



BEIHANG
UNIVERSITY



北航物理学院

SCHOOL OF PHYSICS, BUAA

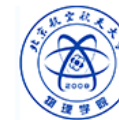
北京航空航天大学医学物理简介

张高龙

北京航空航天大学·物理学院

2024年7月22日

背景及意义



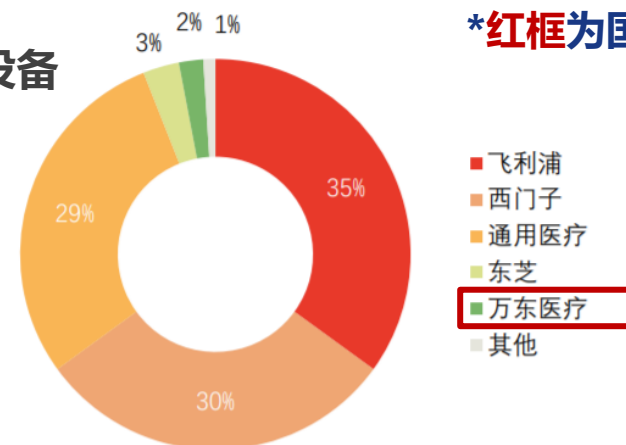
□ 我国医学物理研究水平在近年有长足的进步，但是接受放疗患者比例和生存期偏低，高端诊疗设备基本被发达国家厂商垄断。发展医学物理，可提高人民健康水平、推动高端医疗器械国产化战略，解决医疗设备领域“卡脖子”技术问题。

企业	中国64排及以上CT市场占有率
GE医疗	26.3%
西门子医疗	21.2%
飞利浦医疗	17.4%
联影医疗	14.0%
东软医疗	10.1%

企业	中国3.0T及以上MR市场占有率
西门子医疗	36.3%
GE医疗	24%
飞利浦医疗	22%
联影医疗	17.1%
日本东芝	0.7%

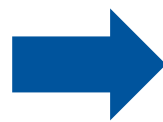
企业	中国高能放疗设备市场占有率
西门子医疗	54.2%
医科达	43.7%
新华医疗	2.1%

中国放射介入设备市场占有率



*红框为国产厂商

- 发达国家完善的医学物理培养机制，**2年临床企业轮转**。
- 我国医学物理研究生教育**尚未形成统一标准**。
- 医学物理**人才匮乏**。
- 按目前的规模，即使人员培养规模再扩大10倍，近20年内也不能满足需要（15-20万）。



- 无法正确设定诊疗参数，对患者造成伤害。
- 无法充分发挥昂贵设备的功能。
- 无法形成消化吸收的环境，缺乏开发设备功能的人才。
- 企业没有消化吸收再创新的源头
- 产学合作失位

- 习近平总书记在科学家座谈会上指出：“...**医疗设备等领域科技发展滞后**问题日益凸显...面向**世界科技前沿**、面向**经济主战场**、面向**国家重大需求**、面向**人民生命健康**...坚持“四个面向”，就要坚持**需求导向**和**问题导向**。”



物理学-医学物理

北京航空航天大学物理学院
北京大学医学部、中国人民解放军总医院



中国人民解放军总医院



学位授予单位：北京航空航天大学

所属一级学科名称：物理学

二级学科名称：医学物理

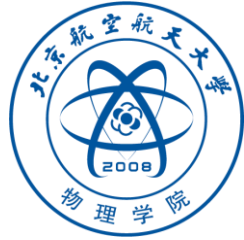
二级学科代码：0702Z1

学科授权级别：博士、硕士



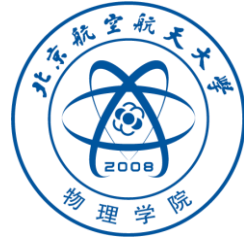
201504

北航物理学院与北京大学医学部放射肿瘤学系**首次接触**，筹备工作正式启动。



201708

物理学院与北大医学部、解放军总医院**达成合作办学协议**，共同完成培养方案。



201709

召开**专家评议会**。形成《自主设置目录外二级学科论证方案》，**上报教育部**学位与研究生教育发展中心公示。



201711

北航第九届学位评定委员会第八次会议同意在物理学一级学科下自主设置目录外二级学科**博士学位授权点医学物理学**。



- 2015年4月28日，北航物理学院（肖志松、耿立升、王星歌）与北京大学医学部放射肿瘤学系王俊杰主任等多位专家首次接触（宇航学院周付根教授），筹备工作正式启动
- 2016年，吕广宏院长提出“能源物理”、“信息物理”、“空间物理”、“医学物理”学科、科研四大板块。
- 2017年8月12日，物理学院与北大医学部、解放军总医院（曲宝林主任、徐寿平副教授）达成合作协议。40天内完成培养方案（吕广宏、耿立升、竺礼华、张高龙、孙保华、乐小云、北医、301）
- 2017年9月22日，召开专家评议会（中候补委员，欧阳晓平院士为专家组组长）。
- 2017年9月27日，提交正式版至学校，上报教育部学位与研究生教育发展中心公示
- 2017年11月23日北航第九届学位评定委员会第八次会议同意在物理学一级学科下自主设置目录外二级学科博士学位授权点医学物理学—成为国内首个培养医学物理高级人才的物理学院



