

Algorithms in Tomography and Related Inverse Problems

Subjects: Others

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In the ever-evolving landscape of tomographic imaging algorithms, a diverse array of themes shaping the field's progress. It encompasses foundational principles, special innovative approaches, tomographic implementation algorithms, and applications of tomography in medicine, natural sciences, remote sensing, and seismology. This choice is to show off the diversity of tomographic applications and simultaneously the new trends in tomography. Accordingly, the evaluation of backprojection methods for breast tomographic reconstruction is highlighted. After that, multi-slice fusion takes center stage, promising real-time insights into dynamic processes and advanced diagnosis. Computational efficiency, especially in methods for accelerating tomographic reconstruction algorithms on commodity PC graphics hardware, is also presented. In geophysics, a deep learning-based approach to ground-penetrating radar (GPR) data inversion propels us into the future of geological and environmental sciences.

Keywords: optical coherence tomography ; tomographic imaging ; tomographic implementation algorithms ; Inverse problems

1. Tomographic Reconstruction Techniques, Principles, and New Approaches

In the realm of tomographic reconstruction, the journey begins with a fundamental categorization of algorithms, as detailed by Gordon and Herman ^[1]. This classification neatly segments the methods for reconstructing objects from their projections into four distinct categories. These categories include the summation technique, the Fourier transform utilization, solving integral equations analytically, and employing series expansion methodologies. This initial categorization not only provides a structured approach to the field but also offers a basis for understanding the diversity of techniques at play.

As researchers delve into this domain, according to Colsher ^[2], a pivotal study is provided where four key algorithms are adapted to directly reconstruct three-dimensional objects from projections. This transformative step showcases the practical application of these methods. Among the selected algorithms, the Algebraic Reconstruction Technique, the Simultaneous Iterative Reconstruction Technique, and the Iterative Least Squares Technique are featured. This comprehensive approach exemplifies the potential for substantial streamlining of calculations and introduces the concept of tomographic projections. Diving further into the fine distinction of tomography reconstruction, Clackdoyle and Defrise ^[3] distinguish between the 2D and 3D reconstruction problems. To comprehend the foundations of computed tomography image reconstruction, Hornegger, Maier, and Kowarschik provide essential insights in their work ^[4]. These foundational principles are paramount for understanding the core concepts and techniques applied in the field. In the realm of classical tomography, the 2D problem is prevalent, but as researchers move into 3D, considerations expand to density functions and lines with arbitrary orientations in space. Building upon this knowledge, the research conducted by Khan, Yasin et al. ^[5] offers an overview of cutting-edge 3D modeling algorithms developed over the past four decades. This rich resource equips researchers and practitioners with the latest advancements in tomographic reconstruction techniques. This differentiation is crucial, as it influences the choice of reconstruction methods in various applications.

Of particular significance is the enhanced temporal resolution for cardiac imaging and the ability to acquire dual-energy information by operating the two tubes at varying voltages. The synergy of technological innovation and practical application is exemplified by Goshtasby and Turner ^[6]. This reference introduces an automated technique capable of converting a series of tomographic image slices into an isotropic volume dataset. By establishing correspondence between points in consecutive slices and employing linear interpolation, this method offers a substantial enhancement in data accessibility. As reported by Fessler ^[7], the research delves into algorithms tailored for reconstructing attenuation images from transmission scans characterized by a low count of photons per beam. In situations where the average

