Physics in Medicine & Biology

PAPER

Improved iterative tomographic reconstruction for x-ray imaging with edge-illumination

Peter Modregger¹,², Jeff Meganck², Charlotte K Hagen¹, Lorenzo Massimi¹, Alessandro Olivo¹ and Marco Endrizzi³

¹ Department of Medical Physics and Bioengineering, University College London, Gower Street, WC1E 6BT London, United Kingdom
² Research & Development, Discovery & Analytical Solutions, PerkinElmer, 68 Elm Street, Hopkinton, MA 01748, United States of America
³ Author to whom correspondence should be addressed.

E-mail: p.modregger@ucl.ac.uk

Keywords: x-ray phase contrast imaging, edge illumination, iterative tomographic reconstruction

Abstract

Iterative tomographic reconstruction has been established as a viable alternative for data analysis in phase-sensitive x-ray imaging based on the edge-illumination principle. However, previously published approaches did not account for drifts of optical elements during a scan, which can lead to artefacts. Up to now, the strategy to reduce these artefacts was to acquire additional intermediate flat field images, which were used to correct the sinograms. Here, we expand the theoretical model to take these effects into account and demonstrate a significant reduction of (ring)-artefacts in the final reconstructions, while allowing for a significant reduction of scan time and dose. We further improve the model by including the capability to reconstruct combined absorption and phase contrast slices, which we experimentally demonstrate to deliver improved contrast to noise ratios compared to previously employed single shot approaches.

Introduction

Compared to conventional x-ray radiography, which provides absorption contrast only, refraction sensitive x-ray imaging methods deliver phase and absorption contrasts simultaneously (Bravin et al 2013). This complementarity as well as the improved soft-tissue contrast provided by phase-sensitive imaging implies a high potential for biomedical applications. At least three different methods are currently under investigation: analyser-based imaging (ABI) (Chapman et al 1997, Arfelli et al 2000), grating interferometry (GI) (David et al 2002, Momose et al 2003, Pfeiffer et al 2007a) and edge-illumination (EI) (Olivo and Speller 2007, Endrizzi et al 2013). Examples for biomedical applications include mammography (Stampannoni et al 2011, Olivo et al 2013, Eggl et al 2018), pulmonary diseases (Yaroshenko et al 2013, Modregger et al 2016, Hellbach et al 2018) and imaging of specimens (Hagen et al 2015, Birnbacher et al 2018).

Acquiring a series of radiographic images taken from different viewing angles and subsequent tomographic reconstruction provides a cross-section of the sample. This method, called computed tomography (CT), is a staple in current diagnostic imaging and the refraction sensitive techniques mentioned above have been successfully combined with tomography (Dilmanian et al 2000, Pfeiffer et al 2007b, Hagen et al 2015). In recent years, iterative approaches to tomographic reconstruction of phase contrast data have been intensively studied (Xu et al 2012, Fu et al 2013, Gaass et al 2013, Nilchian et al 2013a, 2013b, Chen et al 2017, Teuffenbach et al 2017) as they provide the potential for using fewer viewing angles, which enables a considerable reduction of total scan time and dose.

Here, we will substantially extend the capabilities of a model for iterative tomographic reconstruction of data sets acquired with EI. EI constitutes a non-interferometric phase-sensitive x-ray imaging technique that takes advantage of the full spectrum provided by incoherent laboratory-based x-ray sources (Munro et al 2010, Endrizzi et al 2015). EI utilises two apertured masks (figure 1). The sample mask shapes the x-ray beam into beamlets, which are deviated from the main propagation direction due to refraction. The resulting lateral offset of the beamlets is transformed into an intensity contrast by the detector mask, which covers a fraction of the
detector pixels. A scan of the sample mask over one period (i.e. varying \(m\)) provides a Gaussian-like intensity distribution, which is called the illumination curve (IC). The absorption signal appears as decreased intensity over the entire IC, while the refraction (i.e. differential phase) signal shifts the IC (see inset in figure 1).

