

人工智能在 CT 辐射剂量优化中的应用现状与挑战

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摘要 X射线计算机断层扫描成像(Computed Tomography, CT)在临床诊断中具有重要的价值,但同时也为受检者带来了潜在致癌风险。人工智能(Artificial Intelligence, AI)技术凭借其强大的数据驱动能力和学习能力,正在深刻改变现代社会的方方面面。在放射诊断领域, AI技术有望优化临床CT检查的全流程,进一步降低受检者辐射剂量。本文从CT检查的全流程出发,系统地梳理了人工智能在CT检查各主要环节优化辐射剂量的应用现状。在扫描准备过程中, AI可通过实时识别受检者位置实现自动摆位。在数据采集过程中, AI能够根据受检者体型实现自动曝光控制。在图像重建过程中, AI可以实现高质量的图像重建,包括低剂量CT降噪和稀疏角图像重建,实现CT辐射剂量的显著降低。在扫描完成后,人工智能还可以用于精确评估受检者的辐射剂量,实时反馈调节临床扫描参数,为受检者提供个体化的扫描方案。最后,本文分析了人工智能在临床CT检查应用中面临的挑战,包括可解释性问题、受检者数据安全隐患及重建图像的诊断可信度验证。随着人工智能技术,尤其是大语言模型的不断突破,智能CT系统未来将重塑现代医学影像的诊疗模式,实现辐射剂量最优化的目标。

关键词 计算机断层扫描成像, 人工智能, 辐射剂量优化, 图像重建

医疗实践中, X射线计算机断层扫描成像(Computed Tomography, CT)已成为精准诊断不可或缺的工具, 全球范围内CT检查占医疗照射总人次的9.0%^[1]。虽然CT扫描有重要的诊断价值,但同时也使受检者暴露于高频次的电离辐射中^[2,3]。UNSCEAR发布的2020/2021报告中显示,在所有放射诊断成像中, CT检查对集体有效剂量贡献高达61.6%,远高于X射线平片和核医疗诊断等其它放射诊断手段对公众的剂量贡献^[4]。一项对美国6151万受检者(9300万人次CT检查)的调查中发现, CT检查所造成的辐射预计诱发10.3万例癌症的产生^[5]。此外,这项研究还表明,近年来由辐射引起的癌症数量比早期CT检查高出3到4倍,且儿童的辐射风险比成人和青少年更高。2023年, Nature Medicine上发布的针对近百万例儿童CT检查的研究指出儿童CT辐射累积剂量与所有血液系统恶性肿瘤发生之间存在正相关关系^[6]。因此,在确保临床CT成像诊断价值的前提下,将辐射剂量控制在合理最低水平是放射防护的最终目标^[7-9]。

人工智能(Artificial Intelligence, AI)被认为是近年来最具有颠覆性的新兴技术,其已经深刻影响了当今社会的各个领域^[10]。在医疗领域, AI已经可以实现器官勾画、疾病诊断、图像合成和剂量预测等多种任务^[11-14]。随着DeeSeek和ChatGPT等大模型的出现, AI算法的应用进入了一个新的高度,基本做到了全民普及的程度^[15,16]。相比传统机器学习而言,深度学习往往包含更多的参数且具有更深的网络结构,适合用来解决高度复杂的问题。其中,卷积神经网络(Convolutional Neural Network, CNN)具有局部感知和参数共享等特点,主要用于处理图像任务^[17]。循环神经网络(Recurrent Neural Network, RNN)能够处理序列数据,常用于文本分析、语音识别和机器翻译等自然语言处理领域^[18]。强化学习(Reinforcement Learning, RL)通过构建智能体与环境交互学习得到奖励或惩罚,在不断地学习过程中逐步实现奖励的最大化。强化学习常用于决策优化和辅助,在围棋、电子竞技和医疗决策等领域展现了强大的潜力^[19,20]。

在CT辐射剂量优化研究中,人工智能技术已被广泛应用于CT检查的各个环节^[21],如图1所示。在受检者定位过程中,当受检者检查位置与设备等中心点出现偏差时,人工智能可以用于检测受检者体表轮廓上的标志点并自动修正受检者摆位偏差,最终使检查床位于CT设备的等中心位置。在扫描参数选择时,人工智能可以用于辅助决策,根据检查需求推荐最优的扫描参数,在满足诊断需求的同时尽可能地降低受检者辐射剂量。此外,在扫描过程中,人工智能可以实现自动曝光控制(Automated Exposure Control, AEC),在受检者z轴方向和旋转角度上自动控制管电流分布,以最大限度地减少受检者辐射剂量。在图像重建过程中,已有大量研究开展基于人工智能的图像质量提升技术,与滤波反投影(Filtered Back Projection, FBP)和迭代重建(Iterative Reconstruction, IR)相比,该技术能在更低剂量下为各类CT检查生成高质量图像^[22,23]。在CT检查完成后,人工智能技术还可以用于受检者辐射剂量的评估,以便于临床工作人员了解受检者的累积辐射剂量并开展相关