number of photons per beam is modest enough to warrant caution when employing traditional filtered backprojection imaging techniques, these algorithms offer a critical solution. The ongoing evolution underscores the dynamic nature of tomographic image reconstruction. As reported by Yu and Fessler [8], their research indicates a critical advancement by integrating nonlocal boundary information into the regularization approach. This incorporation stems from the insights drawn from the reference and demonstrates the growing importance of statistical methods in tomographic image reconstruction. Beyond mere system modeling, these methods offer statistical models and adherence to physical constraints that surpass the traditional filtered backprojection method. Addressing specific challenges, Chandra et al. [9] introduce a swift and precise approach to tackle circular artifacts that often stem from missing segments of the Discrete Fourier Theorem. This method refines the precision and efficiency of image reconstruction, contributing to the overall quality of results. This approach is rooted in the precise partitioning of the Discrete Fourier Theorem space under the projective Discrete Radon Transform, as denoted in the Discrete Fourier Theorem. To further augment image quality and move beyond the confines of conventional backprojection methods, Zhou, Lu et al. [10] precede two innovative backprojection variants: the α -trimmed backprojection and the principal component analysis-based backprojection. These variants offer the promise of superior image quality, which is a critical factor in numerous tomographic applications. As researchers advance in researchers' exploration, Chetihand Messali [11] adopts a comprehensive methodology by implementing both the Algebraic Reconstruction Technique and Filter Backprojection methods. The study then rigorously compares the ensuing experimental results using performance metrics across various test cases. Such comparisons are instrumental in assisting researchers in selecting the most suitable method for their specific scenarios.

As researchers delve into the field of computed tomography, Somigliana, Zonca et al. [12] focus on the correlation between the thickness of acquired computed tomography slices and the accuracy of three-dimensional volume reconstruction. This correlation is pivotal for radiation therapy planning and disease diagnosis. On the theoretical front, Gourion and Noll [13] explore the theoretical framework of emission-computed tomography. The article delves into novel numerical approaches based on regularization methods. Understanding the theoretical underpinnings of the image reconstruction process is instrumental in advancing the field. In a noteworthy departure from conventional approaches, Petersilka, Bruderet al. [14] point out a pioneering system concept and design for a computed tomography scanner. This innovative design, featuring two X-ray tubes and two detectors, holds the potential to surmount the limitations of traditional multi-detector row computed tomography. In the pursuit of innovation, Saha, Tahtali et al. [15] center on an innovative computed tomography acquisition method. This method enables simultaneous projection captures, potentially offering exceptionally rapid scans and reductions in radiation doses. This innovation exemplifies the ongoing efforts to optimize technology in the field. Continuing the pursuit of efficiency, Miqueles, Koshev et al. [16] introduce a novel rapid backprojection operator for processing tomographic data. This algorithm offers a cost-effective solution and is compared against other swift transformation techniques using extensive real and simulated datasets. Peering into the future, as outlined by Willemink and Noël [17], forthcoming advances are anticipated in both hardware and software. Innovations like photon-counting computed tomography and the integration of artificial intelligence are poised to reshape the field. Returning to the practical realm, Wang, Ye et al. [18] emphasize the real-world impact of tomographic reconstruction, particularly in the realm of medical imaging. This reference provides a broader context, shedding light on representative outcomes and the pressing concerns that demand attention in the field.

Beyond algorithmic aspects, the technological side of tomographic imaging is illuminated by Jung [19]. This article presents an assessment of the fundamental physical principles and technical facets of the computed tomography scanner. It encompasses noteworthy advancements in computed tomography technology, positioning the field at the forefront of diagnostic and research applications. In the paper authored by Withers, Bouman et al. [20], the authors delve into the fundamental tenets of computed tomography, offering insights into the methodologies for acquiring computed tomography scans. These methods employ X-ray tubes and synchrotron sources, as well as various feasible contrast modes. Such a thorough understanding of the technology underpinning tomographic imaging is vital for researchers and clinicians alike. Understanding the impact of acquisition parameters on reconstruction quality is essential. The significance of post-processing techniques comes to the forefront in work by Seletci and Dulu [21]. As outlined by Mia, Förster et al. [22], the research introduces the concept of equally inclined tomography, an advanced method for reconstructing three-dimensional objects from multiple two-dimensional projections. This innovative approach supersedes traditional tomography, which relies on equally angled two-dimensional projections. The result is a significant enhancement in three-dimensional reconstruction quality.

