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Review

Basics of iterative reconstruction methods in computed tomography: A vendor-independent overview

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A R T I C L E I N F O

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A B S T R A C T

Over the past two decades, technical innovations in computed tomography (CT) have constantly extended its spectrum of clinical applications and made new radiodiagnostic applications accessible. At the same time, concerns have arisen with respect to the radiation exposure to the patients caused by CT examinations. In order to address this issue, different strategies for radiation dose reduction in CT have been introduced, spanning technical approaches as well as specific examination techniques applied in clinical practice, such as reduced-dose CT. Developed technical approaches for reducing radiation dose in CT by improvements of CT scanner hardware and acquisition mechanisms, however, have not been sufficient to address the degradation of image quality caused by increasing noise and susceptibility to artifacts inherent to reduced-dose CT acquisitions. Recent advances in computing power have enabled the development of software-based methods for iterative image reconstruction (IR) in CT enabling simultaneous reduction of image noise and improvement of overall image quality. Thereby, IR allows for dose reduction by reconstruction of low-noise image data from intrinsically noisy reduced-dose CT acquisitions, thereby preserving diagnostic image quality equivalent to current clinical standards.

This review provides an overview of the underlying basic principles of iterative image reconstruction methods currently available for and applied in CT imaging, independent of vendor-specific details regarding algorithms and implementations. It discusses potential strengths and weaknesses of these CT image reconstruction techniques in view of their application in clinical routine, especially in view of the potential of IR for noise and artifact reduction as well as for radiation dose reduction. Furthermore, the effect of statistical (hybrid) and model-based IR methods on image quality are exemplarily illustrated in comparison to filtered back projection (FBP) traditionally used for image reconstruction in CT.

1. Introduction

Through a number of technical innovations over the past two decades, the spectrum of clinical applications of computed tomography (CT) has been constantly extended, and new radiodiagnostic applications have become accessible. Since CT examinations always require exposure of patients to ionizing radiation, the increasing range of clinical applications as well as some of the recent technical advances have also added to the still increasing contribution of CT examinations to the collective exposure of patients to ionizing radiation. Therefore, the reduction of radiation dose is an imperative in CT imaging and there is great interest in approaches for reducing the dose associated with the application of CT in clinical practice.

To date, different strategies for radiation dose reduction in CT have been developed, spanning technical approaches [1] (this issue), [2], e.g. automated tube current modulation and tube potential selection as well as dynamic beam collimation, and specific examination techniques applied across all body regions in clinical practice [3–6] (this issue), e.g. reduced-dose CT acquired with reduced tube current-time product (mAs), at lowered tube potentials (kV_p), or using a combination of both methods.

While past efforts for reducing radiation dose in CT by technical approaches have mostly been directed at improving CT scanner hardware and acquisition mechanisms, the degradation of image quality by

Abbreviations: CNR, contrast-to-noise ratio; CT, computed tomography; $CTDI_{vol}$, volumetric computed tomography dose index; FBP, filtered back projection; IQ, image quality; IR, iterative image reconstruction; kV_p, kilovolt peak (unit of tube potential); mAs, milliampere second (unit of tube current-time product); MBIR, model-based iterative reconstruction; MTF, modulation transfer function; NPS, noise power spectrum; ROI, region-of-interest; SD, standard deviation (image noise); SNR, signal-to-noise ratio

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Table 1
Overview of iterative image reconstruction algorithms commercially available from the four major vendors of computed tomography systems, classified by method of function (alphabetically ordered by acronym of algorithm).

Acronym	Name of algorithm / product name	Vendor
Statistical iterative image reconstruction algorithms (hybrid)		
AIDR 3D	Adaptive iterative dose reduction 3D	Canon Medical Systems, Nasu, Japan
ASIR	Adaptive statistical iterative reconstruction	GE Healthcare, Milwaukee, WI, USA
ASIR-V	Adaptive statistical iterative reconstruction – V	GE Healthcare, Milwaukee, WI, USA
iDose[4]	*Product name*	Philips Healthcare, Best, The Netherlands
SAFIRE	Sinogram-affirmed iterative reconstruction	Siemens Healthineers, Forchheim, Germany
Model-based iterative image reconstruction algorithms		
ADMIRE	Advanced modeled iterative reconstruction	Siemens Healthineers, Forchheim, Germany
FIRST	Forward projected model-based iterative reconstruction solution	Canon Medical Systems, Nasu, Japan
IMR	Iterative model reconstruction	Philips Healthcare, Best, The Netherlands
VEO (MBIR)	*Product name* (model-based iterative reconstruction)	GE Healthcare, Milwaukee, WI, USA

the increase of image noise and the susceptibility to artifacts inherent to reduced-dose CT which potentially compromise diagnostic image quality, e.g. in morbidly obese patients, has only recently come into focus. Of late, advances in computing power have enabled the development of software-based methods for iterative image reconstruction (IR) in CT. Differing from established analytical image reconstruction methods such as traditional filtered back projection (FBP), the common technical principle of IR algorithms is the iterative improvement of measured projection and/or reconstructed image data by application of filters based on statistical data models or mathematical models of the CT imaging process. Compared to FBP these IR algorithms enable the simultaneous reduction of image noise and the improvement of overall image quality (IQ). Since noise and overall IQ are directly linked to the radiation exposure of a CT acquisition, a reduction or suppression of noise via the application of IR algorithms consequently allows for a reduction in dose.

At present, several iterative image reconstruction algorithms are commercially available from the four major vendors of CT systems, cf. Table 1. Based on their method of function they can roughly be classified into statistical (hybrid) and model-based iterative algorithms, which differ in the level of detail of the modelling of the imaging process as well as of the elements and properties of the imaging system [7–9]. The technical details of commercially available reconstruction algorithms and their actual computational implementation are, however, generally considered proprietary and information provided by the manufacturers is scarce.