防护和优化措施。图2中展示了CT辐射剂量优化中常用的人工智能算法。本文系统性地调研了人工智能技术在CT检查辐射剂量优化中的研究现状,包含自动定位技术、自动曝光控制、图像重建和辐射剂量评估。同时,分析了CT检查辐射剂量优化的机遇与挑战,在借助人工智能技术优化CT检查流程中,确保在满足诊断需求的前提下尽可能降低受检者辐射风险。

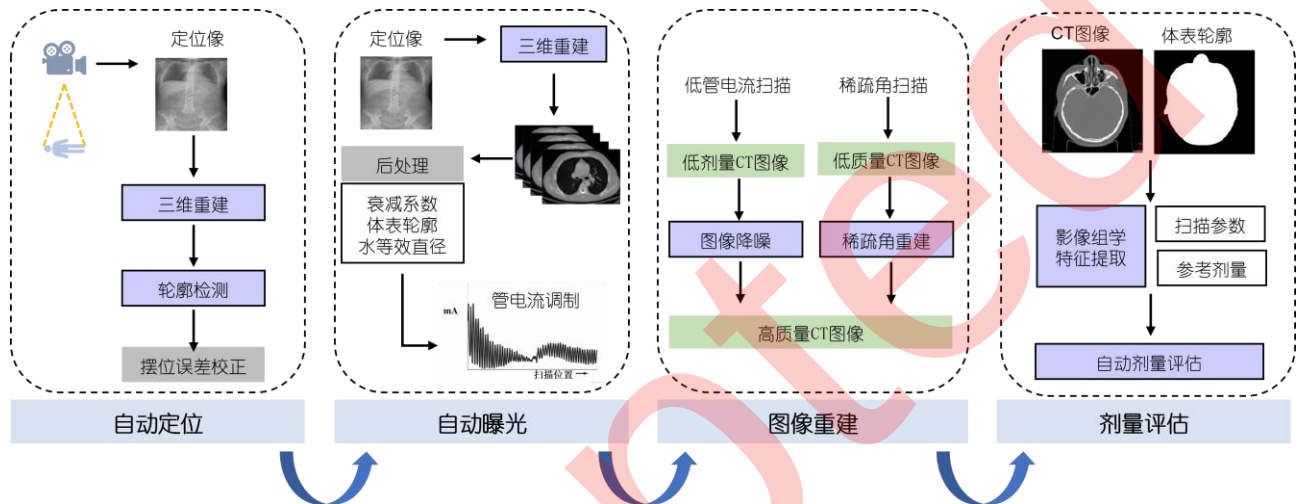


图 1 人工智能技术在CT检查各个流程中的应用

Figure 1 The application of artificial intelligence technology in various processes of CT examination

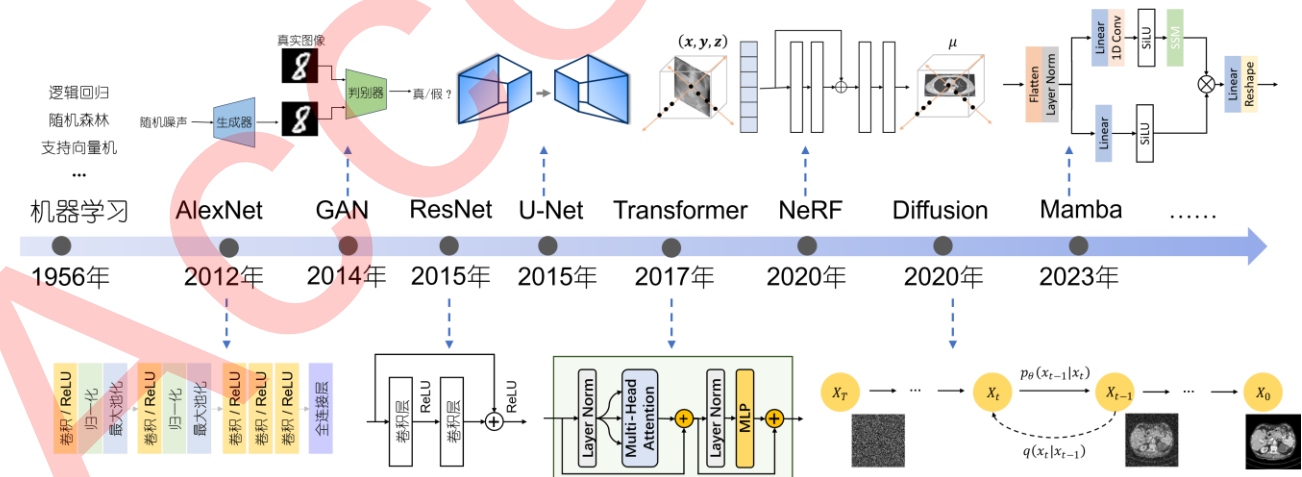


图 2 CT辐射剂量优化中常用的人工智能算法演进

Figure 2 Evolution of commonly used AI algorithms in CT radiation dose optimization

