Contemporary Challenges and the Future of Reconstruction Algorithms in CT: Current Problems and Directions of Development

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Abstract

In recent years reconstruction algorithms in medical imaging have undergone significant evolution, largely using artificial intelligence and deep learning techniques. Traditional approaches such as filtrated back-projection are increasingly being replaced by iterative reconstruction algorithms that do a better job of reducing noise and artifacts in low-dose radiation images. Data compression and hybrid models, which connect classical methods with innovative AI technologies, make possible faster and more efficient image reconstruction. Of note is the developing phase contrast technique, which has the potential to revolutionize soft tissue diagnostics. This article discusses the latest trends and innovations in reconstruction algorithms, with particular emphasis on their medical applications and future directions.

Keywords: computed tomography, artificial intelligence, dark-field tomography, phase contrast

Introduction

It is undeniable that there is a substantial demand for research utilizing computed tomography (CT). This imaging modality is based on computerized X-ray imaging, in which narrow beams of X-rays rotate around the patient, enabling the acquisition of cross-sectional images of internal organ structures. The obtained slices are then processed computationally to reconstruct a detailed representation of the scanned region of the body. It can be confidently stated that computed tomography is a cornerstone of modern medicine. Advanced reconstruction algorithms allow for the generation of highly detailed anatomical images, reducing the need for certain invasive medical procedures and enhancing treatment efficiency.

Despite its numerous advantages, computed tomography (CT) also has certain limitations. One of the primary concerns associated with CT imaging is the patient's exposure to high doses of radiation. This involves ionizing radiation, a well-documented carcinogenic factor that poses a potential risk to public health. Growing concerns among patients regarding the risks associated with X-ray radiation have driven ongoing efforts to minimize unnecessary CT examinations and reduce radiation doses wherever feasible.

The Institute of Medicine (IoM) [1] published a report stating that ionizing radiation contributes to the development of breast cancer more than any other form of routine radiation exposure. Approximately half of the annual exposure to ionizing radiation in the United States originates from natural sources, such as cosmic radiation. In the case of medical exposure to ionizing radiation, the responsibility for determining population dose levels lies with the Health Information and Quality Authority (HIQA). The average annual dose per individual resulting from medical exposure to ionizing radiation (excluding radiotherapy) accounts for the amount of radiation an individual may be subjected to as part of medical diagnostics. HIQA calculates this value based on diagnostic reference level (DRL) data and current demographic information. For more information on

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HIQA's regulation of medical exposures and efforts to establish national diagnostic benchmarks, visit the HIQA website [2].

In 2023, HIQA determined that an average annual dose of 0.43 mSv per person in Ireland is associated with medical exposure to ionizing radiation. In comparison, in 2014 the average dose was 0.55 mSv. This decrease can be explained in part by the increase in population from 4.6 million in 2014 to 5.1 million in 2023. The decrease in the average dose is also influenced by technological advances and optimization of medical procedures.

It is noteworthy that the largest share of the average annual dose from medical radiation exposure comes from CT scans. It accounts for as much as 62% of the total dose from medical exposure to ionizing radiation, even though it represents only 11% of all procedures performed. Over the past 10 years, dose values associated with CT, general X-ray, mammography, PET and nuclear medicine have remained relatively constant. HIQA, however, has observed a decrease in dose for fluoroscopic procedures [3].

Advanced reconstruction algorithms

Advanced reconstruction algorithms play a key role in improving the accuracy and efficiency of diagnostic computed tomography (CT), but their implementation has technological and ethical challenges that require further research and development. Various difficulties are encountered when using different reconstruction algorithms, such as optimizing parameters, managing large amounts of data, and balancing between improving image quality and minimizing radiation doses. The introduction of advanced algorithms also requires consideration of ethical issues, such as ensuring patient safety and transparency in diagnostic decisions.

The iterative method is based on finding the radiation absorption coefficient in the different elements of the object volume in such a way that it is consistent with the measured values [4]. A major challenge in using these methods is that they require a lot of computing power, which directly affects data processing time. An additional problem is the variety of imaging types and patients, which affects the versatility and scalability of this technology. A key challenge, however, remains matching the lowest possible radiation dose. Traditional reconstruction methods often require a higher dose, which increases the risk to patients. Commonly used algorithms can lead to artefacts that hinder further diagnosis, as well as low-resolution images. The solution to these problems is precisely the use of iterative algorithms.

It is well known that filtered back projection (FBP) has been the standard method of CT image reconstruction for four decades. It is a simple, fast and reliable technique that provides high-quality images for many clinical applications. However, with the development of faster and more advanced CT scanners, FBP is becoming increasingly obsolete. In situations where the radiation dose is reduced or larger patients are scanned, the limitations of FBP become more apparent in the form of higher noise levels and more artefacts [4].