Meanwhile, Whiteled, Luk et al. [23] take a pioneering step in the realm of neural network design for positron emission tomography. The direct PET neural network is proficient in reconstructing multi-domain image volumes from sinograms, underlining the growing role of artificial intelligence in the field. As reported by Lee, Choi et al. [24], the research sets the stage for a deep learning revolution in tomographic imaging. The primary objective of the study is to attain high-quality three-dimensional reconstructed images in the context of sparse sampling conditions. Deep learning methods promise to

revolutionize accuracy and efficiency in the field. In a fusion of innovation and network architecture, Zhou, Kevin Zhou et al. [25] introduce a cascaded residual dense spatial-channel attention network. This network aims to reconstruct tomographic images from a limited number of projection views, amplifying the power of deep learning and data fidelity layers. For scenarios with limited data, Luther and Seung [26] present a direct approach for limited-angle tomographic reconstruction, employing convolutional networks. The network training process involves minimizing the mean squared error between the network-generated reconstructions and a ground truth three-dimensional volume. This reference underscores the importance of employing software tools like Adobe Photoshop, ImageJ, Corel PHOTO-PAINT, and Origin to enhance the quality of images for quantitative analysis. Such post-processing techniques are instrumental in distinguishing between various diseases and disorders. These guide us from fundamental principles to cutting-edge innovations, all emphasizing the real-world impact in medical, industrial, and scientific applications. All these underscore the dynamic evolution of the field as it adapts to emerging technologies, harnesses the power of artificial intelligence, and continually strives for higher quality and efficiency. In this ever-advancing discipline, these references serve as beacons, illuminating the path for researchers and practitioners, ensuring that they remain at the forefront of tomographic imaging, and delivering high-quality solutions for an array of applications.

2. Special Topics in Tomography

In this part, the particulars of advanced imaging techniques was embarked on. This comprehensive recall provides explanations on pivotal areas within the field of tomography, uncovering the latest innovations and theoretical considerations. From multi-slice computed tomography to Super-Resolution Reconstruction in magnetic resonance imaging, researchers delve into cutting-edge technology and novel algorithms. As researchers navigate this field, researchers also examine the creation of detailed 3D phantoms for various imaging applications, ultimately emphasizing the relevance of these 'Special Topics in Tomography' across the spectrum of medical and scientific research.

The introduction of multi-slice CT scanners, as detailed by Hu [27], represents a significant leap forward in the world of CT technology. These advanced scanners enable high-resolution imaging of extensive longitudinal volumes while introducing unique challenges. As observed by Dawson and Lees [28], multi-slice systems are placed in the broader context of CT technology, dropping light on their origins and enduring relevance. These collectively address challenges and innovations in CT scanning, offering insights into the technology's evolution. As reported by Majee, Balke et al. [29], a pioneering algorithm known as "multi-slice fusion" is introduced. This approach combines various denoising techniques within low-dimensional spaces and finds applications in 4D cone beam X-ray CT reconstruction.

Singh, Kalra et al. [30] conducted a comparative analysis of image quality in abdominal CT images, considering different X-ray tube current-time products and reconstruction techniques. Therefore, collectively, there is a need for improved MRI reconstruction techniques and image quality. As examined by Aibinu, Salami et al. [31], the tutorial places significant emphasis on three key aspects related to the utilization of Inverse Fast Fourier Transformation in Magnetic Resonance Image reconstruction. Furthermore, it delivers a succinct introduction to the fundamentals of Magnetic Resonance Image physics, the instrumental perspective of Magnetic Resonance Image systems, K-space signal processing, and the procedures involved in Inverse Direct Fourier Transformation and Inverse Fast Fourier Transformation for one-dimensional (1D) and two-dimensional (2D) data. Super-resolution imaging in MRI is explored in [32][33]. The authors Plenge, Poot et al. [32] introduce an innovative method for Super-Resolution Reconstruction in MRI, leveraging deep learning techniques, specifically a three-dimensional convolutional neural network. This technique harnesses high-resolution content in 2D slices to reconstruct high-resolution 3D images. The field of magnetic resonance imaging (MRI) reconstruction sees noteworthy advancements as well. Zhang, Shinomiya, and Yoshida [33] advocate the use of two-dimensional super-resolution technology to enhance the resolution of MRI, further enhancing the quality of MRI images.