Standard analysis for tomography consists of two steps. First, one (Diemoz et al 2015) or several radiograms (Hagen et al 2015, 2016) are analysed to provide joined or separate absorption and differential phase contrast images for each viewing angle \(\theta\). Second, filtered back projection (Kak and Slaney 1988) is applied in order to perform tomographic reconstruction. Using an iterative approach to data analysis, it was recently demonstrated that tomographic reconstruction can also be achieved in a single step (Chen et al 2017).

In the following, we will substantially extend the previously published model for iterative reconstruction in EI, which features the suppression of ring artefacts and opens the possibility for significantly reduced scan times.

Theory

The first steps of developing the theoretical framework have been already been described in literature (Diemoz et al 2015, Chen et al 2017) and are reiterated here for the convenience of the reader. The Radon transform constitutes the mathematical basis for tomographic reconstruction and can be expressed as the line integral (Kak and Slaney 1988)

\[
\mathcal{R} [h(x, y)] (t, \theta) = \int_L h(x) \, d|x|
\]  

for an arbitrary, two-dimensional function \(h(x, y)\) with \((x, y)\) the coordinate system fixed to the sample and \(x = (x, y)\). \(L\) defines the line of integration, which is parameterised by the pixel position at the detector \(t\) and the projection angle \(\theta\) (see figure 1).

The absorption signal \(A\) after transmission through the sample constitutes the negative exponential of the projected (i.e. Radon transformed) x-ray attenuation coefficient \(\mu(x, y)\)

\[
A(t, \theta) = \exp (-\mathcal{R} [\mu(x, y)]) .
\]  

The accumulated phase shift \(\Phi(t, \theta)\) of the x-rays during transmission through the sample is given by

\[
\Phi(t, \theta) = \mathcal{R} [K \delta(x, y)] ,
\]  

where \(K\) is the modulus of the wave vector of the assumed monochromatic x-ray beam and \(\delta(x, y)\) is the local refractive index decrement. The observable refraction signal \(\alpha(t, \theta)\) is proportional to the derivative of the phase signal (Born and Wolf 1999)

\[
\alpha(t, \theta) = -\frac{1}{K} \partial_\theta \Phi(t, \theta) = \partial_\theta \mathcal{R} [\delta(x, y)] .
\]  

Now, let us denote intensity of ICs acquired without a sample present in the x-ray beam as \(f(t, m)\) with \(m\), the lateral offset of the sample mask (i.e. the scan parameter) and \(t\), the pixel position at the detector. Note that \(f\)’s dependency on \(t\) takes into account local mask imperfections. The sample’s absorption signal, \(A(t, \theta)\), decreases the total signal while the refraction signal, \(\alpha(t, \theta)\), shifts the experimentally obtainable ICs \(s(t, \theta, m)\). Both effects can be modeled by

\[
s(t, \theta, m) = A(t, \theta) f(t, m - 2\alpha(t, \theta)) ,
\]
where $z$ is the sample to detector distance and we have assumed negligible scattering from the sample, which would additionally broaden the ICs (Endrizzi et al 2014, Modregger et al 2016). Substituting the absorption and refraction signal defined above, yields this model’s prediction for the observable sinogram $s_{\text{mod}}$ based on the attenuation coefficient $\mu$ and refractive decrement $\delta$:

$$s_{\text{mod}}(t, \theta, m) = \exp \left( -\mathcal{R} \left[ \mu(x, y) \right] \right) f(t, m - z\delta, \mathcal{R} \left[ \delta(x, y) \right]) .$$

(6)

In Chen et al (2017), the flat field IC $f$ was further simplified by a first order Taylor approximation at the mask position $m$, which we will forgo here. This implies that our model will be better suited for larger refraction angles.

The Taylor approximated version of equation (6) formed the basis for iterative tomographic reconstruction in Chen et al (2017). This was done by minimising the cost function

$$S = ||s_{\text{exp}}(t, \theta, m) - s_{\text{mod}}(t, \theta, m)||^2$$

(7)

with a batch gradient iterative approach including an additional noise reduction term. Chen et al demonstrated that the absorption and phase signal can be retrieved independently from a scan with a single mask position $m$.