Therefore, the purpose of this review is to provide an overview of the underlying basic principles of iterative image reconstruction methods applied in CT imaging for radiologists and clinicians, independent of vendor-specific details regarding algorithms and implementations. Furthermore, potential strengths and weaknesses of image reconstruction techniques currently available for CT imaging are discussed in view of their application in clinical routine, especially regarding their potential for noise and artifact reduction as well as for radiation dose reduction, and the effect of different IR methods on image quality is exemplarily illustrated in comparison to traditional filtered back projection.

2. Technical background

2.1. Computed tomography imaging process

In order to ease the understanding of iterative image reconstruction methods the fundamentals of the imaging process in CT will be briefly reviewed in the following. More detailed information on the physico-technical principle of CT imaging can be found in the literature, e.g. [10].

The goal of CT imaging is the determination of the distribution of attenuation values in the three-dimensional volume imaged, i.e. within the patient. To this end, a fan beam of photons emitted by an X-ray tube is sent through the body. The number of photons emitted by the X-ray tube is statistically distributed, i.e. according to the Poisson distribution. Statistical processes also govern photon absorption within the patient's body and photon detection at the detector [11]. Due to its inherent statistical processes, CT imaging can thus not be deterministically modeled. Within the body, tissues and anatomical structures of different absorption properties contribute to the total absorption of each ray of the transmitted beam measured in the elements of the

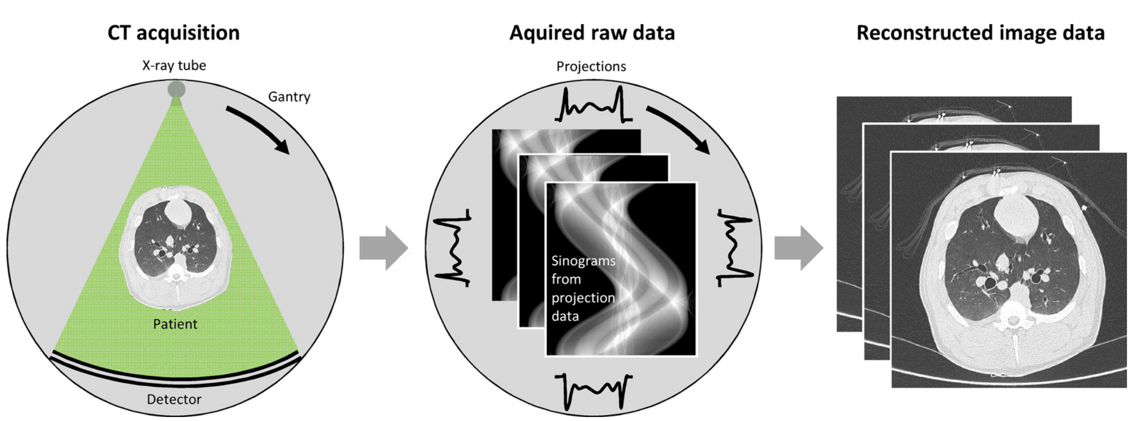

Fig. 1. Simplified schematic of the imaging process from data acquisition to image reconstruction in (spiral) computed tomography (CT). *Left:* Continuous rotation of the X-ray tube – detector system around the patient allows for acquisition of projections from a large number of different views (angles). *Middle:* Acquired raw data consist of a set of sinograms into which these projections are sorted, with each projection corresponding to a line within a sinogram. *Right:* Image data are reconstructed from projection data by means of image reconstruction algorithms suited for CT, e.g. by filtered back projection (FBP) or iterative image reconstruction (IR).

detector opposite the X-ray tube (Fig. 1, *left*). The attenuation profile measured in the detector from a certain view (angle) is called projection. By continuous rotation of the X-ray tube – detector system around the patient, projections are acquired from a large number of views (angles) making up the raw data (Fig. 1, *middle*). By sorting of projections, so-called sinograms can be derived, representing the raw data necessary for reconstruction of transverse image data by means of an image reconstruction algorithm suited for CT, e.g. filtered back projection (FBP) or iterative image reconstruction (IR) (Fig. 1, *right*).

2.2. Analytical image reconstruction – filtered back projection (FBP)

For being able to fully appreciate the different properties of iterative image reconstruction methods and the resulting improvements in image data compared to the analytic method of image reconstruction by filtered back projection, a brief overview of the basics of FBP will be given. Still being the most widely used CT image reconstruction algorithm, FBP has been the standard of reference for reconstructing CT image data for the past four decades. Due to the relatively low complexity of the underlying linear transformation from projection space (raw data) to the image space, i.e. the back projection, the method is fast and robust (Fig. 2a) and only requires limited computing power for CT image reconstruction applicable in clinical routine.

Before back projection, measured projections are first convoluted with a so-called filter or kernel, controlling the characteristics of reconstructed image data. The filter is necessary to compensate for the blurring resulting from nonuniform data sampling inherent to the CT acquisition process, and restores or enhances the edges of the structures of the imaged object [12]. Filter choice has a direct influence on spatial resolution (e.g. the 'sharpness' of edges) and image noise, with higher filtration ('sharper' kernel/filter) enabling a better definition of edges and a clearer delineation of structural detail but implying an increase in image noise. In clinical practice, several kernels with different characteristics are available: 'soft' kernels reducing image noise but impairing image sharpness optimized for visualization of low-contrast detail, and 'sharp' kernels enhancing depiction of fine details in structures of high contrast but subject to high levels of image noise impairing detectability and delineation of low-contrast structures [11–13]. After sorting of filtered projections into sinograms (see section *'Computed tomography imaging process'* above, Fig. 1), these are back projected to image space along parallel rays by equally distributing measured total attenuation to the pixels of the image matrix (voxels of the image

