Electron tomography based on a total variation minimization reconstruction technique

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The 3D reconstruction of a tilt series for electron tomography is mostly carried out using the weighted backprojection (WBP) algorithm or using one of the iterative algorithms such as the simultaneous iterative reconstruction technique (SIRT). However, it is known that these reconstruction algorithms cannot compensate for the missing wedge. Here, we apply a new reconstruction algorithm for electron tomography, which is based on compressive sensing. This is a field in image processing specialized in finding a sparse solution or a solution with a sparse gradient to a set of ill-posed linear equations. Therefore, it can be applied to electron tomography where the reconstructed objects often have a sparse gradient at the nanoscale. Using a combination of different simulated and experimental datasets, it is shown that missing wedge artefacts are reduced in the final reconstruction. Moreover, it seems that the reconstructed datasets have a higher fidelity and are easier to segment in comparison to reconstructions obtained by more conventional iterative algorithms.

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1. Introduction

Due to the continuous development of new applications of nanostructures, heavier demands are imposed on the characterization of these structures. Transmission electron microscopy (TEM) is a valuable technique for investigating the properties of these nanomaterials at the nanometer scale. However, as the complexity of the investigated nanostructures increases, two-dimensional (2D) projections of the three-dimensional (3D) nanostructures are no longer sufficient to provide a quantitative characterization of these structures and a reliable 3D reconstruction of the morphology is needed. 3D characterization can be achieved through electron tomography, which is a technique to create a 3D reconstruction out of 2D projection images [1,2]. These 2D projection images are acquired using an electron microscope by different techniques such as high angle annular dark field (HAADF) scanning transmission electron microscopy (STEM) [1], energy filtered transmission electron microscopy (EFTEM) [3], bright field TEM (BFTEM) [4], dark field TEM (DFTEM) [5], annular DFTEM [6] or electron holography [7]. The projections are acquired at different tilt angles of the specimen. After alignment of the projection images, the series is used as input for a mathematical algorithm leading to a 3D reconstruction. Whereas weighted backprojection is frequently used for X-ray (micro)tomography, this algorithm is limited for electron tomography because reconstructions obtained in this manner suffer from artefacts caused by, for example, the missing wedge. This missing wedge of information in a tilt series is mostly inevitable due to the limited space between the polepieces of the objective lens of the electron microscope. As a consequence, only a limited number of tilt angles can be reached during the acquisition of a tomographic tilt series. Alternatively, iterative reconstruction algorithms such as the simultaneous iterative reconstruction technique (SIRT) [8] typically yield more accurate reconstructions than a weighted backprojection for such limited data problems, and are therefore widely used in electron tomography. However, as the correspondence between the reconstructed image and the measured projection data improves at each iteration, also the noise in the reconstruction increases. Therefore, most of the time, a compromise between quality and signal to noise ratio (SNR) has to be found and the number of iterations is limited to approximately 20 or 30 [9]. A promising new reconstruction algorithm is given by the discrete algebraic reconstruction technique (DART) [10]. This technique makes use of the prior knowledge that a reconstruction only contains a limited number of grey values. Because of this extra prior knowledge, several artifacts such as the elongation of the point spread function caused by the missing wedge can be avoided leading to reconstructions with a higher fidelity. An extra advantage of discrete tomography is that the segmentation and consequently the quantification of the reconstruction is straightforward since thresholding is already applied in the reconstruction algorithm itself.
In this work, a new reconstruction algorithm [11] is used for electron tomography which is based on compressive sensing (CS). This relatively new field in image processing is specialized in finding a sparse solution to a set of ill-posed linear equations. The idea of total variation minimization (TVM) in compressive sensing in combination with tomography was proposed by Donoho et al. [12,13]. A perfect reconstruction of a phantom object could be obtained even when the number of projections did not satisfy the Nyquist–Shannon criterion [14].