201801
合作研讨会

北航 - 北医 - 解放军医学院医学物理研究生联合培养推进会
2019.5.9



201905
推进会



201909
第一届新生入学

北航-北医-解放军医学院医学物理学科建设推进会
2019.11.10



201911
设立“医科达”奖学金



202109
设立“国科离子”奖学金

• **7名**校内导师, 11名兼职硕导



耿立升 教授



乐小云 教授



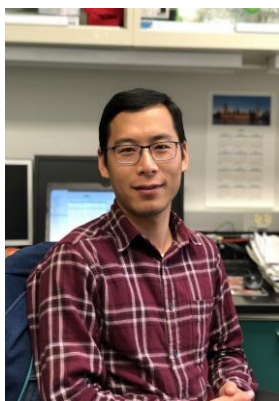
孙保华 教授



张高龙 教授



竺礼华 教授



赵维 教授

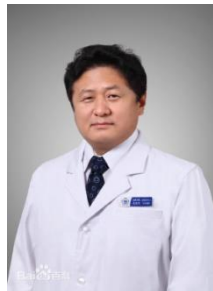


姜寅 副教授

• 7名校内导师, **11**名兼职硕导



高献书
北京大学第一医院
主任/教授



王俊杰
北京大学第三医院
主任/教授



朱广迎
中日友好医院
主任/教授



吴昊
北京大学肿瘤医院
副主任/教授级高级工程师



张艺宝
北京大学肿瘤医院
副主任/高级工程师



杨瑞杰
北京大学第三医院
副研究员



曲宝林
解放军总医院第一医学中心
主任/教授



徐寿平
中国医学科学院肿瘤医院
高级工程师



王军良