However, this model does not account for a shifting mask position during a tomographic scan, which can occur due to mechanical vibrations or drift. Since these can lead to significant artefacts in the tomographic reconstructions (Zamir et al 2016), we will include an additional degree of freedom in the argument of $f$ denoted $m_r(t)$, which models an offset position for each projection angle $\theta$ of a rigid mask (i.e. a constant offset over the field of view).

Similarly, reconstructed slices can show strong ring artefacts, which can occur due to a mismatch between the actual flat field ICs $f(t, m)$ during a tomographic scan and the reference ICs acquired before, where the latter is used for iterative reconstruction in equation (6). This mismatch may result from systematic mechanical errors in the optical elements or from insufficient photon statistics for the reference ICs. A heuristic approach for taking this effect into account is to include another degree of freedom in the argument of $f$ denoted $m_s(t)$. This approach works as follows. In an ideal experiment without noise, ring artefacts would occur by using the locally shifted flat field ICs $f(t, m - m_s(t))$ instead of the correct $f(t, m)$. Conversely, including $m_s(t)$ in the model allows for reducing ring artefacts during iterative reconstruction.

Finally, we will take advantage of the previously published approach to retrieve a combined absorption/phase contrast image by assuming the phase signal of the sample to be proportional to the absorption signal, i.e. $\mu(x, y) = \gamma \delta(x, y) = h(x, y)$ (Paganin et al 2002). It was shown that the projected electron density $\rho(t, \theta)$ can be retrieved from a projection $s(t, \theta, m)$ acquired on a single offset position $m$ by calculating (Diemoz et al 2015)

$$\rho(t, \theta) \propto \gamma^{-1} \log \left[ \mathcal{F}^{-1} \left[ \frac{\mathcal{F} [s(t, \theta, m) / f(m)]}{1 + iqz\gamma^{-1} f^*(m) f(m)} \right] \right]$$

(8)

with $\mathcal{F}$ the Fourier transform with respect to $t$, its inverse $\mathcal{F}^{-1}$ and $q$ the variable conjugate to $t$. Here, we have also omitted the free space propagation part, which can be neglected for laboratory-based setups. Standard filtered back projection (Kak and Slaney 1988) can then be applied to the retrieved sinogram $\rho(t, \theta)$ in order to reconstruct a tomographic slice. Here we will use this well established single shot approach as a reference for comparison later.

While the utilised assumption of proportionality between absorption and phase contrast is strictly true only in the case of a single homogeneous material present in the beam and precludes a quantitative interpretation for more complex material systems, in practice qualitative interpretation of the images such as morphological information (e.g. pore size distribution) is frequently of interest. Further, this assumption has been demonstrated to improve image quality for EI in some cases (Zamir et al 2016) and simplifies the iterative reconstruction as the number of retrieved values are only half compared to the previously published method (Chen et al 2017).

Including the three improvements listed above, yields the proposed model for iterative tomographic reconstruction:

$$s_{\text{mod}}(t, \theta, m) = \exp \left( -\mathcal{R} \left[ h \right] \right) f(t, m - m_r(t) - m_s(t) - z\gamma \delta, \mathcal{R} \left[ h \right]) .$$

(9)

The dependency of $h$ on $(x, y)$ was suppressed for readability. Retrieving the combined contrast $h(x, y)$ from the experimentally obtained sinogram $s_{\text{exp}}(t, \theta, m)$ can now be achieved by an iterative minimisation of the cost function

$$S = ||s_{\text{exp}}(t, \theta, m) - s_{\text{mod}}(t, \theta, m)||^2 + \lambda ||h(x, y)||^2 ,$$