2. Notation and concept

For simplicity, the concept of electron tomography is explained using a 2D reconstruction out of 1D projections. Extension to 3D objects is then straightforward since these can be regarded as a set of 2D slices. During the acquisition of a tomographic experiment, \( N \) projections (all with \( k \) pixels) are acquired at tilt angles \((\theta_1, \theta_2, \ldots, \theta_k)\) from an object \( f(u,v) \) with a width \( w \) and a height \( h \). As can be seen from Fig. 1, the acquisition of projections during this tomographic experiment can be seen as a set of linear equations

\[
Ax = b,
\]

where \( b \) is the measurement vector of size \( m \times 1 \) (\( m = N \times k \)) representing the projections, \( x \) is a vector with dimensions \( n \times 1 \) (\( n = w \times h \)) representing the imaged object and \( A \) is the projection matrix of size \( m \times n \). The element \( a_{ij} \) equals the contribution of pixel \( i \) to projection ray \( j \). To make a reconstruction of the object, one has to solve the inverse problem of recovering the unknown vector \( x \) from the measurements \( b \). As the number of pixels \( n \) in the reconstructed object is typically much larger than the number \( m \) of projection rays, the system is underdetermined and an infinite number of solutions may exist. To make matters worse, noise and other errors in the measured data will typically make the equation system inconsistent, so that no exact solution exists at all. Therefore, most reconstruction algorithms aim to minimize the difference between \( Ax \) and \( b \) (i.e. projection distance) by using the \( L_2 \) norm which corresponds to a weighted least square sum problem.

2.2. Total variation minimization (TVM) based reconstruction technique

The field of compressive sensing aims to exploit the knowledge that the reconstructed object has a sparse representation. The set of basis functions has to be chosen prior to the reconstruction in such a way that the unknown object can be approximated by a linear combination of just a small number of such basis functions [15,16]. This is illustrated in Fig. 2. Although the image in Fig. 2(a) is not sparse, Fig. 2(b) shows that the gradient is sparse. Also for nanostructured materials, it is often possible to assume that the gradient of the object is sparse.

When incorporating this assumption in the reconstruction algorithm, this results in a reconstruction where sharp transitions between specific grey values are preferred over gradual changes. A convenient way to implement this constraint concerning the sparsity in a tomographic reconstruction is by minimizing the norm of the discrete gradient (i.e. the total variation) of the reconstructed image. In other words, the aim is to find the solution to the reconstruction problem \( Ax = b \) which has the lowest total variation. This can be accomplished by simultaneously minimizing the projection distance between the reconstructed object and the original projections and the total variation of the reconstructed object

\[
\hat{x} = \arg\min_x [TV(x) + \frac{\mu}{2} \|Ax-b\|^2].
\]

In this equation, \( TV(x) \) is the total variation computed as the norm of the discrete gradient of the reconstructed object and \( \mu \) is a regularization parameter. As can be seen from this equation, the projection distance of the tomographic problem is minimized simultaneously with the norm of the discrete gradient of the reconstructed object. As a result, a solution to the ill-posed equation is obtained which both satisfies the measured projections and has a low total variation. The regularization parameter \( \mu \) indicates the importance of both terms and it is therefore very
important in the algorithm. A large value of $m$ leads to a result that resembles a SIRT reconstruction. Both missing wedge artifacts and noise will be present in the resulting reconstruction. An underestimation of $m$ will lead to a reconstruction in which noise is suppressed, but high frequency details of the reconstruction will be lost as well. Simulations, presented in Fig. 3, show that $m = 0.5$ can be considered as a good starting value. Since the argument in Eq. (2) is not a convex or differentiable function of $x$, it is not straightforward to minimize this function. In the literature, several methods have been proposed to solve this problem, but most of them are only capable of solving small problems and are therefore not suited for tomography. Li et al. [11] proposed the TVAL3 scheme which is able to minimize the total variation of large systems. The algorithm they used is based on the minimization of augmented Lagrangian functions through an alternating minimization scheme where the multipliers are updated after each iteration. The augmented Lagrangian functions that need to be minimized can be seen as regular Lagrangian functions with an additional penalty term. This iteration scheme stops when the average difference between two successive reconstructions becomes smaller than a predefined tolerance value. This algorithm, implemented in Matlab by Li et al., is adapted in this study and used in the remainder of this work to solve the total variation minimization problems and is called Total Variation Minimization (TVM) reconstruction technique.

