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Editorial

Towards real-time radiotherapy planning: The role of autonomous treatment strategies

Today's radiation therapy (RT) is a lengthy process, where the patient needs several appointments for consultation, simulation and fractioned treatment. In recent years accelerated treatment regimens including hypofractionation and single-fraction treatments have gained attention and may improve patient comfort, workflow efficiency and reduce costs [1]. Palacios et al. [2] described in this volume of our journal a same-day consultation, simulation and treatment workflow for stereotactic ablative radiotherapy (SABR) using a magnetic resonance imaging linear accelerator (MRI-Linac). The study included ten patients with small lung tumors eligible for single fraction treatment. For all patients, the consultation, treatment simulation, planning and delivery were realized on the same day. The median time reported for the whole process was 6.6 h, with a median of 2.6 h for the treatment planning as the most time-consuming step. Good patient satisfaction was reported in a post treatment questionnaire.

In Palacios et al.'s study, a main component to ensure a fast radiotherapy planning process was a pre-planning step based on the diagnostic computed tomography (CT) data set [2]. This pre-planning was used to facilitate the whole process for the involved physician and physicist and also to steer the planning constraints in order to reduce time for manual tweaking of the patient individual constraints on the planning day. Such pre-optimization might also be a way to increase efficacy of conventional planning procedures and speed-up this part of the workflow. Recent studies have proposed to predict radiation dose distributions based on deep learning (DL) models applied to diagnostic CT [3]. Such DL based decision support tools, applied to diagnostic imaging information, might in the future enable to estimate potential side effects and risks related to RT already at the time of patient consultation and thus enable the physician as well as the patient to take informed treatment decisions. Potentially, pre-planning based on diagnostic imaging might be used directly as input for online-adaptive RT, which has to the best of our knowledge not yet been investigated.

The one-day workflow proposed by Palacios et al. [2] used automation only to a minor extent and it is therefore highly dependent on the availability of staff throughout the day and not easily scalable to increasing patient numbers. Automated tools for various steps in the radiotherapy planning workflow such as automatic contouring [4–8] and radiotherapy planning [9–13] recently gained attention. For instance, Johnston et al. [7] showed the usability of a convolutional neural network for segmentation of thoracic organs at risk. Although auto-contouring of targets is more challenging, Xie et al. [8] recently introduced a 3D neural network for lung lesion contouring. Also, for treatment plan optimization different approaches were proposed [9–13]. While automation tools for single workflow steps are already in clinical use, the next goal should be an autonomous workflow integrating contouring and plan optimization. Xia et al. [14] already showed the feasibility of a full-process solution for rectal cancer, integrating artificial intelligence based automated contouring and planning. For prostate cancer Künzel et al. [15,16] proved that such automated tools can be combined to an autonomous treatment planning workflow without human interaction for reference plans in magnetic resonance guided radiotherapy. In such a way the treatment planning process would be accelerated in a scalable approach.

The work published by Palacios et al. [2] has demonstrated the potential related to timing efficiency with respect to the whole RT chain, i.e. simulation, data annotation, planning, patient-specific quality assurance and RT delivery. In their study, the authors impressively showed that the whole treatment planning and delivery chain can be effectuated in one day. In the same way of thought, several recent studies have shown that fully automated contouring and RT planning is possible [14–17]. Future developments might therefore enable real-time annotation, planning and delivery. Consequently, this might allow for one-stop-shop simulation and treatment delivery making separate simulation exams obsolete.

In conclusion, the work published by Palacios et al. [2] in this virtual special issue of *Physics and Imaging in Radiation Oncology* focusing on highlights of ESTRO 2022 medical physics contributions impressively showed that developments towards low latency time or real-time RT simulation and planning is a current research focus. To enable future clinical implementation of such artificial intelligence driven real-time applications [18], further research is needed in the fields of automation in data annotation and target contouring, RT planning including dose calculation but also dedicated tools for the quality assurance of fully automated workflows need to be developed. Furthermore, ethical aspects related to autonomous cancer treatments including definitions of dedicated checkpoints for human interaction to allow expert checks and stopping rules need to be defined and investigated.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: DT reports institutional collaborations with Elekta, Philips, TheraPanacea, Kaiku Health, Dr. Sennewald and PTW Freiburg. LK has no conflicts of interest to declare.

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