(10)

where the second term constitutes a regularisation term that minimises noise with a simple L2-norm. Please note that the number of degrees of freedom for the reconstruction does not increase significantly by including $m_r$ and $m_s$ as additional parameters. For example, if the number of acquired projections is $N_\theta$ and the number of pixels at the detector is $N_x$, then the number of voxels in the slice $h(x, y)$ to be retrieved would be $N_x \times N_t$, while $m_s(t)$ constitutes only $N_\theta$ and $m_r(t)$ only $N_t$ additional parameters.
We have used the limited memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) implementation (Byrd et al 1995) in the SciPy library for Python (Jones et al 2001) to minimise the cost function (equation (10)). The knowledge of the gradients of $S$ with respect to $h(x, y)$, $m_0(\theta)$ and $m_1(t)$ greatly improves iteration speed. Using the abbreviations

$$f_s(t, \theta, m) = \exp(-R[h])f_s(t, m - m_0(\theta) - m_1(t) - z\gamma \partial_z R[h])$$

(11)

and

$$D(t, \theta, m) = [s_{\exp}(t, \theta, m) - s_{\text{mod}}(t, \theta, m)]$$

(12)

the gradients are, with respect to $h(x, y)$

$$\nabla_h S = 2 \sum_{t, \theta, m} D(t, \theta, m) [s_{\text{mod}}(t, \theta, m)\nabla R[h] - z\gamma f_s(t, \theta, m)\nabla \partial_z R[h]],$$

(13)

with respect to $m_0(\theta)$

$$\nabla_{m_0} S = 2 \sum_{t, \theta, m} D(t, \theta, m) f_s(t, \theta, m),$$

(14)

and with respect to $m_1(t)$

$$\nabla_{m_1} S = 2 \sum_{y, \mu, \nu} D(t, \theta, m) f_s(t, \theta, m).$$

(15)

The Radon transforms and their gradients occurring in equations (9)–(15) can be regarded as sparse matrix operations that can be efficiently computed by using lookup tables. The lookup tables were computed prior to iterative reconstruction and used to calculate the corresponding Radon transforms and gradients.

Experimental results

The experiments were performed in-house with the laboratory-based EI implementation at University College London (Hagen et al 2014a). Two different experiments with different type of samples and different setup configurations were carried out to demonstrate the versatility of the proposed approach.

In the first experiment, we have imaged three different types of plastic spheres (i.e. polystyrene (PS), propylene (PP) and poly methyl methacrylate (PMMA)) as a straightforward example. The source was a Rigaku M007 rotating anode (Rigaku Corporation, Japan) with a Mo target and operated at 40 kV and 20 mA. The Hamamatsu C9732DK flat panel (Hamamatsu, Japan) was used as a detector with a pixel size of 50 µm. Both masks were manufactured by electroplating of Au on a graphite substrate (Creatv Microtech Inc., USA) featuring a pitch of 38 µm for the sample mask and 48 µm for the detector mask, respectively. The total setup length was 85 cm and the sample to detector distance was 20 cm.

In order to obtain the experimental flat field ICs $f_s(t, m)$ the sample mask was scanned over one period with 33 steps. The tomographic scan was performed with the sample mask on a slope position of the ICs (i.e. $m = 9 \mu m$ offset from the maximum position; see inset of figure 1) and over 360 degrees under continuous rotation of the sample with a speed of 1 deg s$^{-1}$ leading to a total scan time of 6 min. During the scan, 300 projections were acquired with an exposure time of 1.2 s each. Subsequent iterative reconstruction of the acquired data set was carried out with $\gamma = 3$ for both reconstruction methods and $\lambda = 5 \times 10^{-3}$ for the iterative method, which were manually found by visual inspection. The retrieved tomographic slice consisted of $N_t \times N_r = 220 \times 220$ voxels.

The iteration was carried out until satisfying convergence was reached, which took 58 iteration steps and 93 s on a single core of a standard modern desktop PC.