1 人工智能在自动定位中的应用

在CT检查时,当受检者未能以机架等中心点为基准定位时,受检者所受的辐射剂量将会产生偏差,图像质量也会受到不同程度的影响。为了减少CT检查中受检者的摆位误差,一些CT设备在检查床上方安装了3D摄像头,并利用人工智能算法检测受检者体表轮廓来实现自动精确定位。Wang等人设计了U-HAPPY (United

imaging Human Automatic Planbox for Pulmonary) CT以实现肺部扫描精确定位,其首先通过RPN(Region Proposal Network)网络检测面部边界,随后采用V-Net网络对肺区域进行分割来确定起始扫描位置^[24]。这种实时自动化技术能精准覆盖需扫描的部位和区域,从而显著减少受检者检查过程中受到的辐射剂量。Booi等人开了一款用于身体轮廓检测的3D摄像头,可实现儿科受检者CT检查中的自动化精确定位,其使用深度学习算法DARWIN(Deformable Patient Avatar Representation With Deep Image Network)来自动检测受检者体表轮廓^[25]。同样地,Saltybaeva等人的研究也验证了深度神经网络用于CT检查受检者自动定位的准确性,定位误差从40-50%降至0^[26]。Afrieda等人开发了一种使用便携式Kinect相机进行CT检查的定位系统,相机放置在受检者的任意一侧即可应用到CT设备的定位过程^[27]。2023年,Salimi等人也提出了一种基于深度神经网络的自动定位方法,该方法仅使用CT图像定位像即可实现受检者的自动定位^[28]。其通过深度学习模型从前位定位图像生成3D图像,并从中提取身体中心线。结果表明,该方法性能可与外部3D相机的精度相媲美。2021年,Gang等人比较了COVID-19患者进行CT检查时手动定位与自动定位的效果。研究结果显示,与手动定位相比,自动定位总时间缩短28%,受检者偏离等中心距离显著减小,辐射剂量降低16%^[29]。同时,图像噪声降低9%,且肺外周区域病灶的噪声更低、信噪比更高。上述研究结果表明,人工智能技术可以用于CT检查中受检者的自动精确定位,显著降低受检者不必要的辐射剂量。

2 人工智能在自动曝光控制中的应用

CT检查中常使用自动曝光控制技术来降低辐射剂量,其目的是通过实时调整管电流以适应由受检者解剖结构、体型和尺寸导致的衰减差异,从而在可达到的最低剂量下保持稳定的图像质量^[30,31]。在自动曝光控制时,系统根据CT定位像提供的衰减信息,自动确定各投影角度和扫描位置的管电流,以满足预设的目标。然而,从定位图像中直接计算受检者衰减特性较为困难。Salimi等人利用深度学习算法从二维前后位定位图像中预测了受检者的三维体型、形状和衰减参数,可以为管电流调制技术(Tube Current Modulation, TCM)提供更准确的输入信息,从而实现更精准的管电流调整,减小了受检者的辐射剂量^[32]。

目前,许多有关管电流自动调制的技术已经整合至CT系统中,以降低受检者辐射暴露^[33,34]。2022年,Klein等人提出了一项新型的以辐射风险为导向的自动管电流调制方案(riskTCM),该研究认为自动管电流调制应以最小化受检者的辐射风险为目标而非扫描的总管电流值^[35]。riskTCM技术的关键步骤与人工智能技术密切相关。首先,利用两张X射线像或结合定位像与3D摄像头数据来重建先验CT图像,该先验CT的图像质量仅需满足器官定位和衰减特性测定需求即可^[36-38]。之后,通过人工智能算法分割先验CT图像来识别辐射敏感器官,并据此计算每个投影角度的假设剂量分布,随后应用经典算法将剂量分布与分割结果相乘得出单次投影的有效剂量^[39]。采用类似TCM的优化方法,最终找到在保持图像质量前提下使总有效剂量最小化的最优管电流曲线^[40]。研究结果显示,在现有TCM几乎无效的身体区域(如近似圆形的腹部或骨盆),riskTCM可实现33%的剂量降低。由此可见,人工智能技术可用于辅助CT检查自动曝光控制,从而显著优化受检者在接受CT检查时的辐射剂量。

3 人工智能在图像重建中的应用

为了降低CT辐射剂量,在成像方式上主要有降低管电流和减少投影视图两种方案。然而,在临床上,CT图像质量与辐射剂量之间存在权衡关系,较高的管电流和完备的数据采集会产生较清晰的CT图像。同样地,降低管电流和有限角度扫描会使得图像上呈现噪声和伪影,不利于临床的诊断^[41]。使用先进的图像重建技术可以提升图像的质量,并产生辐射剂量降低的效果。相较传统滤波反投影,迭代重建的图像噪声和伪影更少,虽然存在整体图像表现改变及细小解剖结构丢失的隐忧,但可实现显著辐射剂量降低^[41,42]。人工智能在CT图像重建中广泛应用,其能学习更复杂的先验信息,从而修复缺失细节并提升图像质量^[43]。