Fig. 2. (a) Shepp logan phantom object and (b) gradient image of this phantom object. It can be seen that the gradient image is a sparse representation of the original object.

Fig. 3. (a) Shepp logan phantom object used to investigate the influence of the regularization parameter $m$ on the quality of the reconstruction. (b) TVM reconstruction of phantom object with $m = 0.1$. (c) shows the reconstruction with a regularization parameter that equals 0.5 and (d) shows the reconstruction with a parameter equal to 1. For these reconstructions, projections are simulated with angles ranging from $-70^\circ$ to $+70^\circ$ with a $2^\circ$ increment.
3. Different case studies

To investigate the quality of the reconstructions computed by the TVM reconstruction algorithm in comparison to the widely used SIRT algorithm, three different datasets are used. All of these datasets are acquired at different electron microscopes operated by different microscopists. Both the TVM algorithm and the SIRT algorithm [17] are implemented in Matlab. The SIRT reconstructions always uses 100 iterations to assure convergence of the reconstruction. From our experience, this is a convenient number of iterations to certify convergence in our implementation. The first sample that has been investigated exists of small Ag nanoparticles with a diameter of 1–5 nm. For such small particles, it is known that the intensity in the reconstruction scales with the size of the particles [18]. As a consequence, reconstructions made with regular tomographic reconstruction algorithms have problems with segmentation and quantification of these particles. The second sample of which the 3D structure is investigated using the TVM reconstruction algorithm consists of PbSe–CdSe core shell particles. These particles form good test objects as they contain different chemical components, but have a fairly regular geometry. The last sample that has been investigated is a Si matrix containing Pb inclusions. Mounted on a dedicated on–axis tomography holder, a needle shaped sample can be tilted over 360° in the electron microscope. This experiment enables us to investigate the influence of the missing wedge on the quality of the TVM reconstruction. For all the simulated and experimental datasets, the TVM reconstruction uses a regularization parameter that equals 0.5 and the iterative scheme stops when the average difference in intensity between pixels of two successive reconstruction steps becomes smaller than 0.001. For this value, no visual improvement is observed anymore when comparing two successive iterations.

4. Ag nanoparticles

4.1. Sample description

The first sample that has been investigated by 3D reconstruction based on the TVM algorithm, consists of Ag nanoparticles with a diameter ranging from 1 to 5 nm. This sample is ideal as a first test sample for the algorithm, because it has a regular geometry and consists of a single chemical element. For this sample, a tilt series is acquired with angles ranging from −72° to +74° and an increment of 2° between consecutive projections. The tilt series is acquired at a Tecnai G2 microscope operating in HAADF-STEM mode with an inner collection angle of 58 mrad to avoid diffraction contrast and using a Fischione tomography tilt holder. The HAADF-STEM projection acquired at 0° tilt angle is shown in Fig. 4. Alignment of the tilt series is performed using the feature tracking option in the FEI Inspect3D software.

4.2. Phantom experiment

To gain more insight concerning the quality of the reconstruction, a 2D phantom object is created resembling a slice through the specimen that contains several Ag particles. 1D projections at the same tilt angles as the experimental tilt series are simulated from this phantom object using a linear projection model. It must be noted that the simulated tilt axis is perpendicular to the original experimental tilt axis. A small amount of gaussian noise and a small misalignment are applied on the simulated tilt series to make the phantom experiment more realistic. Both a SIRT reconstruction and a TVM reconstruction are made. The phantom object is shown in Fig. 5(a) and its gradient image is displayed in Fig. 5(b). The corresponding SIRT and TVM reconstruction are displayed in Fig. 5(c) and (d) respectively. From these reconstructions, it is clear that the TVM reconstruction suffers less from missing wedge artifacts in comparison to the SIRT reconstruction. Moreover, it is clear that some small Ag particles, present in the phantom object, are not reconstructed well in the SIRT reconstruction.

Fig. 4. HAADF-STEM projection of Ag nanoparticles dispersed on a C grid. The diameter of the particles varies from 1 to 5 nm.