Figure 2 demonstrates a clear suppression of ring artefacts provided by the proposed iterative approach (b) as compared to the result of the single shot algorithm (a). Further, the iterative approach provides visually less noise, which we confirmed by determining the contrast to noise ratio (CNR) between the different materials. The CNR is defined as

$$\text{CNR} = \frac{|\bar{h}_1 - \bar{h}_2|}{\text{std}(\bar{h}_1)^2 + \text{std}(\bar{h}_2)^2}$$

(16)

with $\bar{h}$ the mean of an area and std($h$) its standard deviation. Table 1 lists the CNRs between the different structures as determined by a circular area with a radius of 40 voxels. The iterative approach provides an increase of about 30% between the materials.

In order to assess the validity of the offsets for the lateral mask position $m_0(\theta)$ and for the suppression of ring artefacts $m_1(t)$ retrieved by iterative reconstruction, we have compared them to predicted values as follows. For the offset of the lateral mask position $m_0(\theta)$, we used a background area of the acquired sinogram. Here, the
offset of the lateral mask position during a scan due to drift or vibrations will appear as intensity variations $I$ in dependence of the projection angle $\theta$. Thus, the known flat field IC $f(t, m)$ can be used to transform the intensity variations into a lateral offset $m_0(\theta)$ by using its inverse, i.e. $m_0(\theta) = f^{-1}(t, I)$, and numerical interpolation. We found an excellent agreement between the thusly predicted and iteratively retrieved values for $m_0(\theta)$ (figure 3(a)) featuring a correlation coefficient of $r = 0.98$.

Predicting the offset for ring artefact suppression $m_r(t)$ is not straight forward since the sample and ring artefact information overlap in the sinogram. However, we demonstrated self consistency of the retrieved $m_r(t)$ values in the following way. We used the iteratively retrieved slice $h(x, y)$, the retrieved offset $m_0(\theta)$, the experi-

---

**Figure 2.** Tomographic reconstruction of three different plastic samples with (a) the single shot approach (equation (8)) and (b) iterative tomographic reconstruction (equations (9) and (10)) from the same data set. A very significant reduction of ring artefacts in (b) is clearly visible.

**Table 1.** CNR between the different areas (first column) of the single shot reconstruction (second column), the iterative reconstruction (third column) and the relative difference between the latter two (fourth column). Iterative reconstruction provides improved CNR of about 30% between the materials.

| Area       | Single shot | Iteration | Difference (%) |
|------------|-------------|-----------|----------------|
| PP-PMMA    | 6.7         | 8.7       | +30            |
| PP-PS      | 1.5         | 2.0       | +33            |
| PMMA-PS    | 5.2         | 6.7       | +29            |
perimental flat field IC \( f(t, m) \) in equation (9) with \( m(t) \equiv 0 \) in order to obtain a sinogram that was virtually unaffected by ring artefacts. The difference between this sinogram and the experimentally acquired one then quantified the intensity modulations due to the ring artefacts, which were again transformed into the estimated offsets via the flat field IC \( f(t, m) \). Figure 3(b) shows a very good agreement between the estimated and the retrieved offsets \( m_r(t) \) with a correlation coefficient of \( r = 0.85 \). The large correlation coefficients found here and in the numerical simulations above validated our suggested extension for iterative tomographic reconstruction.

For the second experiment, we repurposed a previously acquired data set of a freeze-dried rabbit esophagus as an example for a biomedical sample and the versatility of the proposed approach. Details of sample preparation and ethical approval can be found elsewhere (Hagen et al 2015). We used the same x-ray source as above but operated at 40 kV and 25 mA. The detector was a Pixirad-2 photon counting detector (PIXIRAD Imaging Counters s.r.l., Italy) featuring a pixel size of 62 \( \mu \text{m} \). The periods of the masks were 79 \( \mu \text{m} \) and 98 \( \mu \text{m} \), respectively.