Due to these limitations, a new reconstruction method - the iterative method - was created. In theory, it was supposed to overcome these difficulties back in 2009. The MBIR (Model-Based Iterative Reconstruction) method, which uses reconstruction steps in both forward and backward directions, was introduced for clinical use [7]. The MBIR algorithm can model the statistics of the system as well as its optics. As a result, it reduces the number of approximations and limits the propagation of errors at each reconstruction step compared to the filtered back-projection algorithm. The MBIR method is designed to reduce radiation dose, enabling dose reductions of up to 98% for lung imaging [8] and up to 50% for abdominal imaging [9]. This is a significant step forward in improving patient safety while maintaining high-quality diagnostic images.

To overcome the computational burden of MBIR, the Hybrid Iterative Reconstruction (HIR) method was developed[7]. HIR consists of iterations in the sinogram domain, one back-projection and more iterations in the image domain. One back-projection is less computationally demanding, but also less capable of reducing noise and artifacts than MBIR[10]. A common denominator could be seen in both approaches, namely a limitation concerning the texture of the noise. This noise in an image could be measured as the standard deviation in HU (Hounsfield Units) in a homogeneous region of interest. Although both MBIR and HIR result in reduced image noise, using the standard deviation to define image noise does not capture differences in noise texture. Such noise is often referred to as 'plastic' or 'speckle' by experts in the industry literature. It makes it difficult to detect low-contrast tissue[10].

The role of reconstruction algorithms in creating high-quality images

Reconstruction algorithms make it possible to significantly increase the resolution of CT images, which is crucial for diagnosing fine anatomical structures in the early stages of diseases. In addition, artefacts in the images, such as noise or shadow effects, can be significantly reduced with advanced reconstruction algorithms that analyze and process data from multiple angles. One can't help but notice that artificial intelligence, particularly convolutional neural networks, is playing an important role in recent trends in improving the quality of reconstructed images.

Super-resolution reconstruction algorithms are mainly based on interpolation, focusing on creating high-resolution images from lower-resolution ones. Using traditional reconstruction methods provides high computational speed because these interpolation-based techniques [11] are efficient in real-time, which is important in real-world operating environments. Nevertheless, these methods have their limitations because they are non-adaptive, meaning they cannot be optimized for specific image content.

When reconstructing super-resolution images, these techniques can generate quality problems such as aliasing, ghosting, noise or image blurring. This causes interpolation algorithms to only mathematically smooth existing pixels, unable to accurately reconstruct the high-frequency signal, limiting their effectiveness in reproducing fully detailed images.

Image quality vs. radiation dose reduction

One of the most desirable functionalities of modern reconstruction algorithms is the reduction of radiation risk. At the same time, advanced techniques used in reconstruction algorithms should preserve image detail, even at low radiation doses. The trend among reconstruction algorithm designers toward reducing radiation dose while maintaining high-quality diagnostic images remains similar to that of several years ago. A new method that offers significant advantages over traditional CT is Photon Counting CT. This technology uses detectors in which a scintillator converts single X-ray photons into visible light, which is then detected by a photodiode and converted into electrical signals [12].

Photon-counting detectors can distinguish single photons. They use a semiconductor material in which X-ray photons are converted into a measurable charge cloud, and transported to electrodes or pixels by an applied polarization voltage [13]. A short electrical pulse allows the counting of single X-ray photons, but it requires fast electronics and small pixel sizes to avoid the so-called pileup effect. This effect occurs when high X-ray flux causes pulses formed by concurrent photons to pile up, leading to loss of counts and degradation of energy resolution [14].

In clinical practice, automatic exposure control techniques are used to reduce the risk of detector saturation due to high counts. Although high resolution is not always necessary, it can significantly facilitate clinical workflow, and data acquired in high-resolution modes provide better image quality with low noise levels below the resolution limit of the system [15]. It is worth mentioning that the Naeotom Alpha dual-source CT system (Siemens Healthineers) is the first available clinical photon-counting CT system that uses this technology. Our goal is to evaluate the impact of small pixels in this clinical system and quantify the potential dose reduction it can offer in clinical practice [16]. The world's first photon-counting CT scanner premiered in October 2021, and Naeotom Alpha devices have been installed in more than 50 centres in the United States and Europe. The National Institute of Cardiology in Warsaw-Annin was the first place in Poland where this new type of CT scanner was installed.

Challenges of implementing CT equipped with AI and other modern technologies

Deep learning is a subset of machine learning that is widely used in medical imaging, as indicated by several scientific articles published in recent years. The main idea behind deep learning is to create a model composed of multiple layers, where mathematical operations such as convolutions, maximal combinations and normalizations are performed to extract features from data - both in radiological images and in electronic medical records.