Fig. 5. (a) Phantom object resembling the imaged cluster with Ag nanoparticles. (b) Gradient image of the phantom object. (c) SIRT reconstruction based on 74 simulated projections from the phantom object. Streaking artifacts caused by the missing wedge are visible. From this figure, it can be seen that some small Ag particles that are encircled are not reconstructed well. (d) TVM reconstruction based on the same projections. In this reconstruction, no streaking artifacts are present and all the particles are reconstructed well. (The intensities are linearly scaled between the minimum and maximum value of every image.)
where they disappear because of the streaking artifacts caused by the missing wedge. Also when no noise and misalignment are introduced in the simulated tilt series, the smallest particles are not observed in the reconstruction. These particles (indicated by circles in Fig. 5) can be observed in the TVM reconstruction in Fig. 5(c).

4.3. Results for tomographic experiment

Also for the experimental tilt series, both a SIRT and a TVM reconstruction are performed. They are both shown in Fig. 6. Fig. 6(a) shows an isosurface rendering of the SIRT reconstruction. The corresponding isosurface rendering of the TVM reconstruction with the same threshold value is shown in Fig. 6(b). From these figures, it is clear that some small Ag particles that are indicated by circles are reconstructed well in the TVM reconstruction, but not in the SIRT reconstruction. This is in agreement with the simulation experiment where the SIRT algorithm is also not able to recover the smallest particles. Fig. 6(c) and (d) shows two orthoslices through the SIRT and the TVM reconstruction respectively. Also in these orthoslices, it is clear that some small particles are not reconstructed well in the SIRT reconstruction. A slice through the SIRT reconstruction perpendicular to the

![Fig. 6.](image_url)

Fig. 6. (a) Isosurface rendering of reconstruction of Ag particles made with the SIRT algorithm. (b) Isosurface rendering of TVM reconstruction of Ag particles with the same threshold value as in (a). From these images, it is clear that some small particles that are encircled are not reconstructed well in the SIRT reconstruction. (c) and (d) show orthoslices through the SIRT and the TVM reconstruction respectively. Also in these orthoslices, it is clear that some particles are reconstructed well in the TVM reconstruction and not in the SIRT reconstruction. (e) and (f) show two slices through the SIRT and the TVM reconstruction that are perpendicular to the missing wedge. It can be seen that streaking artifacts are much more present in the SIRT reconstruction. Also the elongation in the direction of the missing wedge is more present in the SIRT reconstruction than in the TVM reconstruction. The intensities in the orthoslices are linearly scaled between the minimum and maximum value of every image.
missing wedge is shown in Fig. 6(e). The corresponding slice through the TVM reconstruction is shown in Fig. 6(f). In the SIRT reconstruction, streaking artifacts and an elongation in the direction of the missing wedge are present. In the TVM reconstruction, these artifacts are less pronounced.

5. PbSe–CdSe core shell nanoparticles

5.1. Sample description

The second sample that was subject to a 3D reconstruction based on the TVM algorithm consists of PbSe–CdSe core shell nanoparticles with an average diameter of 9 nm. Electron tomography is required to investigate the overall shape of the PbSe core in the particles. The tilt series of the cluster is acquired using angles ranging from $-75^\circ$ to $+75^\circ$ with an increment of $1^\circ$. HAADF-STEM images acquired with an inner collection angle of 56 mrad are used as projections to avoid unwanted diffraction contrast. The acquisition is performed at a cubed FEI TITAN 50–80 microscope using a Fischione tomography tilt holder and operated by the FEI Xplore3D software. The projection acquired at 0° tilt angle is shown in Fig. 7. Alignment of the tilt series is done by a combination of cross-correlation in FEI Inspect3D software and a manual alignment in IMOD [19].