人工智能在CT图像重建中解决的主要问题是如何从不完整的投影或低质量图像中恢复出高质量的CT图像,从而在低剂量条件下也能获得清晰的诊断级图像。基于深度学习的CT图像重建可以分为四类,包括投影域CT图像重建、图像域CT图像重建、双域联合CT图像重建和直接映射CT图像重建^[44]。投影域CT重建以投影数据出发来恢复图像,其利用深度学习算法估计在信号采集阶段由于采用低剂量扫描条件导致的数据缺失部分,在恢复完整的信号后再通过传统滤波反投影算法进行重建。然而投影域中任何一个位置的数据都可能是其对应CT图像上全局信息的一个反映,对投影域的不正确恢复可能在重建后的图像中引入额外的伪影,从而影响临床诊断。图像域CT重建以欠采样数据重建后的图像出发来获得高质量图像,其主要目的是利用深度学习算法对图像进行后处理。然而,图像中的噪声和微小结构有时难以区分,对图像的不当操作可能会导

致诊断信息的缺失,且初始投影域重建后图像可能包含难以去除的复杂伪影和噪声。由于单一数据域的信息有限,部分相关研究选择从投影域数据和图像域数据同时出发进行CT图像的重建,双域联合优化可以实现双域信息交互,弥补单一域下诊断信息可能缺失的问题。基于双域的人工智能CT图像重建方法在近年来是一个热门的研究方向,但同时其重建过程更为复杂,参数量相对较大,对计算能力的要求较高,因此往往需要更强大的算力来进行训练。直接映射CT图像重建通过学习投影空间和CT图像空间之间的映射,使用深度神经网络直接从投影域数据解码为CT图像。该方法与深度学习模型的多级抽象和自动特征提取能力密切相关,在CT图像重建领域也开始广泛应用。

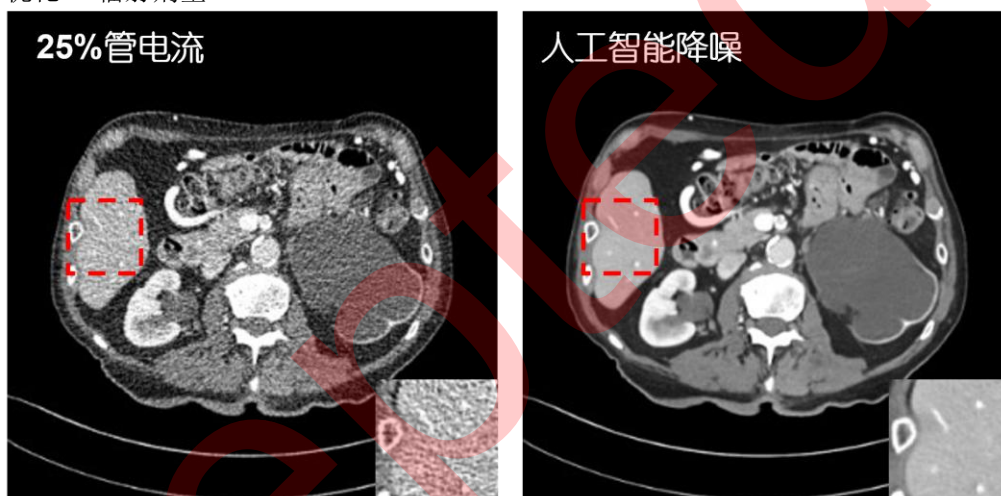
在人工智能实现低剂量CT图像降噪的任务中(图3a),Chen等人于2016年首次将深度学习与低剂量CT图像降噪相结合,提出了基于残差连接的编码解码器结构的卷积神经网络,显著地降低了低剂量CT图像中的噪声^[45]。但该网络以均方误差作为损失函数,其降噪后的CT图像较平滑,从而导致了图像部分细节信息的丢失。Wolterink等人基于生成对抗网络实现低剂量CT图像去噪,该网络使用对抗损失作为损失函数,极大保留了图像细节信息^[46]。之后,Yi等人提出基于条件生成对抗网络与图像锐度探测网络相结合的低剂量CT降噪模型,能很好地保留低对比度区域的图像信息^[47]。2021年,Huang等人基于生成对抗网络提出了DU-GAN,该模型将生成对抗网络判别器常使用的分类器替换成两个UNet结构,分别应用于图像域分支和梯度域分支,对图像的全局和局部结构同时优化,很好的消除了去噪过程中易产生的条纹状伪影^[48]。Li等人设计了DDoCT(Dual-Domain joint Optimization CT)模型,该方法通过投影域与图像域的联合优化来重建高质量CT图像,不仅解决了降低管电流带来的噪声问题,还特别关注了投影数量减少导致的条纹伪影等问题^[49]。近期,扩散模型在图像生成领域中展现了强大的性能,其通过逐步学习噪声添加与去除过程来生成图像,在图像修复和编辑等任务中已超越基于生成对抗网络的方法^[50,51]。目前,该技术已被成功应用于CT图像去噪领域^[52,53]。Gao等人基于去噪扩散概率模型(Denoising Diffusion Probabilistic Models, DDPMs)设计了CoCoDiff模型,将低剂量图像作为条件信息来指导噪声估计网络的预测,能很好地保留清晰的细节^[54]。受自然语言处理序列建模思想的启发,Zhang等人基于Transformer模型设计了TransCT,将低剂量CT图像分解为高频和低频两个部分,低频部分反映了图像内容特征和潜在纹理特征,高频部分反映了图像的细节信息,最终显著改善了低剂量CT图像的质量^[55]。Li等人基于Mamba模型提出了一种用于低剂量CT图像去噪的混合卷积状态空间模型CT-Mamba,该模型结合了卷积神经网络的局部特征提取优势和Mamba捕获长距离依赖的能力,使其能够同时捕获局部细节和全局信息,在CT图像降噪任务中展现了强大的性能^[56]。