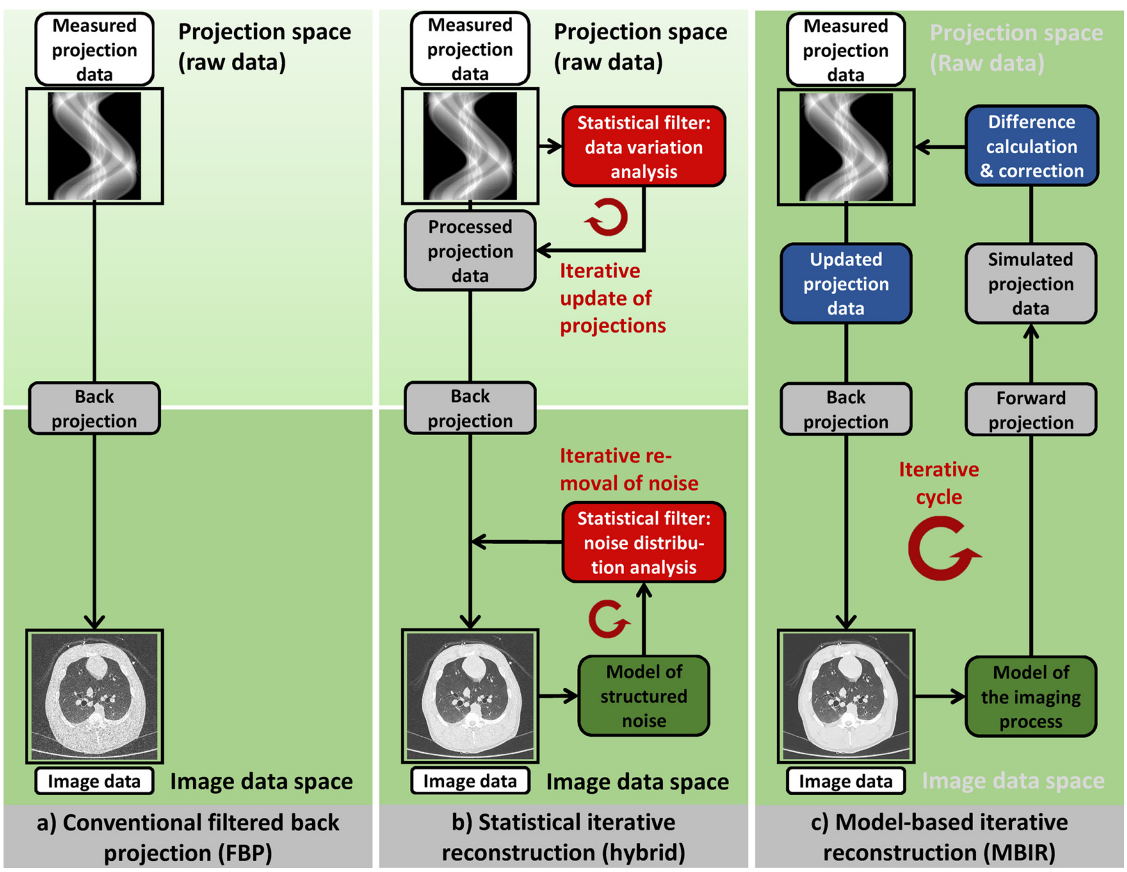

Fig. 2. Schematic overview of image reconstruction techniques available and applied in CT imaging. (a) Conventional filtered back projection (FBP): Measured projection data is linearly transformed to image space by back projection after application of a filter (kernel), i.e. mathematical convolution of each measured projection with a filter function. The filters control image characteristics such as spatial resolution (e.g. sharpness of edges) and image noise. Simplifications of the CT data acquisition process such as an infinitely small, point-like X-ray source, a pencil beam X-ray geometry, and an intensity measurement at the central point of each detector element are assumptions inherent to FBP. (b) Statistical iterative reconstruction: Based on statistical models, e.g. of data variation caused by projections subject to photon-starvation, and of noise structures characteristic for the depicted anatomy within specific body regions, data is iteratively filtered in projection and image space, respectively. Relying on the principle of filtered back projection for reconstruction of image data, this class of IR algorithms is also often termed *hybrid iterative reconstruction*. (c) Model-based iterative reconstruction (MBIR): From measured projection data an initial image data estimate is calculated, e.g. by means of FBP. Applying a model of the CT imaging process, subsequent forward projection of the estimated image data yields simulated projection data. Comparison of simulated and measured projection data then allows for computation of an image data update through back projection of a correction term. The iterative cycle is repeated until a predefined stopping criterion is met. This class of IR algorithms is characterized by repeated application of back and forward projection steps for transition from projection to image space and vice versa. Note that additional filters, e.g. similar to those used in statistical iterative reconstruction, can also be applied *(not shown)*.

Table 2
Compilation of potential strengths and weaknesses of image reconstruction techniques available for CT imaging in view of their application in clinical routine.

	Filtered back projection (FBP)	Statistical iterative reconstruction (hybrid)	Model-based iterative reconstruction (MBIR)
Strengths	• speed of image reconstruction (high) • user control over image characteristics (high, i.e. by indication-specific choice of reconstruction kernel) • well-known image texture • conventional image quality metrics globally valid	• image noise reduction (moderate) • improvement of low-contrast detail (slight) • artifact reduction (moderate) • potential for radiation dose reduction (moderate)	• image noise reduction (strong) • improvement of low-contrast detail (moderate) • enhancement of spatial resolution (slight - moderate) • artifact reduction (strong) • potential for radiation dose reduction (high)
Weaknesses	• notable image noise • limited depiction of low-contrast detail • susceptibility to artifacts, e.g. streaking • potential for radiation dose reduction (low - none)	• speed of image reconstruction (moderate) • user control over image characteristics (moderate) • risk of oversmoothing • lack of familiar noise structure and texture	• speed of image reconstruction (slow) • user control over image characteristics (low) • risk of oversmoothing • artificial image appearance (blotchiness, plastics textures) • unfamiliar image texture • conventional image quality metrics only locally valid • potential need to adapt reference standards for quantitative CT

volume). CT image data thus reconstructed are the sum of all back projected filtered attenuation profiles.