The development of detailed phantoms is also a crucial aspect of medical imaging research. As outlined by Hoffman, Cutler et al., the study in [34] describes the creation of a three-dimensional brain phantom for simulating studies related to cerebral blood flow and metabolism in positron emission tomography. Additionally, Collins, Zijdenbos et al. [35] outline the construction of a digital volumetric phantom of the human brain, offering valuable tools for simulating head tomographic images. Glick and Ikejima [36] provide an overview of research efforts aimed at developing digital and physical breast phantoms to advance breast imaging studies. All of these collectively address the need for realistic phantoms for various imaging modalities. The study of Klingenberg-Regn, Schaller et al. [37] delves into the theoretical aspects of multi-slice scanners, with a focus on detector design and strategies for spiral interpolation. Moreover, it validates these theoretical constructs through phantom measurements. The authors Aibinu, Salami et al. emphasize Inverse Fast Fourier Transformation in MRI, highlighting the significance of K-space signal processing. Michael O' Connor, Das et al. [38] focus on the creation of high-resolution models for simulating three-dimensional breast imaging techniques, addressing the need for realistic breast tissue simulations.

In conclusion, the central issues explored across these references include enhancing image resolution, improving image quality, and providing tools for realistic simulations and studies. Together, these references form integral pieces of the puzzle, addressing interconnected issues across various imaging modalities in the field of medical imaging.

3. Tomographic Implementation Algorithms

In this part, the topics of image quality improvement and artifact reduction, elucidating techniques and strategies to increase the accuracy and fidelity of tomographic images were focused on. Dobbins and Godfrey ^[39] take us into the realm of tomosynthesis reconstruction algorithms. The discussion of residual blur minimization expands the dialogue that was initiated, emphasizing the practical challenge of improving image quality and accuracy, especially in 3D reconstruction. Goosens, Labate et al. ^[40] further investigate the challenge of region-of-interest computed tomography in the presence of measurement noise. They introduce a relaxation of data fidelity and consistency requirements, highlighting the complex nature of handling real-world imperfections in imaging processes. Su, Deng et al. ^[41] lead us to improve image quality and reduce artifacts through the deep learning process in breast tomosynthesis, illustrating the impact of state-of-the-art technology. This is in line with the theme of advancing tomographic reconstruction using modern computational techniques. Additionally, Quillent, Bismuth et al. ^[42] add deep learning to the discussion for mitigating sparse-view and limited-angle artifacts in digital breast tomosynthesis, highlighting the role of artificial intelligence in improving tomographic image quality. The pioneering approach presented by Lyu, Wu et al. ^[43] concerning metal artifact reduction emphasizes the critical practical aspect of image artifact reduction, further linking to the general issue of image quality improvement.

Referring to the optimization process, Abreu, Tyndall, and Ludlow ^[44] investigate the effect of projection geometry on caries detection. This is crucial as it addresses the real issue of optimizing image acquisition for specific diagnostic purposes, highlighting the importance of tailored imaging strategies. The authors Pekel, Lavilla et al. ^[45] lead us into the field of optimizing X-ray CT trajectories. Customizing imaging paths for specific samples addresses the practical challenge of efficient data acquisition and high-quality image production, coordinating the need for precision in tomographic imaging. Moving on to more widespread and synchronous processes, Jin, McCann et al. ^[46] bridge the gap between iterative methods and deep learning, highlighting the potential of convolutional neural networks in dealing with ill-posed inverse problems. The regression approach discussed by Hou, Alansary et al. ^[47] demonstrated the integration of deep learning techniques with 3D spatial mapping, contributing to the multidimensional understanding of tomographic images. Finally, Morani and Unay ^[48] incorporate the current trend of image preprocessing and hyperparameter tuning using convolutional neural networks.