The flat field ICs \( f(t, m) \) were acquired with 30 steps evenly distributed over one period of the sample mask. The tomographic scan was performed with the sample mask on a slope position of the ICs (i.e. \( m(t) = 10 \mu \text{m} \) offset from the maximum position) and over 180 degrees in 900 steps (\( N_\theta = 450 \) of which were used here) with 2 s exposure per projection. Sample dithering was used with 8 steps to improve spatial resolution (Hagen et al 2014b). An additional flat-field was taken at each projection angle for the purpose of flat field tracking (Zamir et al 2016), which was not used for the data analysis in this study. Due to the overhead of moving the motors this resulted in a total scan time of \( \approx 18 \text{ h} \). The reconstructed slice consisted of \( N_t \times N_t = 720 \times 720 \) voxels and iterative reconstruction was performed with \( \gamma = 20, \lambda = 2 \times 10^{-2} \) and took 47 steps and about 20 min.

Figure 4 demonstrates a substantial reduction of ring artefacts provided by iterative reconstruction compared to standard single shot analysis. In fact, some sample details (e.g. at the center of rotation) that are not visible in the single shot slice are recovered by the iterative approach. However in this example, the separation of the sample from the background is slightly worse for the iterative result. Numerical investigations not shown here revealed that this a consequence of using a larger proportionality factor between absorption and phase signals.
As mentioned above, the scan for the utilised data set was set up for flat-field tracking in order to reduce ring artefacts, which requires the acquisition of additional flat-field images during the tomographic scan. Moving the sample out and back into the field of view caused a significant time overhead as can be seen by comparing the actual scan time of 18 h to the time used for pure data acquisition of $900 \times 8 \times 2 \times s = 4$ h. Since we demonstrated that iterative reconstruction renders flat field tracking obsolete, the proposed approach has the potential to decrease total scan times by a factor of more than four.

**Numerical simulations**

To further demonstrate the validity of the proposed iterative approach we used numerical simulations with parameters that model the experiment described above. The numerical simulations were carried out in two parts.

First, the forward simulation of the observable intensity was based on equation (9) and yielded the sinogram used as input for the subsequent iterative reconstruction. The simulated sample (i.e. $h(x, y)$) consisted of three circles with different materials and equations (1)–(4) were used to simulate the Radon transform of the absorption, $A(t, \theta)$, and refraction contrast, $\alpha(t, \theta)$, respectively. The flat field IC (i.e. $f(t, m)$) was modelled as a Gaussian distribution and the scan parameter, $m$, was chosen on one inflection point. Random offsets for the lateral
The simulated sinogram was then calculated by linear interpolation of \( f(t, m) \) in equation (9) with the input data described above. Finally, Poisson noise was added to both the sample sinogram, \( s(t, \theta, m) \) as well as the flat field IC \( f(t, m) \).

Second, iterative tomographic reconstruction was carried out based on equations (9) and (10). The sinogram consisted of \( N_t = 180 \) detector pixels and \( N_\theta = 90 \) projections. The proportionality factor was chosen to match one of the materials (i.e. \( \gamma = 10 \)) and iteration was performed until convergence was achieved.

Figure 5 demonstrates the influence of the different utilised parameters for artefact suppression on iteratively reconstructed slices. The single shot reconstruction (figure 5(a)) based on equation (8), included for comparison, shows clear ring artefacts. These artefacts are significantly reduced by iterative reconstruction that uses both noise regularisation and includes the offsets as additional parameters (cmp. figure 5(d)). Further, the input offsets were highly correlated with the iteratively retrieved values (\( r = 0.9965 \) for \( m_0 \) and \( r = 0.9075 \) for \( m_r \)).

In addition, we turned off either the noise reduction term in figure 5(b), i.e. setting \( \lambda = 0 \), or the offsets in figure 5(c), i.e. setting \( m_0 = m_r = 0 \). The expected effects (occurrence of ring artefacts or significant noise) demonstrate that the additional degrees of freedom in the iterative reconstruction have their desired effects.

Conclusions

We have substantially extended and experimentally validated a previously developed model for iterative tomographic reconstruction of data sets acquired with an x-ray EI setup. We included additional degrees of freedom that account for offsets in the sample mask position due to drift or vibrations and that allows for a significant reduction of ring artefacts. This rendered flat field tracking obsolete and allows for a reduction of total scan time. In addition, we incorporated the possibility to retrieve a combined absorption/phase signal, which was demonstrated to yield higher inter-material CNRs than established single shot approaches to data analysis. Further, we showed the versatility of the proposed iterative reconstruction framework by successful application to different experimental setups as well as scan types/parameters.