Although many tools based on deep learning models have been designed, few have found real applications in clinical practice [17]. The reason for this is the complexity of implementing and adapting AI-powered systems, which is a lengthy process, especially in clinical settings. The process begins with the acquisition of relevant data, the design of AI models and their validation, supported by clinical evidence. The system must then be approved by the relevant regulatory authorities, after which only

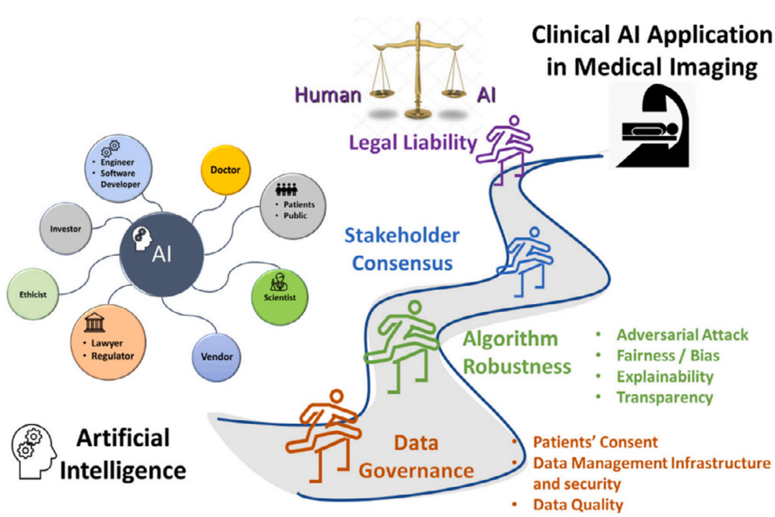

Fig 1 Challenges to overcome before AI systems can find clinical application in medical imaging
Source: [27].

then can it be deployed clinically. Numerous challenges can arise at each stage of this long process, which can slow down or hinder the adaptation of these solutions in everyday medical practice.

As you can see in the figure (Fig. 1), the various risks have been sorted into specific categories. Let's start with data, or more specifically, data management. Artificial intelligence, to learn effectively, requires a lot of data. In health care, this is usually sensitive data, i.e. patient data. Implementing an AI system into clinical practice involves meeting several stringent requirements. On the other hand, the algorithm must be designed to make efficient use of the data provided. Studies can be divided into two categories: retrospective and prospective. Retrospective studies often do not require patient consent, unlike prospective studies. Obtaining access to a closed database is a difficult process, requiring a lot of paperwork. In the case of closed databases, such as the Alzheimer's Disease Neuroimaging Initiative (ADNI) collection, the process of obtaining data usually takes about two weeks and includes a detailed review of the investigator and the planned studies. Only proposals that are complete and clearly state the purpose of the research are approved. After a positive review, investigators obtain log-in data for the LONI Image and Data Archive (IDA) [18].

Despite the difficulties in acquiring data, new tools are emerging to aid AI research. In 2014, an open medical database was proposed to facilitate the development of AI in clinical trials. However, the idea was met with much opposition in Europe due to concerns about data privacy [19]. There are now platforms that offer anonymized medical images in DICOM format, such as The Cancer Imaging Archive, funded by the National Cancer Institute. This platform provides images that are freely available to the public for cancer research [20].

Unfortunately, the availability of such data still does not solve the problem of lack of access to raw data, which by its very nature is unlikely to ever be made publicly available. Researchers often have to turn directly to the institutions holding this data, and some of it may not be made available for further research.

Another challenge of implementing artificial intelligence algorithms is the possibility of an algorithm making a mistake, which can lead to serious consequences, such as misdiagnosis. In the United States, patients can claim compensation if they are harmed by medical negligence. However, medical device manufacturers are protected from such claims by the so-called "learned intermediary doctrine." This means that doctors are responsible for fully understanding the risks associated with using a particular device. Although this principle does not function in Polish law, there are similar provisions in EU law and in the Polish Civil Code, the Law on Medical Devices and court decisions.

Computational complexity of advanced reconstruction algorithms

Artificial intelligence has found wide application in image de-noising, including algorithms such as ResNet, DnCNN, FFDNet, CBDNet and Tokens-to-Token ViT. The first of these algorithms, ResNet, was used in a study [21], which included the introduction of blocks of spatial and channel attention mechanisms, leading to the optimization of model performance. The main goal of the project was to improve the classification of medical images using ResNet with a dual attention mechanism and to study the impact of these mechanisms on model performance in a clinical context.

The Denoising Convolutional Neural Network (DnCNN) architecture introduces a novel approach to image de-noising, extending the typical CNN architecture. DnCNN is one of the popular neural networks specifically designed to reduce noise from images, including computed tomography (CT). Essentially, it learns the noise map, or the difference between a noisy image and a reference image, so it can effectively remove noise without losing important image details. The first application of this architecture was in 2016, where a publication [22] described DnCNN's ability to remove hidden noise from images, making it possible to train a single model to handle a variety of tasks, such as Gaussian de-noising, super-resolution and JPEG image de-noising.

