ARTICLE

Interests of new deep learning image reconstruction algorithms for the improvement of image quality and the potential for dose reduction in CT

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Abstract: Deep learning has recently showed a great potential in imaging, notably to improve image quality. CT manufacturers have used this new AI technique to develop new reconstruction algorithms based on deep learning. The first results obtained with these new algorithms confirm the improvement of image quality compared to that with iterative reconstruction algorithms. The first results are very promising with the implementation of low-dose protocols and a great interest for ultra-low dose protocols.

Keywords: Deep learning image reconstruction; low dose; healthcare

1. Introduction

The dose delivered to the patients in CT examinations is a public health concern and the optimization of the doses for each CT protocol is essential [1]. Many tools have been developed to reduce this dose such as iterative reconstruction (IR) algorithms. They led to a significant reduction in delivered doses and low-dose (LD) and ultra-low dose (ULD) CT protocols have been developed and are now used in clinical routine. The LD protocol was defined to correspond to the first quartile of the diagnostic reference level (DRL) distribution, i.e. a dose reduction of more than 50% compared to a standard CT acquisition. The ULD protocol was defined, for the CT-scans, as an effective dose level inferior or similar to the X-ray effective dose for a given organ [2]. However, the use of IR algorithms has its limitations and new reconstruction algorithms have been developed with the emergence of artificial intelligence.

Artificial intelligence (AI) is now widely used and has demonstrated its potential in various branches of science, including medical imaging [3-5]. Among the machine learning techniques, deep learning has recently showed a great potential in imaging, notably to improve image quality [6-23]. CT manufacturers have used this new AI technique to develop new reconstruction algorithms based on deep learning (Deep Learning image reconstruction algorithm, DLIR) [24; 25]. These new DLIR algorithms feature a deep neural network (DNN), trained with high quality datasets from patients and/or phantoms from different types of reconstruction algorithms such as the filtered back projection (FBP) or iterative reconstruction algorithms (IR). This DNN is trained with high quality images, to differentiate the useful signal from noise as to remove it. In clinical routine, these algorithms are now able to do so on all types of both high quality and degraded (low-dose) images.

2. Advantages of DLIR compared to IR algorithms

The advantage of these new DLIR algorithms is that they allow improving image quality by reducing the image noise for a given dose level, and therefore reduce the dose for a same image quality. The IR algorithms used until now also allowed such distinction but their intrinsic properties induce modifications of the image characteristics. Indeed, IR algorithms have non-linear and non-stationary properties that make the spatial resolution dependent on the image contrast and the dose (and noise magnitude) [26]. Modifications of the image texture are also reported with IR algorithms because the spatial frequencies of the noise shift towards the low frequencies. These smoothed, blotchy, plasticized images are often harder for radiologists to interpret, which limit their use in clinical practice. CT manufacturers have announced for the new DLIR algorithms a preservation of the image texture and anatomical/pathological details (GE Healthcare) [25] but also an exceptional detectability at low contrast with a preserved spatial resolution and reduced artifacts (Canon Medical Systems) [24]. Numerous studies have been performed on phantoms and patients to evaluate the contribution of these new DLIR algorithms [6-23]

3. Phantom and patient evaluation of images quality with DLIR

In most phantom studies, the authors used image quality phantoms with different modules, including a homogeneous module, to assess image noise and a module with different inserts (with different densities) to assess CT number, signal-to-noise ratio (SNR) or contrast-to-noise ratio (CNR) and spatial resolution. In most articles, a task-based image quality assessment was performed [6-8; 14; 16; 27]. This new assessment method has been developed to take into account the properties of the images reconstructed with IR algorithms and is now used for all types of images. It consists in the evaluation the noise characteristics by measuring both its magnitude and spatial frequency to assess the noise texture. Spatial resolution is also calculated on inserts with a density close to that of the lesions studied by the radiologists in the clinical CT protocols to be optimized and not on a high contrast structure as was usually performed until now. Finally, a detectability index is calculated for a defined clinical task. This index is an observer model that estimates the radiologist's ability to perform a defined task such as the detection of a simulated lesion with a specific shape, size and contrast.