在人工智能实现稀疏角CT图像重建的任务中(图3b),Han等人基于改进的UNet模型实现了稀疏采样下CT图像的重建,相比传统方法能够更好地恢复高频边缘信息^[57]。Shen等人提出了一种利用单投影重建三维CT图像的深度学习方法,证明了人工智能在CT图像重建中的强大能力。Wu等人提出了一种基于双域残差优化的DRONE(Dual-Domain Residual-based Optimization Network)网络,该方法首先对稀疏数据进行填补来扩展为高维数据,随后在图像域对重建后的初始图像进行后处理,以消除欠采样伪影^[58]。最近,神经辐射场(Neural Radiance Fields, NeRF)在三维目标重建中被广泛应用,Corona-Figueroa等人将NeRF网络应用于医学图像领域并提出了MedNeRF模型,实现了稀疏角视图甚至单视图下的CT图像重建^[59,60]。Zha等人基于NeRF框架设计了NaF(Neural Attenuation Fields)网络并实现了锥形束CT图像的稀疏角重建,该方法将目标衰减系数表示为三维空间坐标的连续函数,并通过全连接深度神经网络进行参数化,通过最小化真实投影与合成投影之间的误差来训练网络^[61]。随后,Zidane等人将主动学习策略与NeRF结合,采用近邻排除法与最差峰值信噪比策略显著提升了NAF重建的CT影像质量^[62]。

目前,已有许多CT厂商开发了基于人工智能的重建系统。GE推出的TrueFidelity采用深度神经网络和大量高质量CT图像数据训练,可从低剂量正弦图重建出高质量图像。在一项对比研究中,人工智能图像重建的图像在低剂量下展现出比FBP和IR技术更好的图像质量,纹理和图像外观与高剂量FBP图像相似,能实现辐射剂量最高达56%的降低^[63]。Canon推出的AiCE算法和PIQE算法将深度学习融入重建过程,旨在增强信号并降低噪声。研究显示,AiCE在冠状动脉CT血管造影图像上与IR技术相比,可使信噪比和对比度噪声比分别提高约51%和49%,从而实现高达40%的辐射剂量降低^[64,65]。Philips于2022年也推出了基于深度学习的图像重建算法Precise Image。Siemens的myExam Companion算法可自动化选择受检者特定的扫描和图像重建参数,为众多临床指征提供优化方案,但目前尚未有公开数据明确其对CT剂量降低的具体影响^[41]。国内厂商也相继推出了基于人工智能的CT图像重建算法,例如联影的DELTA算法和东软医疗的NeuAI算法^[66,67]。此外,市场上也存在独立的深度学习重建技术供应商,例如韩国ClariPi公司的ClariCT.AI和美国AlgoMedica公司的PixelShine等。

这些基于人工智能的CT图像重建技术为降低CT辐射剂量、提升图像质量提供了新的解决方案，展现了人工智能在医学影像领域的巨大潜力和应用前景。Kobayashi等人采用真实临床数据分析深度学习重建技术的效果，研究发现全身CT时平均有效剂量从术前28.1 mSv显著降至15.5 mSv，降幅达45%^[68]。该剂量降低显著减少了辐射诱发癌症风险，尤其在年轻女性群体中更为明显，预估年癌症发病率从术前的0.247%降至术后的0.130%。Cao等人的研究显示深度学习重建的对比增强腹部CT图像具有显著降低的图像噪声和更优的对比噪声比，辐射剂量最高可减少76%^[69]。Lell等人总结了现有基于深度学习的CT图像重建技术在辐射剂量减少中的效果，调查发现不同部位下，CT检查辐射剂量降低值在30%-83%范围内^[70]。由此可见，基于人工智能的CT图像重建方法可以显著优化CT辐射剂量。