解放军总医院第五医学中心
副主任技师



张富利
解放军总医院第七医学中心
副主任技师



周付根
北京航空航天大学宇航学院
教授



X. Allen Li 博士
威斯康辛大学



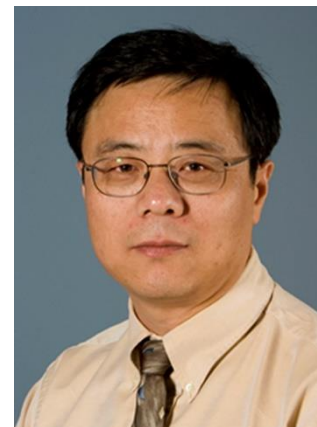
吴秋文 博士
杜克大学



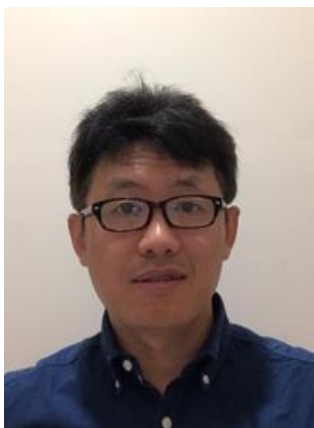
贺莉莉 博士
辛辛那提儿童医院



黄英强 博士
昆山杜克大学



李左峰 博士
佛罗里达大学



陈新 博士
昆山杜克大学



杨泗春 博士
凯斯西储大学



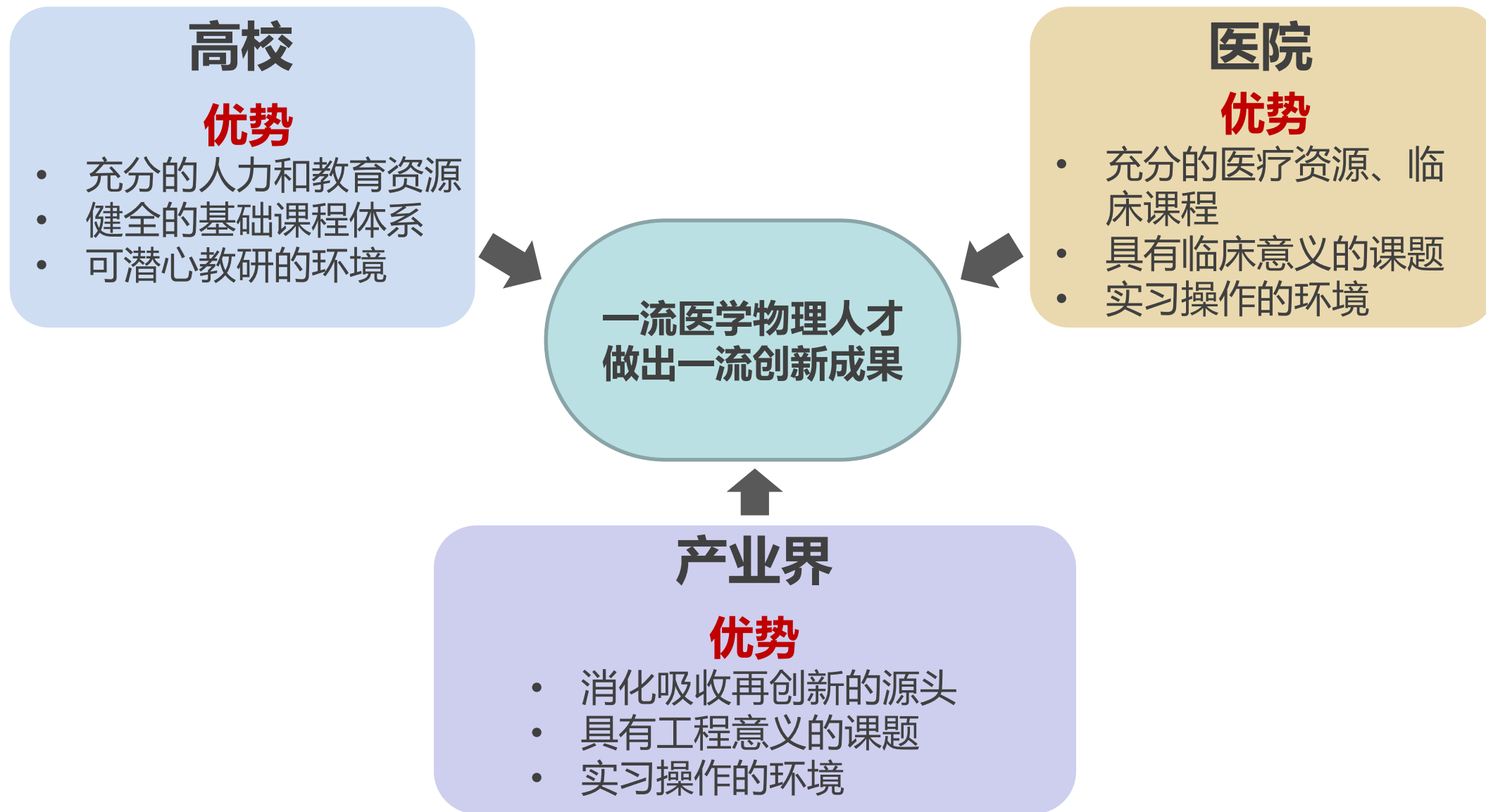
Haga 博士
德岛大学



常城 博士
国科离子医疗科技有限公司

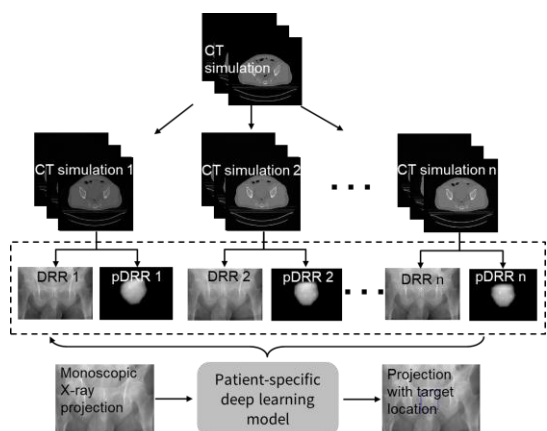


李小萌 博士
香港科技大学



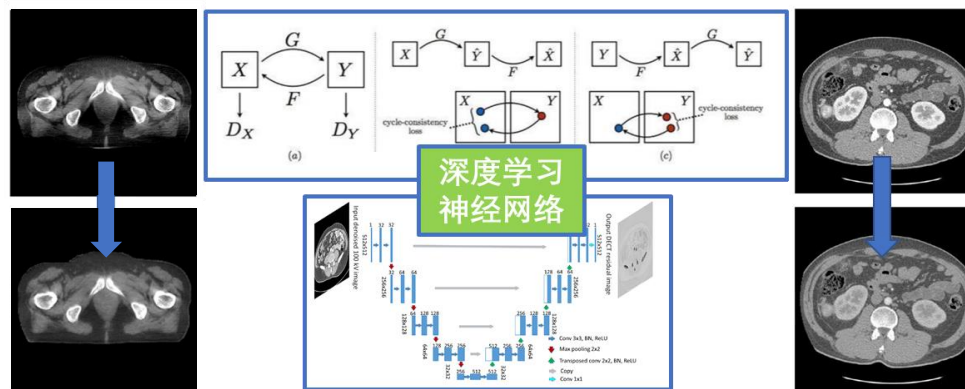
质子（重离子）治疗

- 基于质子CT的精确质子阻止本领比预测
- 质子源模型
- 质子剂量计算
- 无金标图像引导质子治疗



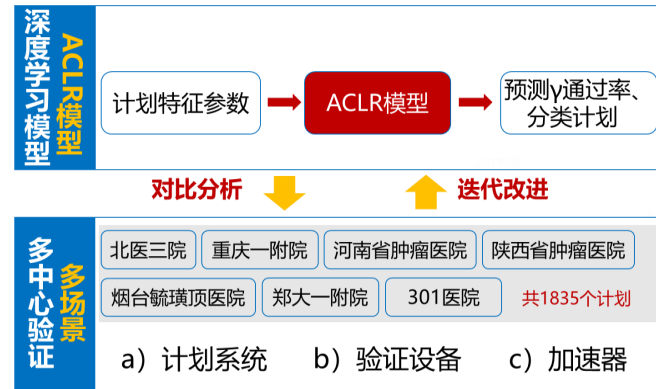
医学影像处理