5.2. Phantom experiment

In order to test the TVM reconstruction algorithm, a 2D phantom object is created resembling a slice through three core shell particles. This phantom object is displayed in Fig. 8(a). To simulate a tomography experiment in a TEM, projections are simulated over a tilt range of $-75^\circ$ to $+75^\circ$ with an interval of $2^\circ$. To obtain a more realistic tilt series, gaussian noise and a small misalignment are introduced. The reconstruction is performed using both the TVM algorithm and a more conventional SIRT algorithm with 100 iterations. Slices through the reconstructions are shown together with a slice through the original phantom object in Fig. 8. These slices show that the surface of the core which is perpendicular to the incoming electron beam at zero tilt is reconstructed better by TVM than by SIRT. Also the elongation in the direction of the missing wedge is less present in the TVM reconstruction. Moreover, segmentation and quantification of the reconstructed volume become much easier because there is less variation in the grey values.

5.3. Results for tomographic experiment

The tomographic reconstruction of the experimental tilt series of the core shell nanoparticles is made using both the SIRT algorithm and the TVM algorithm. Both reconstructions are shown in Fig. 9 where Fig. 9(a) and (b) show two voltex visualizations of the SIRT and the TVM reconstruction respectively. Slices through the reconstructions are shown in Fig. 9(c)–(f). In this figure, streaking artifacts caused by the missing wedge are observed in the SIRT reconstruction and less in the TVM reconstruction. It is also clear that the SIRT...
reconstruction is more elongated in the direction of the missing wedge in comparison to the TVM reconstruction. An additional advantage of the TVM reconstruction is that the reconstruction is easier to segment and has a better signal to noise ratio (SNR). From both the SIRT and the TVM reconstruction, it can be seen that the PbSe cores have irregular morphologies.

6. Pb particles in Si needle

6.1. Sample description

The last sample of which the 3D structure is investigated based on the TVM reconstruction algorithm, is a Si sample that contains
Pb inclusions. The diameter of these particles varies from 5 to 10 nm. A needle shaped TEM sample, prepared by a FEI Nova Nanolab 2011 DualBeam SEM/FIB system, in combination with a dedicated on-axis tomography holder allows tilting the specimen over the full tilt range of 360° [20–22]. This enables us to investigate the influence of the missing wedge on the reconstruction in a more quantitative manner by artificially increasing the missing wedge. The tilt series is acquired at a Jeol 3000 microscope in HAADF-STEM mode using a tilt increment of 2° between consecutive projections. The inner collection angle of the annular detector equals 60 mrad assuring the incoherent imaging. Alignments of the tilt series is performed using cross-correlation in the FEI Inspect3D software.

6.2. Phantom experiment

First a phantom object is created resembling the imaged structure and projections are generated using the full tilt range from −90° to +90° with a 2° tilt increment. The simulated object is shown in Fig. 10(a) and the corresponding SIRT and TVM reconstructions are shown in Fig. 10(c) and (d) respectively. Fig. 10(b) represents the gradient image of the phantom object indicating that it has a limited variation. Prior to reconstruction, a small amount of gaussian noise and a misalignment are introduced to make the simulated tilt series more realistic. Whereas both the TVM and the SIRT reconstruction yield a good reconstruction of the original object, the profile through both reconstructions prove that the intensities are reconstructed more accurately in the TVM reconstruction than in the SIRT reconstruction.

6.3. Results for tomographic experiment

The projection at 0° tilt angle is shown in Fig. 11(a). The reconstructions of the experimental tilt series is shown in Fig. 11(b)–(f). Fig. 11(b) shows a voltex rendering of the TVM reconstruction showing the Pb particles in the Si needle shaped sample. An orthoslice through the SIRT reconstruction is shown in Fig. 11(c) and the corresponding orthoslice through the TVM reconstruction in Fig. 11(d). From these slices, it can be seen that the background in the TVM reconstruction contains less noise and is easier to segment. This can also been seen in the slices shown in Fig. 11(e) and (f) which show an orthoslice along the axis of the needle shaped sample. The dark spots (indicated by white arrows) that are present in the orthoslices through both the TVM and the SIRT reconstruction nearby the Pb particles are probably caused by artifacts similar to beam hardening artifacts observed in X-ray tomography. Also small misalignments of the tilt series and the limited number of projections may lead to residual artifacts.