The use of floating-point GPUs for image reconstruction by Fang and Mueller ^[49] links technology to efficiency, demonstrating the importance of hardware developments in the field of tomography just as Wang, Zhang et al. ^[50] shed light on software solutions to streamline image reconstruction, highlighting the need for user-friendly tools that simplify the often-complex rebuilding process. The focus is shifting toward a hybrid gradient descent approach for region-of-interest CT. This methodology bridges the theoretical concepts, as reported by Pham, Yuan et al. ^[51], with practical applications, aiming to improve the accuracy and efficiency of tomographic reconstruction in specific regions of interest. Lyons, Raj, and Cheney ^[52] introduce innovative methodologies for linear inverse problems in tomography. These methods resonate with the need to develop robust algorithms for accurate image reconstruction, a common thread among the discussed references. In the realm of electrical impedance tomography, Goharian, Soleimani, and Moran ^[53] tackle the intricacies of image reconstruction, bringing forth the importance of regularization methods in dealing with ill-posed problems. The concept of Radon Transformation and its application in Electrical Impedance Topographic Images, as introduced by Hossain, Ambia et al. ^[54], contributes to researchers' understanding of the theoretical principles underpinning tomographic imaging. With the introduction of innovative techniques to create volumetric models from fire images, as denoted by Ihrke and Magnor ^[55], researchers touch upon a unique aspect of tomography, highlighting its diverse applications.

As researchers delve into optical tomography, highlighted by Arridge ^[56], researchers gain insights into both forward and inverse problems. The Fourier reconstruction method detailed by Zhang T., Zhang L. et al. ^[57], specifically tailored for symmetric geometry computed tomography, adds a layer of technical sophistication to researchers' discussion, emphasizing the importance of innovative reconstruction techniques.

In conclusion, the broader picture that emerges is a dynamic field that adapts to emerging technologies and continually strives for higher quality and more efficient solutions. The integration of deep learning techniques underscores the growing role of artificial intelligence in reshaping the landscape of tomography. These references, when woven together, form a comprehensive narrative depicting the multifaceted nature of tomography.

4. Tomographic Imaging: From SAR, Geology, to Medical Advances

The study presented by the authors Reigber and Moreira ^[58] leads us to the sphere of radar tomography (SAR), an innovative achievement that utilizes phase differences for the assessment of soil topography. It addresses a crucial issue, enhancing researchers' ability to solve complex cases of stay-in SAR images, especially in multi-line imaging geometries. Fornaro and Serafino ^[59] expand the understanding of SAR spacecraft, underlining its ability to distinguish the mechanisms of thoughts within pixels. This progress in SAR space tomography is aligned with the need for improved clarity and image accuracy. The acquisition of images based on the circular track, as analyzed by Oriot and Cantalloube ^[60], opens the capabilities of optimizing image processing at various azimuth angles. This approach is particularly beneficial in studies such as building mining, highlighting the practical advantages of SAR data processing.

As researchers deepen researchers' searches, the authors Zhu and Bamler ^[61] focus on the concept of TomoSAR, pushing the limits of 3D imaging. They introduce us to the lifting diaphragm, a new concept that enhances researchers' ability to rebuild reflective functions along the lifting direction. This echoes with the subject of advanced imaging techniques. Sportouche, Tupin, and Denise ^[62] suggest a complete semi-automatic processing chain for the reconstruction of 3D urban buildings, incorporating high-resolution SAR optic pairs. This seamless integration faces the practical challenge of rebuilding urban buildings and presents the need for a fusion cross-section. The spectral analysis approach described by Zhu and Bamler ^[63] treats the reversal of SAR as a spectral problem, emphasizing the role of hyper-analysis in the monitoring of urban infrastructure. The ability to distinguish multiple sources of scattering is vital to urban studies, contributing to continuing research in the field. In addition, Zhu and Ge ^[64] emphasize the importance of the integration of SAR data with visual images because it is an example of the power of the combination of different imaging to create 3D information. This approach opens the doors to more complete and accurate 3D rebuilding.

Synthetic aperture radar data are integrated with optical imagery to generate 3D information using stereogrammetric methods, as described by Bagheri, Schmitt et al. ^[65]. The exploration of Polarimetric tomography SAR (Pol-Tomosar) performed by Budillon, Johnsoy, and Schirinzi ^[66] demonstrates its potential in urban applications by resolving multiple scatterers within the same analysis cell. This innovative technique immediately faces the need for increased accuracy in complex urban environments. Continuing the review in the field of synthetic radar, authors Ren, Zhang et al. ^[67] introduce the concept of Aetomo-Net, a visual network that uses multidimensional features for SAR tomography. This neuronal network highlights the growing role of artificial intelligence in the reconstruction of the tomographic image. By completing the search in this field, the discussion of the performance by Devaney ^[68] expands researchers' exploration beyond SAR, offering information on seismic exploration applications. It highlights the interdisciplinary nature of tomographic imaging, providing valuable information on seismic studies.