The method of FBP is subject to several approximations regarding the CT data acquisition process. These simplifications include: an infinitely small, point-like X-ray source, a pencil beam X-ray geometry, an intensity measurement at the central point of each detector element, and an acquisition of projection data free of noise [8,12]. The approximations made in view of the CT imaging process, especially of noise-free projection data not accounting for the variation of Poisson distributed photon count statistics, lead to a strong impact of image noise and the susceptibility to artifacts, e.g. caused by photon starvation of projections for CT acquisitions at low dose and in morbidly obese patients [8,12–14]. Therefore, FBP does not offer much potential for radiation dose reduction, since reducing radiation dose results in increased image noise compromising diagnostic image quality [8,12,14]. A compilation of potential strengths and weaknesses of FBP in view of its application in clinical routine can be found in Table 2 and is further discussed in comparison to IR techniques in the section *'Potential strengths and weaknesses of CT image reconstruction techniques in view of routine clinical application'* below.

3. Principle of iterative image reconstruction (IR)

From a mathematical point of view, iterative algorithms are characterized by the stepwise repetition of a calculation in which the result of the previous step is accounted for in the current step of the calculation, e.g. by means of a correction or update term. The iterative cycle is repeated until a predefined stopping criterion is met, e.g. if a fixed number of iterations or a sufficiently small difference between the solutions of two subsequent iterative steps (convergence) is reached.

The fundamental idea of iterative image reconstruction is the calculation of image data truly corresponding to acquired projection data. Applying the mathematical definition of an iterative algorithm to CT image reconstruction, an ideal IR process consists of a cycle of forward and back projection steps with repeated transition from projection (raw data) to image space and vice versa, iteratively improving reconstructed image data. Simulating CT image acquisition by means of an exact model of the CT imaging process, the forward projection step generates synthetic projection data that is compared to measured projection data. The back projection step propagates a correction determined from the difference of simulated and measured projections to image space (e.g. by filtered back projection) where it is applied as an update to the current image data estimate. An ideal IR method therefore consists of the following steps [7,13]:

1 Based on an initial image estimate, e.g. derived from reconstruction using FPB, synthesized projections are simulated by forward projection (transition from image to projection space).
2 By comparison of synthesized projections to measured projections a correction term is calculated from their difference.
3 The current image estimate is updated by back projection of the correction term (transition from projection to image space)

This iterative cycle is repeated until a predefined stopping criterion is met. Fig. 3 illustrates the iterative reconstruction cycle by means of a simplified example for a 2×2 object matrix consisting of four unknown attenuation coefficients.

In the forward projection step, simulating projections of the current image data estimate requires a model of the CT imaging process. Such models may include CT system optics as well as system statistics. The term 'system optics' refers to the geometry of the CT system, e.g. distances between X-ray tube, isocenter, and detector, and of its components, e.g. shape and size of the focal spot and the detector elements, as well as to beam and detector geometry. The term 'system statistics' covers the photon spectrum emitted by the X-ray tube, the statistical distribution of photons, and the noise of the detector electronics. Modeling of system optics enables enhancement of spatial resolution while modeling of system statistics allows for reduction of image noise [11]. More detailed and thus more exact but also increasingly complex models potentially improve resulting image data but require more computational power, such that the implicit tradeoff between exactness of the model and required reconstruction time needs to be optimized when aiming at clinical routine use [12,13].

In CT image reconstruction, IR algorithms can be defined as constrained optimization problems, in which the image data is the unknown optimum solution to the problem. Mathematically, the problem can be described by a cost function that tries to simultaneously optimize two different aspects of the reconstruction: the conformity of reconstructed image data with measured projection data (data term) and the suppression of image noise by means of a regularization term that penalizes noisy solutions to the optimization problem [11,13]. Introducing constraints to the optimization problem allows accounting for the system optics and statistics of the CT imaging process model [11,12]. Mathematically, IR reconstruction then consists of minimizing the cost function by repeated update of the image data, thus maximizing conformity between measured and reconstructed data and minimizing image noise.