6.4. Influence of missing wedge

To investigate the influence of the missing wedge on the TVM reconstruction in a more quantitative manner, a missing wedge is artificially introduced in the full tilt series ranging from −90° to +90°. The average diameter of the Pb particles in the Si needle and its standard deviation is then measured. This is done for a missing wedge of 0°, 2°, 4° and 6°. This last missing wedge corresponds to a tilt series with angles ranging from −60° to +60°. Slices through the reconstructions and the measured diameters for these different tilt series are shown in Fig. 12. From the displayed graph, it is shown that a large missing wedge has a big influence on the measured diameters in a SIRT reconstruction whereas the average value in the TVM reconstruction remains almost constant. While the precision is comparable for both reconstructions, the accuracy is much better for the TVM reconstruction which means it has a lower systematic error. This indicates that the TVM algorithm suffers less from missing wedge artifacts than the SIRT reconstruction.

7. Discussion

Total variation minimization yields a good reconstruction of three different experimental datasets. The samples of which the
3D structure is investigated with this reconstruction technique include a cluster of Ag nanoparticles with a diameter of 1–5 nm, PbSe–CdSe core shell particles and a needle shaped Si sample with Pb particles inside with a diameter of 5–10 nm. For these different case studies, first a phantom object is created and reconstructed with both a TVM and a regular SIRT algorithm. The TVM reconstruction algorithm was found to be four times slower in comparison to the SIRT algorithm. The resulting reconstruction however can be segmented in a much more straightforward manner, e.g. using thresholding. This is a major advantage in comparison to the SIRT algorithm where segmenting is mostly carried out manually due to remaining (missing wedge) artifacts. Manual segmentation is not only time-consuming but might also be subjective. The intensity profiles through the reconstructions of the phantom objects show that the intensity is reconstructed faithfully with the TVM algorithm. The experimental reconstructions confirm these results and it is even shown that very small Ag particles are reconstructed well with a TVM reconstruction but not in a SIRT reconstruction because of streaking artifacts and noise present in the reconstruction. Quantification of the Pb–Si tilt series shows that the quantification of the particle diameter based on a TVM reconstruction is less influenced by an increasing missing wedge than with a regular SIRT reconstruction. This is probably caused by the fact that the reconstruction algorithm uses prior knowledge that the reconstructed object has a limited variation on the nanoscale. However, this prior knowledge is less strict than in discrete algorithms where exact knowledge on the different grey levels has to be known. The result of a TVM reconstruction is not influenced in those cases where the reconstructed object has a non-zero background (e.g. a carbon support). This is supported by the fact that the algorithm was successfully used to reconstruct both objects with (Ag nanoparticles and PbSe–CdSe core shell particles) and without a carbon support (Si needle with Pb particles). For the reconstruction of objects with a non-uniform density, the TVM algorithm can still be used albeit in combination with a small regularization parameter $\mu$. As a result, the algorithm will resemble more a regular SIRT algorithm since the assumption concerning limited variation of the sample is no longer valid.

8. Conclusion

In this study, we have investigated a new reconstruction algorithm for electron tomography based on total variation minimization. The algorithm is used to obtain a tomographic reconstruction of three different test objects. Each of these reconstructions is also compared to a SIRT reconstruction which is nowadays widely used in electron tomography for material science. From the different test samples, it is clear that the morphology of the nanostructures can be reconstructed well using the TVM algorithm. This algorithm has the advantage that it suffers less from the incomplete sampling in Fourier space due to the missing wedge. It is able to reconstruct the

Fig. 11. (a) HAADF-STEM projection of Pb particles in a Si needle. (b) shows a voltex rendering of the TVM reconstruction. Orthoslices through the SIRT reconstruction (c and e) and the TVM reconstruction (d and f) show that the TVM reconstruction contains less noise and is easier to segment.
morphology well even with a limited number of projections. In addition, a reconstruction made with the TVM algorithm is easier to segment in comparison to the SIRT algorithm and it has the advantage that no prior knowledge about the different grey levels is required. It is also shown that small particles are not always reconstructed well using a conventional SIRT algorithm whereas they are reconstructed well using the TVM reconstruction.

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