Tokens-to-Token Vision Transformer (T2T-ViT) is a novel approach to image processing for tasks such as classification or segmentation. It can also be used to analyze medical images, including computed tomography (CT) scans. T2T-ViT extends the classic Vision Transformer, allowing for a more efficient representation of local spatial relationships, which is particularly important in processing highly detailed images such as CT images. A practical application of this algorithm can be the reduction of metal artefacts, which are problematic in diagnostic imaging. As noted in the publication [23], simple tokenization can lead to an inability to model local anatomical information, so progressive tokenization is recommended for this type of task.

Phase contrast and dark field tomography

Phase contrast and dark-field tomography are advanced imaging techniques, mainly used in microscopy and computed tomography (CT), that enable better visualization of low-contrast structures compared to traditional X-ray methods. Phase contrast involves detecting changes in the phase of an electromagnetic wave (such as X-rays) passing through an object. Traditional X-ray imaging techniques only record differences in the absorption of radiation by different tissues, which makes some materials, especially soft tissues, more difficult to image.

"Phase-Contrast CT: A Grand Challenge for Radiology" by David A. Bluemke and Amir Pourmortez [24], published in Radiology, discusses phase-contrast computed tomography (CT) technology and the challenges it poses to radiology. The technique enhances contrast imaging of soft tissues, surpassing traditional CT methods, especially in the context of visualizing structures such as the brain, lungs and cardiovascular system. However, the authors point out technical and practical obstacles, such as the need for specialized equipment, higher radiation doses and more complicated data interpretation, which must be resolved before the technique can be widely used in clinical practice.

Darkfield tomography, on the other hand, is an imaging technique that detects the scattering of X-rays by structures too small to be seen using conventional absorption-based methods. This method captures waves scattered at small angles that would not be visible in traditional images. In conventional tomography, radiation scattered at angles does not reach the detector, leaving tiny structures invisible. The dark-field technique, however, allows the detection of scattered radiation, making it possible to see small scattering structures such as fibres or cell boundaries.

In an interesting study described in the publication [25], a new algorithm for phase and dark field tomography based on the X-ray Fokker-Planck equation is presented. This algorithm, needing only a coherent X-ray source, sample and detector, is capable of mapping sample density and dark field and diffusion properties in 3D. Two exposures of the sample at each projection angle are sufficient to successfully reconstruct both the density and Fokker-Planck diffusion coefficients in the dark field. The researchers anticipate that the proposed algorithm could provide significant benefits in both biomedical imaging and industrial applications.

Guidelines for the ethical development of artificial intelligence

Many organizations have developed ethical guidelines to support the development of artificial intelligence in healthcare facilities, including the World Health Organization (WHO). In 2021, the WHO issued the first version of its recommendations for the use of artificial intelligence in health. The latest version in 2024 focuses specifically on generative algorithms, which have gained enormous popularity in recent years. In these recommendations, WHO emphasizes the ethical aspects of using generative artificial intelligence, especially large multimodal models (LMMs).

LMMs are advanced artificial intelligence models that can take different types of input data (e.g., text, images, audio data) and generate a variety of results, regardless of the nature of the input data. These models have potentially broad applications in medicine, scientific research, public health, and drug development. Also known as “general-purpose fundamental models,” LMMs can perform complex tasks, although their full capabilities are still not fully confirmed.

The WHO guidelines for the use of artificial intelligence in healthcare emphasize security, data privacy, and accountability for decisions made by AI systems. It is particularly important to ensure that generative AI models are used ethically and transparently, respecting patient autonomy and protecting personal data.

Summary

In recent years, modern trends in reconstruction algorithms in medical imaging, particularly in computed tomography (CT), have been developing rapidly due to the integration of deep learning and other data-driven techniques. Traditional reconstruction methods, such as backscatter filtering (FBP), have been the standard, but have limitations, especially in low-dose radiation conditions or with limited data.

One key trend is iterative reconstruction (IR) algorithms, such as Adaptive Statistical Iterative Reconstruction (ASIR) and Model-Based Iterative Reconstruction (MBIR), which offer improved image quality, especially for low-dose scans, through iterative image enhancement and reduction of noise and artefacts. A new and growing trend is phase contrast imaging, which offers contrast enhancement of soft tissues that are difficult to image with standard CT. Although this technique is still experimental, it has the potential to improve diagnostics, especially for lung and brain imaging. Also noteworthy are hybrid models that combine traditional physical models with machine learning algorithms. These models optimize both the data acquisition process and image quality, offering faster and more accurate reconstructions.

These trends point to the growing role of artificial intelligence and machine learning in pushing the limits of reconstruction algorithms’ capabilities when it comes to the accuracy, speed and safety of medical imaging.

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