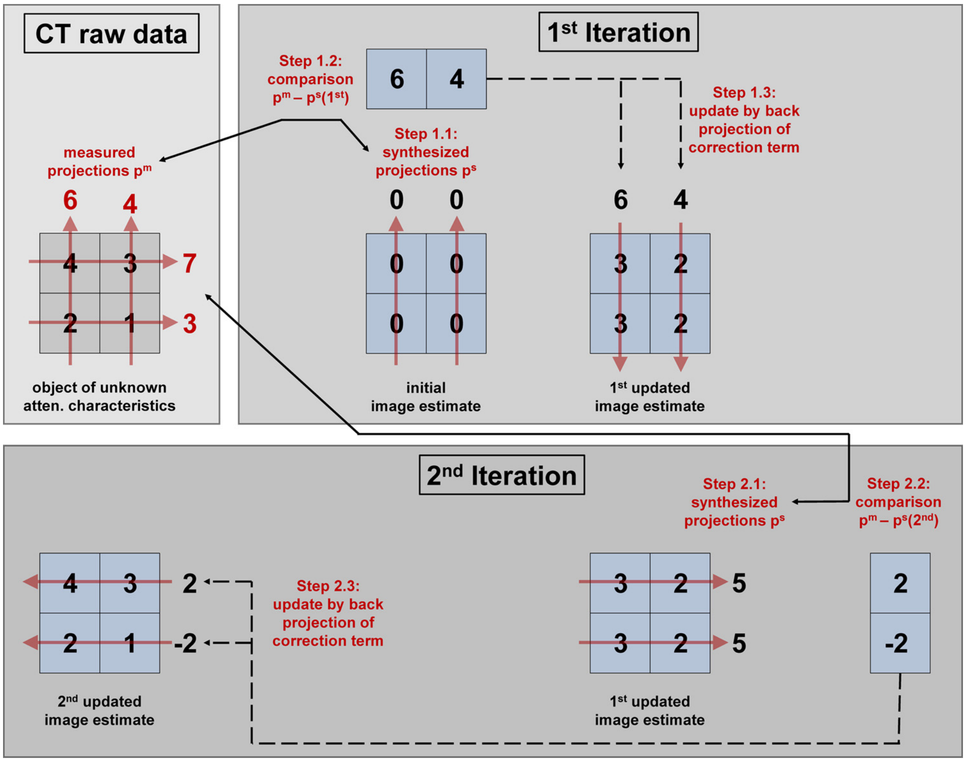

Fig. 3. Simplified example of the iterative reconstruction cycle for a 2 × 2 object matrix consisting of four unknown attenuation coefficients and a corresponding image matrix of 2 × 2 pixels. Acquired CT raw data is represented by the projections p^m measured in vertical and horizontal directions. In the first iteration, synthesized projections p^s are calculated based on an initial image estimate by forward projection in vertical direction *(step 1.1)* and compared to the corresponding measured projections p^m *(step 1.2)*. Subsequently, the image matrix is updated by back projection of a correction term *(step 1.3)* consisting of the difference between measured and simulated projection data. The second iteration repeats these steps in the exact same order based on the projections in horizontal direction. In principle, this iterative cycle could be further continued until a predefined stopping criterion is met. For this simplified example, however, further iterations are not necessary since a match of image and object matrices, and thus also projections measured and synthesized in vertical and horizontal directions, is achieved after only two iterations. Note that while attenuation coefficients of the initial image estimate can freely be chosen and could thus also take non-zero values or be inhomogeneously distributed, an optimal choice of an initial image estimate will result in faster convergence of the IR cycle.

4. Iterative image reconstruction methods applied in diagnostic CT

While IR has become the default method of image reconstruction for emission tomography imaging in nuclear medicine, it should be noted that it was initially proposed for and also applied in CT imaging in the early 1970s [12,15]. Due to the limited computational power available then, it was soon replaced by the fast and robust analytic method of FBP, which became the standard method of image reconstruction in CT. Only recently, the availability of a fair amount of computing power necessary for processing the underlying mathematics and the large amount of data in CT imaging has made application of IR in CT feasible again.

Although information on the technical details and actual implementation of commercially available IR algorithms largely is proprietary, they can roughly be classified into statistical (hybrid) and model-based iterative algorithms, differing in the level of detail of the modelling of the imaging process [7,9]. Whereas the former aim at iteratively optimizing physical models of photon statistics (‘system statistics’, see above) in projection and/or image space, the latter additionally account for technical aspects of the CT system used (‘system optics’, see above). Both IR approaches aim at limiting the number of iterations in order to reduce required computational power and reconstruction times.

4.1. Statistical iterative reconstruction (hybrid)

Statistical iterative reconstruction algorithms are characterized by iterative filtration of data separately performed in projection space and/or in image space (Fig. 2b). It should be noted that the transition from projection to image space, i.e. the actual image reconstruction, usually relies on FBP described above. Therefore, the speed of image reconstruction of this class of IR algorithms, also often termed *hybrid iterative reconstruction*, is roughly comparable to that of FBP since iterative data filtration in projection and/or in image space normally does not require a lot of additional computation time.

In projection space, statistical filtration consists of an iterative data variation analysis. By means of statistical models, projection data of neighboring projections are compared for identifying overly noisy or photon-starved projections, which are then either replaced or modified such that maximum data consistency is achieved, i.e. variation is minimized. Without modification, these projections would significantly contribute to image noise and artifacts such as streaking while only adding very limited information to reconstructed image data [13]. Contrary to FBP where all projections equally contribute to reconstructed image data (equal weighting), modified projections can be assigned a lower weight for preventing potential introduction of bias, such that they contribute less to reconstructed image data than projections that have not been altered [12]. After transition to image space, e.g. by FBP, image data is iteratively filtered by means of statistical models of the noise structures expected in and characteristic for the imaged body regions, enabling further removal of image noise [8,12,13]. To this end, edge-preserving filters are employed in order to minimize effects on the depiction of fine structure and low-contrast detail [13]. While it is possible to only apply iterative filtration in projection or in image space, and predecessors of current statistical IR have been limited to image space, state-of-the art IR algorithms usually perform iterative optimization in both spaces.

4.2. Model-based iterative reconstruction (MBIR)

The main difference between statistical and model-based IR is that MBIR algorithms are characterized by at least one forward projection from image space to projection space for simulating projection data based on the current image estimate (Fig. 2c). To this end, MBIR requires a model of the CT imaging process for forward projection, as well as a model or estimate of the imaged object, a so-called prior for initializing the iterative cycle (e.g. gained by FBP reconstruction). The closer the image prior is to the imaged object the faster the MBIR algorithm will converge. Back projection of a correction term computed by comparing synthetic and measured projection data yields updated image data, which can be used for initializing the subsequent forward projection of the iterative cycle. Since the simulation of synthetic raw data by forward projection in MBIR is complex and requires a large amount of computation time, iterative filtration in projection and image space alike to the statistical filtration processes applied in statistical IR (see above) can additionally be used for limiting the necessary number of iterative forward projection steps and facilitating faster convergence [13].

In comparison to statistical IR that only implements modeling of photon statistics, models of the CT imaging process in MBIR additionally account for the technical properties of the CT system used, e.g. by modeling of system optics and further details of CT imaging physics (see section *'Principle of iterative image reconstruction (IR)'* above). Modeling of the CT imaging process is therefore more exact and detailed than in statistical IR, and in consequence more complex and computation-heavy. Compared to an exact model of the CT imaging process required for ideal IR, cf. *'Principle of iterative image reconstruction (IR)'*, however, the models implemented in state-of-the-art MBIR algorithms are still subject to simplifications and approximations.