Funding

ME was supported by the Royal Academy of Engineering under the RA Eng Research Fellowship scheme.

ORCID iDs

Peter Modregger https://orcid.org/0000-0002-2648-6403
Marco Endrizzi https://orcid.org/0000-0002-7810-2301
References

Arfelli F et al 2000 Mammography with synchrotron radiation: phase-detection techniques Radiology 215 286
Birnbacher L, Maurer S, Scheidt K, Herzen J, Pfeiffer F and Fromme T 2018 Electron density of adipose tissues determined by phase-contrast computed tomography provides a measure for mitochondrial density and fat content Frontiers Physiol. 9 1
Born M and Wolf E 1999 Principles of Optics 7th edn (Cambridge: Cambridge University Press)
Bravin A, Coan P and Suortti T 2013 X-ray phase-contrast imaging: From pre-clinical applications towards clinics Phys. Med. Biol. 58 R1–35
Byrd R, Lu P, Nocedal J and Zhu C 1995 A limited memory algorithm for bound constrained optimization SIAM J. Sci. Statist. Comput. 16 1190
Chapman D, Thomlinson W, Johnston R E, Washburn D, Pisano E D, Gmür N, Zhong Z, Menk R H, Arfelli F and Sayers D 1997 Diffraction enhanced x-ray imaging Phys. Med. Biol. 42 2015
Chen Y, Guan H, Hagen C K, Olivo A and Anastasio M A 2017 Single-shot edge illumination x-ray phase-contrast tomography enabled by joint image reconstruction Opt. Lett. 42 619
David C, Nohammer B, Solak H and Ziegler E 2002 Differential x-ray phase contrast imaging using a shearing interferometer Appl. Phys. Lett. 81 3267
Dilmuan F, Zhong Z, Ren B, Wu X Y, Chapman L D, Orion I and Thomlinson W C 2000 Computed tomography of x-ray index of refraction using the diffraction enhanced imaging method Phys. Med. Biol. 45 933
Diemont P et al 2015 Single-image phase retrieval using an edge illumination x-ray phase-contrast imaging setup J. Synchrotron Radiat. 22 1072
Endrizzi M, Diemoz P C, Munro P R T, Hagen C K, Szafraniec M B, Millard T P, Zapata C E, Speller R D and Olivo A 2013 Applications of a non-interferometric x-ray phase contrast imaging method with both synchrotron and conventional sources J. Instrum. 8 C05008
Eggl F et al 2018 Dose-constructive phase-contrast mammography on mastectomy specimens using a compact synchrotron source Sci. Rep. 8 1
Endrizzi M, Vittoria F A, Kallon G, Basta D, Diemoz P C, Vincenzi A, Delogu P, Bellazzini R and Olivo A 2015 Achromatic approach to phase-contrast enhanced x-ray imaging Phys. Med. Biol. 62 2015
Fu J, Schleede S, Tan R, Chen L, Bech M, Achterhold K, Gifford M, Loewen R, Ruth R and Pfeiffer F 2013 An algebraic iterative reconstruction technique for differential X-ray phase-contrast computed tomography Z. Med. Phys. 23 186
Gaass T, Potdevin G, Bech M, Noel P B, Willem N, Tapfer A, Pfeiffer F and Haase A 2013 Europhys. Lett. 102 48001
Hellbach K et al 2016 Depiction of pneumothoraces in a large animal model using x-ray dark-field radiography Sci. Rep. 6 1
Hagen C K, Endrizzi M, Diemoz P C, Millard T P, Louise Jones I, Speller R D, Robinson I K and Olivo A 2014 Hard X-ray dark-field imaging with incoherent sample illumination Appl. Phys. Lett. 104 024106
Hagen C K, Endrizzi M, Diemoz P C and Olivo A 2016 Reverse projection retrieval in edge illumination x-ray phase contrast computed tomography J. Phys. D: Appl. Phys. 49 255001
