M_d(r, \theta) = \frac{M(r, \theta)}{\langle M(r, \theta) \rangle_{\theta} * K(r)}.$$  \hspace{1cm} (A.2)

Finally, the mask was transformed back to rectangular coordinates and the original image $I$ was corrected with the formula

$$I_{\text{corrected}}(x, y) = M_d(x, y) (I(x, y) + I_m) - I_m$$  \hspace{1cm} (A.3)

see figure A1 for a comparison of images before and after postprocessing.

The flat-weighted images in figures 5 and 9 exhibited only weak ring artefacts and were processed as above but without the detrending step. $I_m = 0$ was used for figure 5 and $I_m = 1000$ HU was used for figure 9. The flat-weighted image in figure 7 was not postprocessed at all.

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