5. Potential strengths and weaknesses of CT image reconstruction techniques in view of routine clinical application

This section reviews potential strengths and weaknesses of the described image reconstruction techniques available for CT imaging in view of their application in clinical routine, a compilation of which can be also found in Table 2.

The main strengths of FBP, the current standard of reference in CT image reconstruction, are its robustness and high speed of image reconstruction. Furthermore, characteristics of FBP-reconstructed image data can be user-controlled, e.g. by indication-specific choice of reconstruction kernel, resulting in images of well-known noise structure and textures. Owing to the linearity of the method, conventional IQ metrics, such as image noise defined as standard deviation of CT numbers (SD) in a region-of-interest (ROI), signal-to-noise ratio (SNR), contrast-to-noise ratio (CNR), and spatial resolution as well as the Fourier metrics modulation transfer function (MTF) and noise power spectrum (NPS), are well-defined and valid throughout all FBP-reconstructed image data.

Weaknesses of FBP include the degradation of IQ by high noise, poor low-contrast detectability, and possibly by artifacts resulting from photon starvation (e.g. streaking) if photon statistics at the detector are very low, e.g. when imaging morbidly obese patients or at low radiation dose, compare Fig. 4(a) and (d) as well as Fig. 5(a) and (d) [8,12]. Therefore, FBP offers negligible dose reduction potential.

Compared to FBP, the main strength of IR methods is an effective reduction of image noise and artifacts, e.g. streaking and blooming, while attenuation values (CT numbers) are preserved, cf. Figs. 4–6. Thereby, signal-to-noise (SNR) and contrast-to-noise (CNR) ratios increase, and visualization of low-contrast features is enhanced; in addition slight improvements in spatial resolution can be observed for model-based IR, cf. Figs. 4(c), 5(c), 6(b, d) [12,13]. Therefore, IR can either be used for improving overall IQ, or noise suppression of IR can be exploited for dose reduction by reconstruction of low-noise image data from intrinsically noisy reduced-dose CT acquisitions (Figs. 4(f), 5(f)). While it seems difficult to directly link the complexity of an IR method to its performance in clinical routine, the aforementioned improvements in IQ, and therefore dose reduction potential, generally are more pronounced for model-based than for statistical IR methods, compare Figs. 4 and 5(b)–(c) as well as Figs. 4 and 5(e)–(f).

Potential weaknesses of IR relate to the speed of image reconstruction, which is slower than that of FBP, depends on the implementation of the algorithm, and decreases with the complexity of the modeling of the CT imaging process [8,13]. While image reconstruction speed of statistical IR and FBP are of comparable order and thus acceptable in clinical routine, model-based IR is more computationally demanding resulting in notably increased reconstruction times potentially limiting use in clinical practice. However, due to the increased computational power readily available, image reconstruction times should be no limiting factor for clinical routine use of commercially available IR algorithms (cf. Table 1). Furthermore, IR methods are subject to the risk of oversmoothing, degrading depiction of fine structure details up to their complete loss, especially for CT acquisitions at very low dose, compare Figs. 4 and 5(f) to (a) and (c). As the capabilities of model-based IR for the improvement of low-contrast detail are also limited, excessive dose reduction may potentially result in a degradation of low-contrast detectability (e.g. liver tumors) [16,17]. Furthermore, in comparison to FBP, IR may yield image data of altered, unfamiliar image texture, i.e. appearing blotchy or pixelated, e.g. at tissue interfaces, or 'plastic-like' [8,12,13]. The lack of statistically distributed noise radiologists are generally expecting and used to can result in subjectively lowered diagnostic confidence despite better overall image quality of IR image data. Additionally, alteration of image characteristics by IR could have a potential influence on quantitative CT analyses, and naively applying reference standards determined based on image data reconstructed with FBP might lead to notably different results [12,18]. Therefore, reference standards for quantitative CT should be revisited when applying IR. The non-linear nature of IR algorithms also implies that conventional IQ metrics, e.g. SNR, CNR, MTF, and NPS, are only locally valid as the underlying assumption of a linear and stationary imaging system is not fulfilled [19]. To this end, novel IQ metrics globally valid for IR image data need to be sought.

6. Summary

Advances in computing power have made software-based methods for IR available in diagnostic CT. While commercially available state-of-the art IR algorithms are vendor-specific and differ in implementation and in complexity of the modeling of the CT imaging process, their common technical principle is the iterative improvement of measured projection data and/or reconstructed image data by employing mathematical models of the CT imaging process.

Compared to traditional FBP, IR algorithms enable a simultaneous reduction of image noise and artifacts (e.g. streaking) resulting in an improvement of overall image quality, e.g. through the enhancement of low-contrast features and an apparent reduction of blooming. The noise reduction potential of IR techniques opens new avenues for dose reduction by reconstruction of low-noise image data from intrinsically noisy reduced-dose CT acquisitions, thereby preserving a diagnostic image quality equivalent to current clinical standards. Furthermore, although image data reconstructed using IR may seem artificial due to a lack of noise and altered, unfamiliar texture, CT numbers of different tissues are generally preserved across the imaged object. Nonetheless, the distinctly different "look-and-feel" of iteratively reconstructed CT image data is a challenge that needs to be addressed when implementing IR in clinical routine.

In diagnostic CT imaging, application of IR across all body regions and clinical indications is an active field of research and has already reached clinical routine [3–6] (this issue), [8,9,12,20,21]. It is to be expected that a growing familiarity of the radiological community with the image characteristics of iteratively reconstructed image data will result in a widespread use of IR. Due to their potential for dose reduction and fostered by further improvements in overall IQ, reconstruction speed, and user control over image characteristics, IR methods will probably replace analytical image reconstruction methods such as FBP in diagnostic CT imaging in the near future.