Different studies have shown that the two algorithms available in clinical practice work in different ways. On the one hand, the algorithm developed by GE Healthcare (TrueFidelity™), which DNN is trained with high quality images of patients and phantoms reconstructed in FBP, have properties close to the latter [6; 8; 14; 16; 25; 27]. Indeed, the spatial resolution was weakly influenced by the dose and the contrast. Compared to images obtained with IR algorithms, TrueFidelity™ reduced the noise, maintained or improved the spatial resolution and improved the detectability of simulated clinical lesions while reporting a very low impact on image texture (**Figure 1**). On the other side hand, the algorithm developed by Canon Medical Systems (AiCE) presented properties close to the images reconstructed with the advanced IR algorithm used to train its DNN [7; 8; 18]. Indeed, the spatial resolution was influenced by the dose and contrast, and the image quality was smoothed, especially for the highest level of AiCE (**Figure 1**). Nevertheless, this algorithm reduced the image noise and improved the detectability of simulated clinical lesions compared to the IR algorithms.

These first results on phantoms were then confirmed in patient studies. Two steps of studies can be found in the literature. First, studies to evaluate the improvement of the image quality by these new DLIR algorithms as compared to the IR algorithms were carried out [9; 10; 19; 23]. The authors compared the image noise, and the signal- and contrast-to-noise ratios of the images reconstructed with these new algorithms and the available IR algorithm in the CT system(s) assessed. They also evaluated the diagnostic confidence level and the diagnostic and overall image quality of these images. For different anatomical locations (skull, thorax, abdomen-pelvis, coronary, vascular) and patient types (adults and pediatrics), they concluded that these new DLR algorithms reduced the noise, and improved the SNR and CNR as well as the diagnostic confidence level and the diagnostic and overall image quality. In a second step, some teams have evaluated the contribution of these new DLIR algorithms in dose reduction compared to usual CT protocols with a standard dose level. With the TrueFidelity™ algorithm, two studies showed that the image quality remained sufficient for diagnosis with dose reductions between -75 and -80% compared to standard abdominal-pelvic and whole-body CT protocols using IR reconstruction algorithm [11; 12]. With the AiCE, a first French team showed that doses could be reduced by -17% for pulmonary CT angiography and by -40% for cardiac CT angiography with lower noise and improved SNR, CNR and overall image quality compared to the usual IR algorithm used [13; 20]. Another team showed the same number of lung and abdominal lesions were detected between a standard protocol with IR and a protocol with -84% less dose with DLIR for an acceptable overall image quality for more than 95% of patients [21].