(a) 降低管电流



(b) 稀疏角采样

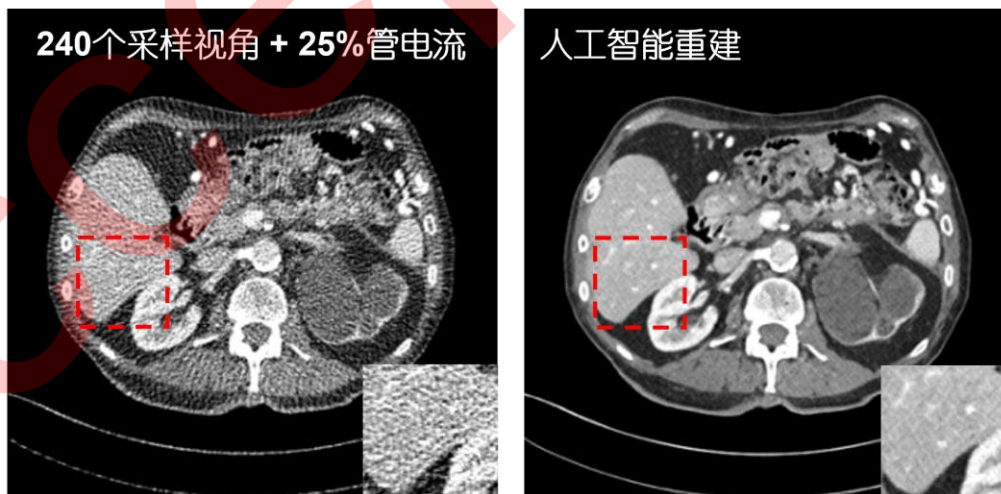


图 3 人工智能算法在两种不同的低剂量CT扫描技术下实现图像质量提升的效果。(a) 降低管电流实现低剂量CT扫描；(b) 缩减采样视图并降低管电流实现低剂量CT扫描

Figure 3 The effect of AI algorithms in improving image quality under two different low-dose CT examination techniques. (a) Reducing tube current to achieve low-dose examination; (b) Reducing sampling views and tube current to achieve low-dose examination

4 人工智能在辐射剂量评估中的应用

人工智能技术还被应用于评估受检者在接受CT检查时的辐射剂量,帮助放射科医生实时了解受检者接受剂量的水平并给出指导性的后续CT检查扫描方案。临床上常用的计算估算方法是使用剂量仿真体模进行剂量沉积测量,这类体模比CTDI (Computed Tomography Dose Index) 体模更能准确模拟受检者解剖结构。然而,由于其对准备时间和设备要求极高,常规应用受到限制。因此,另一种较为便捷的方法是在计算机中建立受检者计算体模并对其进行蒙特卡罗模拟,该方法已成为放射检查辐射剂量评估的金标准。然而,进行蒙特卡罗模拟需要的计算成本高昂,长时间运行往往会阻碍临床上其它常规应用的正常运行。

4.1 基于人工智能的CT辐射剂量快速评估

为了兼顾计算精度与性能, Maier等人提出了基于深度卷积神经网络预测受检者剂量分布的方法,其基本思想是使用神经网络强大的学习能力来代替蒙特卡罗模拟光子与受检者相互作用的过程^[39]。该模型基于U-Net构建,其输入是CT图像与一阶剂量沉积组成的双通道数据,其中CT图像包含了受检者的解剖学信息和剂量衰减信息,一阶剂量沉积定义为由于光电效应以及单次康普顿散射导致的单位质量能量转移,其包含了受检者接受CT检查时的扫描参数信息,神经网络的预期得到的结果则是蒙特卡罗模拟计算得到的辐射剂量金标准。其研究表明,基于深度学习的剂量评估算法能在约1.5秒内完成全身CT扫描数据处理,成为蒙特卡罗模拟的重要替代方案。在此基础上, Shao等人也基于机器学习和深度学习等多种算法提出了一系列基于人工智能的CT辐射剂量评估方法,与Maier等人不同的是, Shao等人通过受检者体表轮廓或人工智能自动勾画的器官轮廓提取了相应的影像组学特征,将提取出的影像组学特征被作为模型的输入来学习蒙特卡罗模拟计算的金标准剂量参考值^[71-73]。其研究方法成功预测了CT扫描中受检者特定器官的辐射剂量,显著提升了人工智能辐射剂量评估的临床效率与可行性。人工智能为剂量评估开辟了新途径,对推进放射性检查所致器官剂量评估技术的发展具有重要启示意义,更为CT检查扫描方案优化提供了全新可能性。

4.2 基于人工智能辅助的计算体模精确建模

除了直接用于辐射剂量评估之外,人工智能技术还被用于辅助蒙特卡罗模拟评估CT检查辐射剂量。在蒙特卡罗模拟中,计算体模的精度直接影响了剂量评估的精度^[74-79]。在计算体模构建过程中需要对受检者所有器官进行逐一勾画,这一过程往往费时费力,而基于人工智能的器官自动勾画方法极大促进了这一过程的进行^[80,81]。2019年, Xie等人利用深度卷积神经网络算法实现了CT图像上部分器官的自动勾画,并将自动勾画的结果用于孕妇计算体模的构建,极大缩短了体模构建所需的时间^[82]。2023年, Wasserthal等人开发了TotalSegmentator算法,这是一款基于深度学习的医学影像自动分割算法,专门用于处理CT和MRI等医学影像数据^[83,84]。TotalSegmentator基于nnUNet框架实现并在1204例CT图像上进行训练,可以实现人体全身117个组织和器官的自动分割^[85]。它能够大大提高医学影像分割的效率,减少人工干预,降低误差率,特别是在一些需要大量人工标注和处理的医学研究中,具有极大的应用潜力。同时,开发者还将Totalsegmentator集成为一个Slicer插件,用户可以直接在3D Slicer平台上使用该工具,从而实现图像处理和分割结果的可视化,方便医生或研究人员进行后续分析。Huang等人利用TotalSegmentator辅助建立了一系列个体化孕妇和胎儿体模库,包含46个0-9不同孕周的孕妇和胎儿体模,还包括30个不同年龄的中国参考人面元模型和29个个体化儿童参考人计算体模。由此可见,基于人工智能的自动勾画算法对计算体模的构建具有强大的辅助作用^[86]。