Declarations of interest

None.

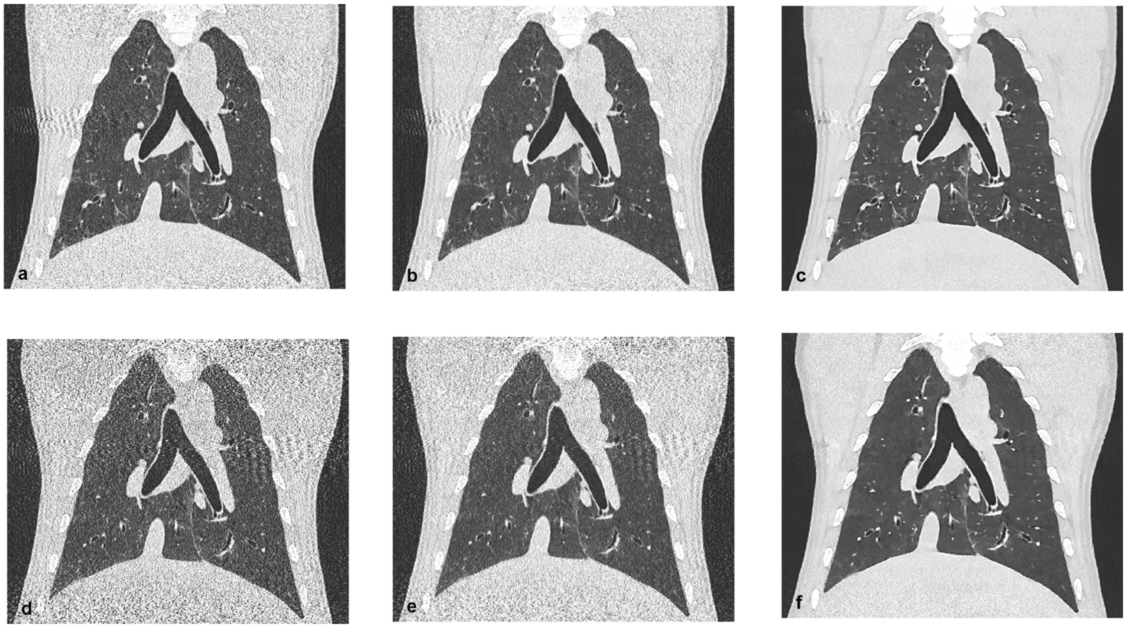

Fig. 4. Comparison of coronal reformations of a non-enhanced chest CT acquired in a porcine model ((a) - (c) 100 kV_p, 120 mAs, $CTDI_{vol}$ 4.95 mGy; (d) - (f) 80 kV_p, 60 mAs, $CTDI_{vol}$ 1.23 mGy) reconstructed with (a), (d) conventional filtered back projection (FBP, sharp lung kernel), (b), (e) statistical iterative reconstruction (sharp lung kernel), and (c), (f) model-based iterative reconstruction (enhancing sharp image features). Compared to FBP ((a), (d)) and independent of acquisition settings and radiation exposure, both IR algorithms reduce image noise notably, e.g. at the lung apex and in the region of the diaphragm, as well as artifacts, e.g. visible in the air and the chest wall at the level of the tracheal bifurcation, improving overall image quality ((b), (c), (e), (f)). Note that while visualization of low-contrast features is preserved or enhanced when using IR for CT data acquired at low radiation dose (compare (f) to (a) and (d)), depiction of fine structure details might not be restored (compare (f) to (a) and (c)). Furthermore, image data resulting from model-based IR ((c), (f)) features a distinctly different texture than image data gained using FBP ((a), (d)) or statistical IR ((b), (e)).