As researchers continue with an overview of the world's seismic tomography, Trampert ^[69] emphasizes the importance of quantitative interpretations in promoting the understanding of geodynamics. He emphasizes the transition from qualitative to quantitative approaches, reflecting the evolution in the field of tomography. Rector and Washbourne ^[70] introduced us to the utilization of cross-well seismic data, emphasizing the importance of the Fourier projection slice theorem and its role in characterizing the resolution and uniqueness of tomograms. This aligns with the theme of the theoretical foundations of tomographic imaging. Akin and Kovscek ^[71] discuss the critical role of X-ray computed tomography in the imaging of porosity, permeability, and fluid phase distribution in porous media. The importance of spatial resolution and adaptability in various flow conditions, connecting with the need for versatile imaging tools, is emphasized. The use of multistatic ground-penetrating radar signals, as analyzed by Worthmann, Chambers et al. ^[72], introduces a novel approach to tomographic imaging, particularly in the context of intensity distributions. This innovative approach highlights the need for adaptive imaging solutions.

Subsequently, in the field of interdisciplinary and theoretical tomography, as mentioned by Patella ^[73], a new interpretation of self-confident data highlights the need for innovative approaches to the interpretation of tomographic data. This is in line with the primary issue of pushing the boundaries of traditional imaging techniques. The introduction of 3DInvNet by Dai, Lee et al. ^[74] addresses the challenges of non-linearity and computational cost in 3D reconstruction algorithms. This innovative scheme demonstrates the evolving landscape of tomographic imaging techniques. Delving into the field of medical tomography, Concharsky and Romanov ^[75] present efficient methods for ultrasound tomography with attenuation. This expands the horizons of tomographic imaging into the realm of medical diagnostics, emphasizing the role of sound wave attenuation in imaging. The application of ultrasound computed tomography in breast tissue imaging, as discussed by Martiatu, Boehm, and Fichner ^[76], highlights the potential for quantitative 3D imaging. The introduction of finite-frequency travel-time tomography underscores the need for precision in medical tomographic applications. The exploration of non-interference three-dimensional refractive index tomography by Hauer, Haberfehlner et al. ^[77] highlights

the application of tomographic imaging in the life science field. This approach focuses on simplicity and robust imaging performance, emphasizing the need for adaptability.

The innovative deep prior diffraction tomography method introduced by Zhou and Horstmeyer ^[78] offers a high-resolution reconstruction of refractive indices within dense biological samples. It demonstrates the potential of unconventional imaging methods in life sciences. Webber ^[79] presents a fast method for reconstructing electron density in X-ray scanning applications. This approach aligns with the theme of efficient imaging solutions, particularly in scenarios dominated by Compton scattering. Finally, as highlighted by Yang, Zhang et al. ^[80], a multi-slice neural network with an optical structure presents the fusion of advanced technology with optical science. This innovative approach highlights the synergy between different disciplines.

Optical Coherence Tomography is a cutting-edge technology used for non-invasive cross-sectional imaging within biological systems. This method utilizes low-coherence interferometry to create a two-dimensional image that reveals the way light scatters from internal tissue microstructures, much like how ultrasound pulse-echo imaging works. Optical Coherence Tomography provides incredibly precise longitudinal and lateral spatial resolutions, down to just a few micrometers, and has the capability to detect extremely faint reflected signals, as minute as approximately one-tenth of a billionth of the incoming optical power ^{[81][82][83][84]}.

In conclusion, whether in the domain of SAR, seismic exploration, medical diagnostics, or life sciences, these references underscore the dynamic nature of tomography and its ever-evolving role in diverse applications. The integration of advanced algorithms, artificial intelligence, and innovative methodologies reflects the continuous pursuit of higher image quality, precision, and efficiency.

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