近年来,数字孪生体模在辐射剂量评估领域是一个热门的研究方向,该体模是指为每个受检者建立一个高度个性化的计算体模,可以精确表示该受检者体型。数字孪生体模的构建方法依赖丰富的面元模型群,首先获取受检者的CT影像,根据受检者CT影像快速建立一个初始化体模,由于常规CT检查获得的往往都是局部影像,该体模并不能包含受检者全身器官信息。因此,需要通过参数匹配的方法从面元模型群中选择一个与目标体模最接近的模板体模。将模板体模与初始化体模进行配准得到形变场,并将形变场作用于模板体模最终得到个体化的受检者数字孪生体模。Chen等人提出了一种基于深度学习的无监督配准方法,通过将XCAT数字人体模型变形适配至受检者CT图像,生成具有高度解剖细节的计算机化体模。实验结果表明该方法具有显著效果,所生成的人体模型展现出高度拟真性,可在医学影像研究的诸多应用领域发挥作用^[87]。Fu等人将人工智能自动勾画和配准技术集成为一个新颖的iPhantom框架,从而实现了数字孪生体模的快速构建,并在大多数器官的辐射剂量估算中显示出小于10%的误差,明显优于当前最先进的方法^[88]。基于精确的剂量评估

结果和大模型的发展,人工智能有望在未来用于优化扫描参数,为受检者推荐个体化的最优扫描方案,针对性地保护受检者安全。

5 当前挑战与机遇

CT技术的普及极大提升了医学诊断能力,但伴随的辐射剂量风险始终是当前各界关心的重大问题。人工智能以其强大的数据处理和学习能力,为精准调控辐射剂量提供了便利。然而,AI在CT剂量优化中的落地面临多重复杂障碍。首要难点在于模型泛化能力,临床真实环境下往往存在不同品牌、型号的CT设备。其硬件构造、扫描协议、原始数据处理方式差异巨大,且受检者体型、扫描部位和诊断需求均存在差别。在特定数据集上训练表现优异的模型,迁移到真实临床场景时,其剂量优化效果可能大幅衰减甚至失效,严重制约了大规模临床部署。其次,人工智能的“黑箱”特性带来的可解释性缺失导致其在临床上难以被信任,医生需要理解AI推荐特定低剂量参数的逻辑依据,若AI无法清晰阐明其决策链,尤其在面对因降剂量可能导致的细微病灶漏诊风险时,临床医生将难以采纳其建议。数据隐私与安全性也是制约AI在临床上大规模开展的重要原因。训练高性能AI模型依赖海量、高质量、标注完善的真实受检者CT数据及其剂量信息。多中心共享这些敏感数据涉及严格的法规遵循和复杂的伦理审查。此外,实现剂量与图像质量的权衡是核心难题。AI虽能大幅降噪,但过度降低剂量必然引入噪声、伪影或模糊结构细节。AI模型需要根据特定的诊断需求动态地调整,确保诊断信息不丢失。最后,在人工智能图像重建技术中,由于真实信息缺失,AI重建图像的临床适用性评判存在困难。基于深度学习的复杂图像重建算法产生的图像,其纹理特征、噪声模式常与传统滤波反投影或常规迭代重建图像显著不同。这种差别导致使得放射科医生难以依据经验自信地判断图像中细微结构是真实病理改变还是算法引入的伪影,导致其在关键诊断中仍倾向于依赖传统重建结果,AI优化的实际临床价值仍然需要认真评判。

为了解决AI模型的“黑箱”问题并缓解临床医生对于AI的信任危机,可解释性人工智能(eXplainable AI, XAI)技术在近年受到广泛关注和探讨,其旨在通过为模型提供透明性和对模型决策过程的解析^[89-90]。主要的XAI技术有SHAP(SHapley Additive exPlanations)分析、扰动分析、Vanilla显著性分析和类激活映射等。这些技术能够帮助用户理解AI算法的内在逻辑或生成透明的推理过程,为弥补AI技术可解释性差与其带来的巨大临床便利之间提供了一种折中的策略。然而,XAI技术存在的解释质量不稳定、计算成本高以及与模型准确性之间的权衡也是不可避免的问题。