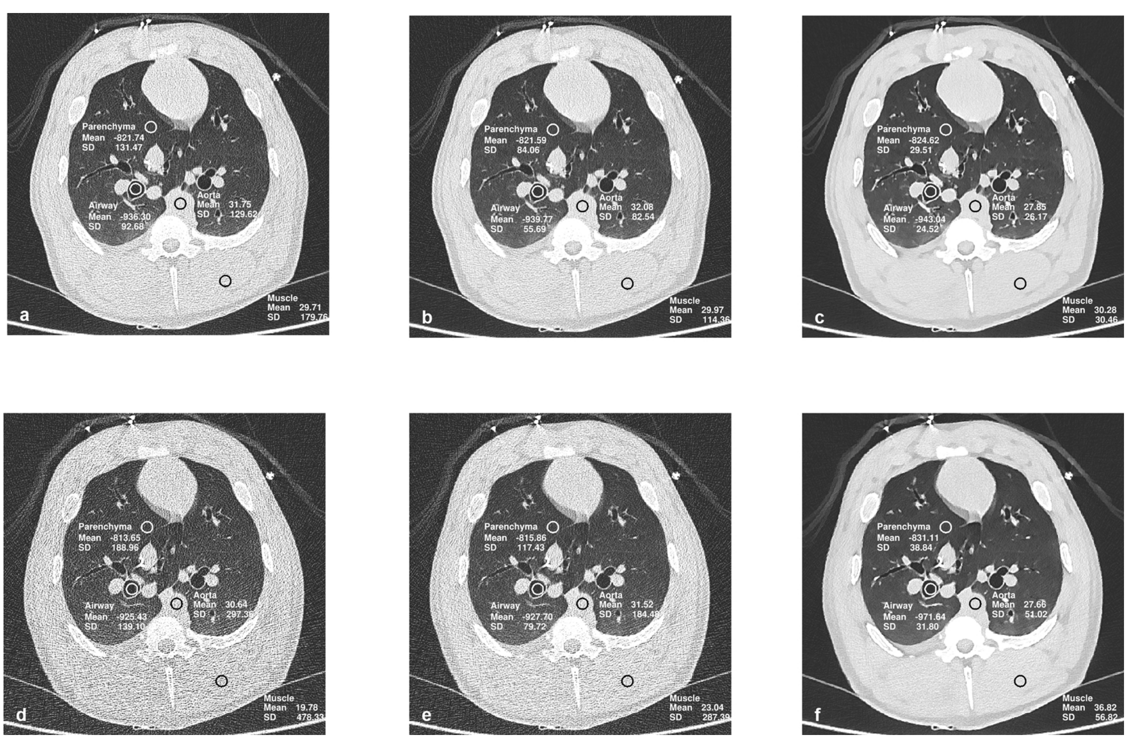

Fig. 5. Comparison of thin transverse sections from a non-enhanced chest CT acquired in a porcine model ((a) - (c) 100 kV_p, 120 mAs, $CTDI_{vol}$ 4.95 mGy; (d) - (f) 80 kV_p, 60 mAs, $CTDI_{vol}$ 1.23 mGy) reconstructed with 0.6 mm slice thickness using (a), (d) conventional FBP (sharp lung kernel), (b), (e) statistical IR (sharp lung kernel), and (c), (f) model-based IR (enhancing sharp image features). Compared to FBP ((a), (d)), statistical and model-based IR enable significant noise (SD, standard deviation) reduction by ~40% ((b), (e)) and ~75-80% ((c), (f)), respectively, while generally preserving CT numbers of different tissues measured in different image regions (diameter of circular ROI: 4.0 mm), e.g. in lung parenchyma, large airways, aorta, and paravertebral muscle. Note that differences in CT numbers between ((a) - (c)) and ((d) - (f)) result from lowering tube potential from 100 kV_p to 80 kV_p. Although visualization of low-contrast features is preserved or enhanced when using IR for CT data acquired at low radiation dose (compare (f) to (a) and (d)), depiction of fine structure details might not be restored (compare (f) to (a) and (c)), and absolute CT number measurements might deviate slightly from expected values (compare (f) to (d) and (e)).

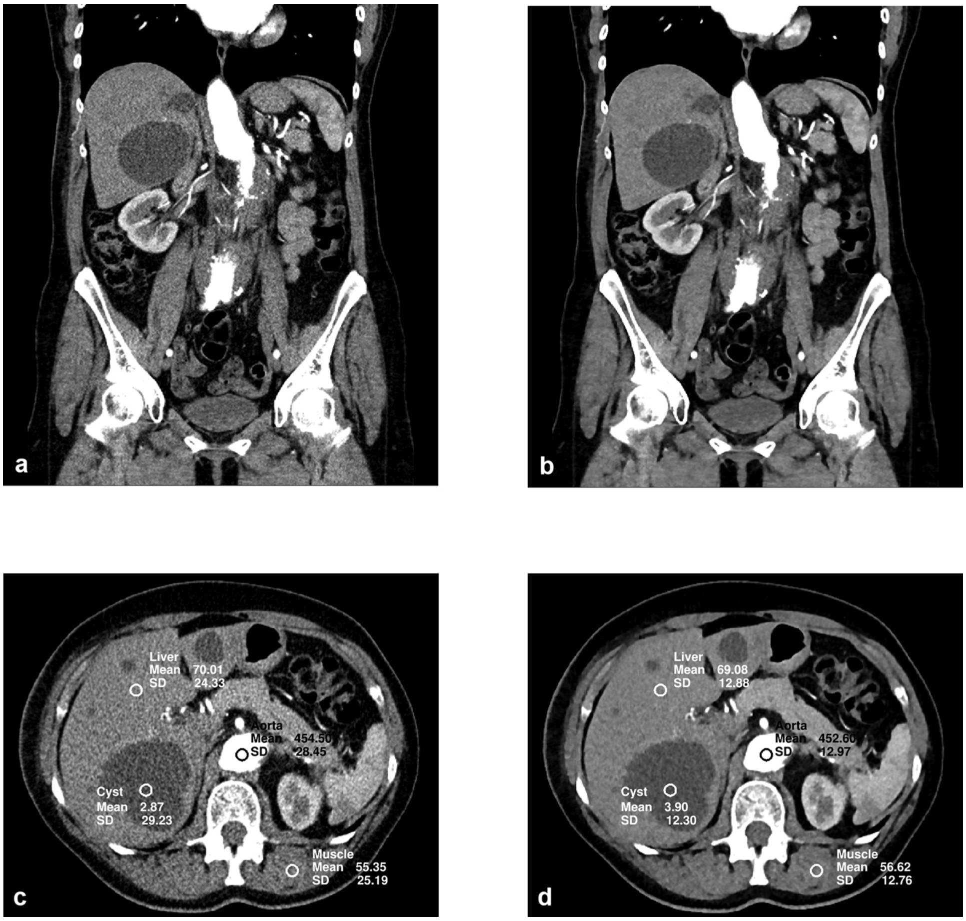

Fig. 6. Coronal reformations ((a), (b)) and transverse sections ((c), (d)) of an arterial phase contrast-enhanced abdominal CT examination (80 kV_p, 133 mAs, $CTDI_{vol}$ 2.61 mGy) in a patient with abdominal aortic aneurysm and hepatomegaly showing multiple liver cysts, reconstructed using (a), (c) conventional FBP (soft tissue kernel) and (b), (d) model-based IR (soft tissue kernel). Compared to FBP (c), model-based IR enables significant noise (SD) reduction by ~50-60% (d), while preserving CT numbers of different tissues measured in different image regions (diameter of circular ROI: 4.0 mm), e.g. in liver parenchyma, cyst, aorta, and paravertebral muscle. Note the enhancement of overall image quality by model-based IR, e.g. the enhancement of low-contrast and the apparent reduction of blooming in the contrasted smaller vasculature such as the branching renal artery of the right kidney (b) or the tiny branches of the hepatic artery in the liver (d).

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