PyMedPhys: A community effort to develop an open, Python-based standard library for medical physics applications

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Software

- Review
- Repository
- Archive

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Summary

PyMedPhys is an open-source medical physics library built for Python by a diverse community that values and prioritizes code sharing, review, continuous improvement, and peer development. PyMedPhys aims to simplify and enhance both research and clinical work related to medical physics. It is inspired by the Astropy Project (Astropy Collaboration, 2013); a highly successful collaborative work of our physics peers in astronomy.

Statement of need

Medical radiation applications are subject to fast-paced technological advancements. This is particularly true in the field of radiation oncology, where the implementation of increasingly sophisticated technologies requires increasingly complex processes to maintain the improving standard of care. To help address this challenge, software tools that improve the quality, safety and efficiency of clinical tasks are increasingly being developed in-house (Arumugam et al., 2016; Bakhtiari et al., 2011; Bhagroo et al., 2019; Chan et al., 2015; Edvardsson et al., 2018; Huang et al., 2021; Inaniwa & Kanematsu, 2018; Keall et al., 2014; Kimura et al., 2021; Kuo et al., 2020; Latala et al., 2020; Li et al., 2010; Maughan et al., 2019; Skouboe et al., 2019). Commercial options are often prohibitively expensive or insufficiently tailored to an individual clinic's needs. On the other hand, in-house development efforts are often limited to a single institution. Similar tools that could otherwise be shared are instead "reinvented" in clinics worldwide on a routine basis. Moreover, individual institutions typically lack the personnel and resources to incorporate simple aspects of good development practice or to properly maintain in-house software.

By creating and promoting an open-source repository, PyMedPhys aims to improve the quality and accessibility of existing software solutions to problems faced across a range of medical radiation applications, especially those traditionally within the remit of medical physicists. These solutions can be broadly categorised in two areas: data extraction/conversion of proprietary formats from a variety of radiotherapy systems, and manipulation of standard radiotherapy data to perform quality assurance (QA) tasks that are otherwise time-consuming or lack commercial solutions with the desired flexibility or true function.

Data extraction and conversion currently includes: two treatment planning systems, an oncology information system, and a linear accelerator vendor family of systems. Data in proprietary formats from these systems are extracted and converted to allow for integration in a myriad of applications. Applications that use planning system information include: electron cut-out factor determination, CT extension, and extraction of dose information for patient QA purposes. Applications that use the oncology information systems include: clinical dashboards that summarise data, quality task tracking, and comparison of dose information to planning systems. Applications that use the linear accelerator data include: patient specific QA analysis against planning data, and analysis of machine performance such as the Winston-Lutz test.

QA tasks using standard radiotherapy data include: anonymisation, extraction of dose data for analysis, manipulation of contour files to allow merging or adjustments/scaling of relative electron density, modifying machine names in plans, and most frequently used, the calculation of a Gamma index, a widely recognised metric in radiotherapy analysis that quantifies the difference between measured and calculated dose distributions on a point-by-point basis in terms of both dose and distance to agreement (DTA) differences.

Many of these tools are in use clinically at affiliated sites, and additionally, aspects of PyMedPhys are implemented around the world for some applications. Many parties have embraced the gamma analysis module (Castle et al., 2022; Cronholm et al., 2020; Gajewski et al., 2021; Galić et al., 2020; Lysakovski et al., 2021; Milan et al., 2019; Pastor-Serrano & Perkó, 2021; Rodríguez et al., 2020; Spezialetti et al., 2021; Tsuneda et al., 2021; Yang et al., 2022), while implementations of the electron cutout factor module and others (Baltz & Kirsner, 2021; Douglass & Keal, 2021; Rembish, 2021) have also been reported. Additionally, the work has been recognized by the European Society for Radiotherapy and Oncology (ESTRO) and referenced as recommended literature in their 3rd Edition of Core Curriculum for Medical Physics Experts in Radiotherapy (Bert et al., 2021).

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