尽管挑战重重,人工智能技术也正在引领各个领域的质变。视觉语言大模型的发展为临床决策提供了新的途径,有望引起智能诊疗体系的巨大变革。在临床其它相关场景中,基于GPT-4Vision开发的自动化放疗计划设计系统已能够充分整合历史临床方案,并为特定患者实时提供优化方案的文本反馈^[91]。基于BERT的AI智能体能够实现放射诊断报告进行分类或生成特定影像的电子病例^[92-93]。然而,CT辐射剂量优化领域中的智能体研究还处于起步阶段,未来可通过在超大规模、多样化和多中心的历史CT检查数据库上进行预训练,以构建CT检查智能体。为特定患者和检查部位推荐最优的扫描方案,提升针对新设备、新协议和特殊病例的适应能力。AI驱动的放射检查全流程自动化与智能化是系统性优化的关键,可贯穿检查定位、扫描方案智能推荐、实时剂量监控与动态调节、直至图像重建与后处理等全流程,确保ALARA(As Low As Reasonably Achievable)原则精准执行于每个环节,极大减少人为操作差异和失误。此外,AI还可以实现个体化的CT辐射风险评估与管理,AI可整合受检者历史累积辐射剂量、年龄、性别、遗传易感性以及未来可能的复查需求等多维度信息,构建个体化风险预测模型。这不仅能够指导本次扫描采用更严格的个性化剂量限制,更能受检者制定长期的影像随访策略,从源头上实现辐射防护的精准化和前移,推动精准防护理念落地。

6 总结与展望

本文系统性地探讨了人工智能在CT检查全流程中的应用现状,包括受检者自动定位、自动曝光控制、图像重建和辐射剂量评估等环节。同时,本文还探讨了人工智能在当前临床应用中面临的挑战和机遇。人工智能算法的可解释性差是阻碍其在临床上应用最重要的原因,人工智能在CT辐射剂量优化领域还存在诸多复杂的挑战与广阔的发展前景。克服模型泛化、可解释性、数据隐私、剂量-图像质量平衡及临床信任障碍,需要医工深度交叉与严格监管框架的建立。基于人工智能的放射诊断全流程智能化将引领一个更安全、更精准、更智能的CT诊疗模式,在最大化为受检者健康服务的同时,将辐射风险降至最低。

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Current Status and Challenges of Artificial Intelligence in Computed Tomography Radiation Dose Optimization

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Computed Tomography (CT) plays a crucial role in modern clinical diagnostics due to its ability to provide rapid and detailed anatomical imaging. However, CT imaging presents substantial concerns regarding ionizing radiation exposure, which can increase the risk of radiation-induced complications, especially with repeated scans. Therefore, minimizing radiation dose without compromising diagnostic accuracy has become a critical research topic. Artificial Intelligence (AI), characterized by its powerful data-processing capabilities and adaptive learning mechanisms, is revolutionizing numerous aspects of modern medicine. In particular, AI demonstrates promising potential to optimize various stages of the CT examination process. This optimization not only improves clinical efficiency but also contributes to a significant reduction in unnecessary radiation exposure. The comprehensive review aims to systematically explore the diverse applications of AI for reducing radiation dose across the entire CT examination pipeline. During the pre-scanning and data acquisition phase, AI enables automated patient positioning by employing real-time visual recognition. AI can identify anatomical landmarks and adjust patient alignment to ensure optimal image acquisition geometry, thereby reducing the need for repeat scans caused by misalignment. In the scanning phase, AI algorithms are employed to determine personalized scanning parameters based on patient-specific characteristics such as body size, anatomical region, and clinical indication. Moreover, AI enhances automatic exposure control systems by integrating historical imaging data and contextual information, ensuring that radiation output is dynamically adjusted during scanning to maintain diagnostic quality at the lowest feasible dose. Following data acquisition, AI has facilitated the advancement of deep learning-based reconstruction algorithms in the image reconstruction stage. These algorithms are particularly effective in low-dose CT denoising and sparse-view reconstruction, producing high-quality diagnostic images even when fewer projections or lower radiation levels are used. This approach enables clinicians to maintain diagnostic confidence while minimizing radiation exposure. After scanning, AI continues to perform automated radiation dose estimation and analysis. These tools provide quantitative feedback on delivered dose metrics and enable the generation of personalized scanning protocols tailored to individual risk profiles. Over time, such feedback mechanisms contribute to the development of adaptive systems that learn from cumulative imaging data to continuously optimize safety and efficacy. Despite the encouraging progress, there are several challenges in translating AI technologies into routine clinical practice. Issues such as limited interpretability of complex models, data privacy and security concerns, and uncertainty in image reliability under extremely low-dose conditions must be addressed. Transparent model design, robust validation across diverse populations, and adherence to regulatory frameworks are necessary to facilitate responsible integration. In conclusion, we highlight how AI can be systematically leveraged to intelligently manage radiation dose throughout the CT workflow. Looking forward, the integration of large language foundation models and

multi-modal data fusion holds great potential to develop end-to-end intelligent CT examination systems that not only minimize radiation exposure but also elevate diagnostic precision and workflow efficiency.

关键词 computed tomography, artificial intelligence, radiation dose optimization, image reconstruction

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