Hagen C K, Diemoz P C, Endrizzi M, Munro P R T, Szafraniec M B, Millard T P, Speller R D and Olivo A 2014a A laboratory-based x-ray phase contrast imaging scanner with applications in biomedical and non-medical disciplines Int. J. Mod. Phys. Conf. Ser. 27 1460150
Hagen C K, Diemoz P C, Endrizzi M and Olivo A 2014b The effect of the spatial sampling rate on quantitative phase information extracted from planar and tomographic edge illumination x-ray phase contrast images J. Phys. D: Appl. Phys. 47 455401
Jones E, Oliphant E and Peterson P et al 2001 SciPy: open source scientific tools for Python
Kak A C and Slaney M 1988 Principles of Computed Tomographic Imaging (Piscataway, NJ: IEEE)
Momose A, Kawamoto S, Koyama I, Hamashi Y, Takai K and Suzuki Y 2003 Demonstration of X-Ray Talbot Interferometry Japan. J. Phys. Phys. 42 L866
Modregger P, Cremona T P, Benarafa C, Schittny J C, Olivo A and Endrizzi M 2016 Small angle x-ray scattering with edge-illumination Sci. Rep. 6 30940
Munro P R T, Ignatyev K, Speller R D and Olivo A 2010 Source size and temporal coherence requirements of coded aperture type x-ray phase contrast imaging systems Opt. Express 18 193681
Nilchian M, Vonesch C, Modregger P, Stampanoni M and Unser M 2013a Fast iterative reconstruction of differential phase contrast x-ray tomograms Opt. Express 21 5511
Nilchian M, Vonesch C, Lefkimmiatis S, Modregger P, Stampanoni M and Unser M 2013b Constrained regularized reconstruction of x-ray-DPCI tomograms with weighted-norm Opt. Express 21 32340
Olivo A and Speller R D 2007 A coded-aperture technique allowing x-ray phase contrast imaging with conventional sources Appl. Phys. Lett. 91 074106
Olivo A et al 2013 Low-dose phase contrast mammography with conventional x-ray sources Med. Phys. 40 090907
Pfeiffer F, Kottler C, Bunk O and David C 2007a Hard x-ray phase tomography with low-brilliance sources Phys. Rev. Lett. 98 1
Pfeiffer F, Bunk O, David C, Bech M, Le Duc G, Bravin A and Cloetens P 2007b High-resolution brain tumor visualization using three-dimensional x-ray phase contrast tomography Med. Phys. 34 2688–2698
Paganin D, Mayo S C, Gureyev T E, Miller P R and Wilkins S W 2002 Simultaneous phase and amplitude extraction from a single defocused image of a holographic object J. Microsc. 206 33
Stampanoni M, Wang Z and Thuring T 2011 The first analysis and clinical evaluation of native breast tissue using differential phase-contrast mammography Invest. Radiol. 46 801
Teufelbach M V, Koehler T, Fehringer A, Viermetz M, Brendel B, Herzen J, Proksa R, Rummenni E J, Pfeiffer F and Noel P B 2017 Grating-based phase-contrast and dark-field computed tomography: A single-shot method Sci. Rep. 7 1
Xu Q, Siddiqy E Y, Pan X, Stampanoni M, Modregger P and Anastasio M A 2012 Investigation of discrete imaging models and iterative image reconstruction in differential X-ray phase-contrast tomography Opt. Express 20 10724
Yaroshenko A, Meinel F G, Bech M, Tapfer A, Vroman A and Schleede S et al 2013 Pulmonary emphysema diagnosis with a preclinical small-animal x-ray dark-field scatter-contrast scanner Radiology 269 427
Zamir A, Endrizzi M, Hagen C K, Vittoria F A, Urbani L, De Coppi P and Olivo A 2016 Robust phase retrieval for high resolution edge illumination x-ray phase-contrast computed tomography in non-ideal environments Sci. Rep. 6 1