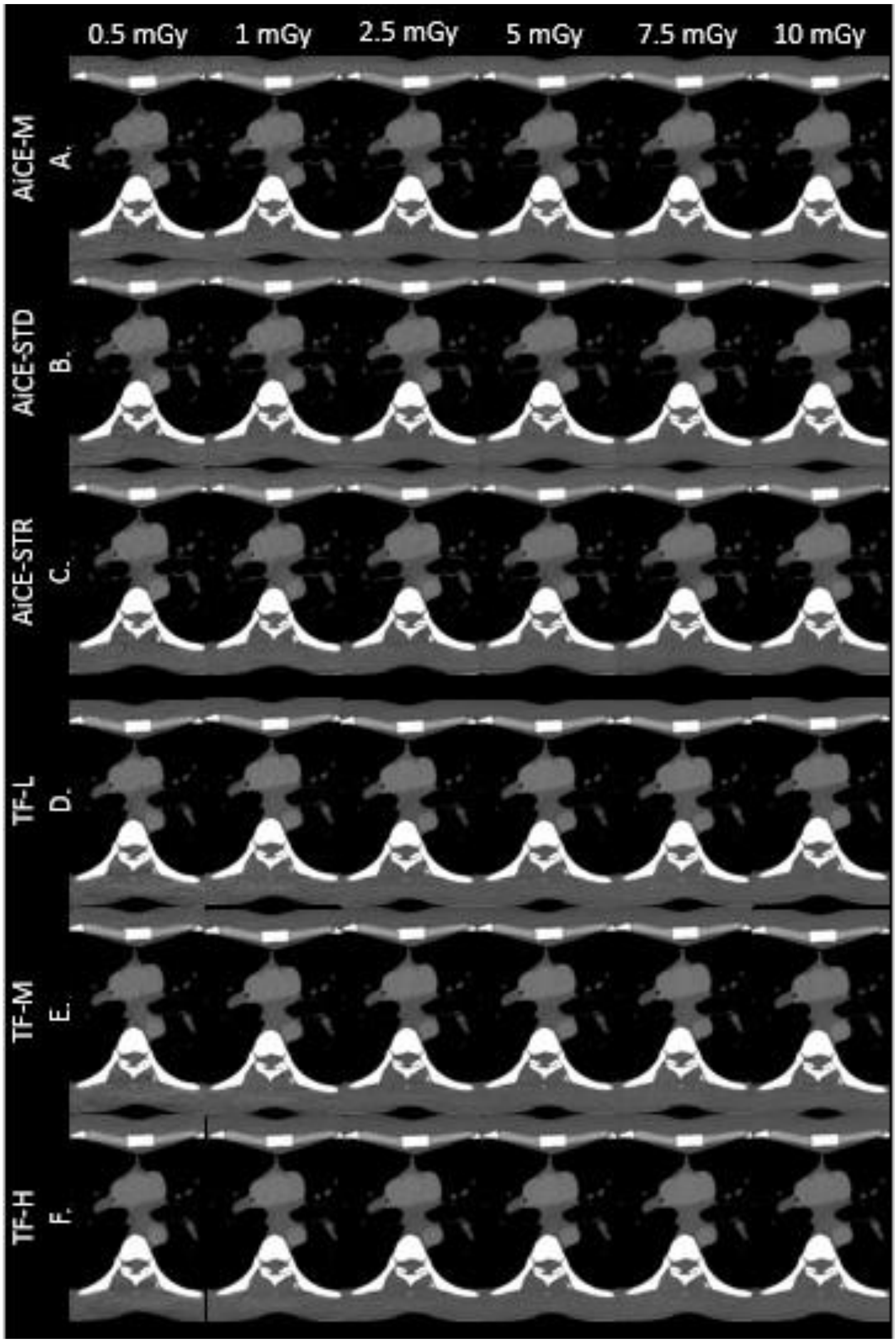

Figure 1. Images of an anthropomorphic phantom in the axial plane obtained for the three levels of AiCE (A, B, C) and TrueFidelity^{TM} (D, E, F) and 6 dose levels. This figure is taken from the published paper "*Comparison of two deep learning image reconstruction algorithms in chest CT images: A task-based image quality assessment on phantom data*" in Diagnostic and Interventional Imaging in 2021 [8].

4. Potential of DLIR algorithms for dose and image quality optimization

The first results obtained with these new DLIR algorithms confirm the improvement of image quality compared to that with IR algorithms. They allow reducing the noise and preserving or improving image texture, which should facilitate the images use in clinical practice by radiologists. The potential of these algorithms in dose reduction is starting to be studied but remains to be determined, particularly regarding the implementation of ULD protocols. The first results are very promising with the implementation of LD protocols and a great interest for ULD protocols. The new DLIR algorithms presented here are continuously trained with new data sets. The models are continuously enriched and the results presented in this article will certainly be developed in the months and years to come, which leaves important research perspectives. Also, other CT-scan manufacturers are working on the development of this type of DLIR algorithm and Philips Healthcare has recently developed their algorithm named Precise Image which is under evaluation [28]. Further studies should be performed on this new algorithm and on the new versions of the available algorithms.

In conclusion, these new reconstruction algorithms based on Deep Learning are still in their beginnings. They are evolving and will keep doing so. New versions have already been developed or are under development by some manufacturers, which suggests even greater dose reductions or improved image quality for a given dose. They are now available and used for dual-energy CT acquisitions favoring the use of lower energy levels on virtual monoenergetic images to improve lesion detection and characterization. The clinical perspectives with these new algorithms are therefore very interesting and should lead to improved practices in the future..

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