- 对抗生成网络在CBCT与CT的图像配准中的应用
- 对抗生成网络将MVCT合成伪kVCT;
- 跨模态图像合成及配准




自动放疗系统

- 自动质量控制
- 患者剂量验证方法
- 靶区勾画
- 剂量预测/增强
- 预后预测

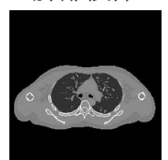


研究方向1——质子（重离子）治疗


KV-kV DECT



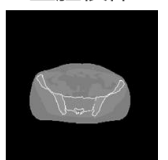
肺部模体



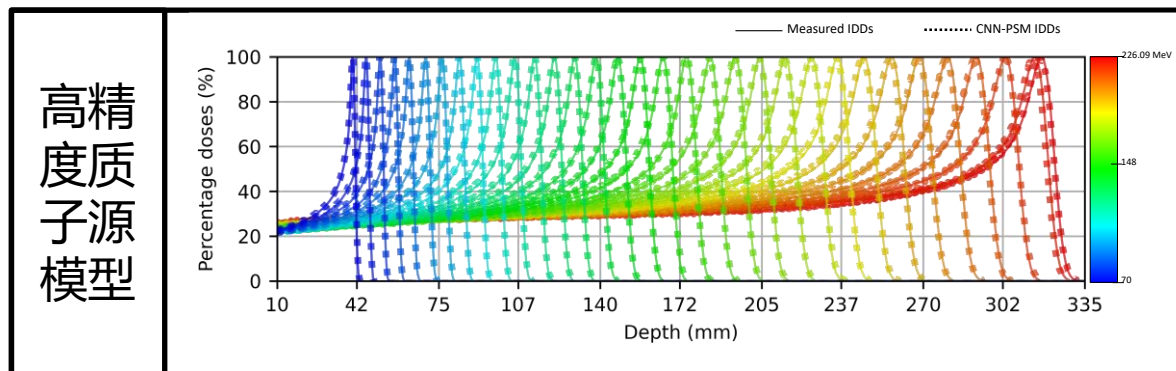
KV-MV DECT



盆腔模体

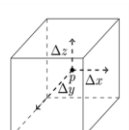


预测质子阻止本领比

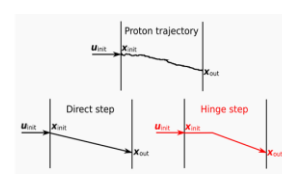


校际合作：国科离子、
医科院肿瘤医院...

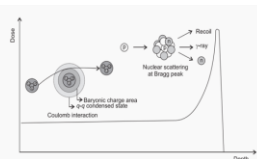
专用质子剂量计算引擎



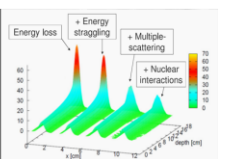
Boundary Crossing



Random Hinge Algorithm

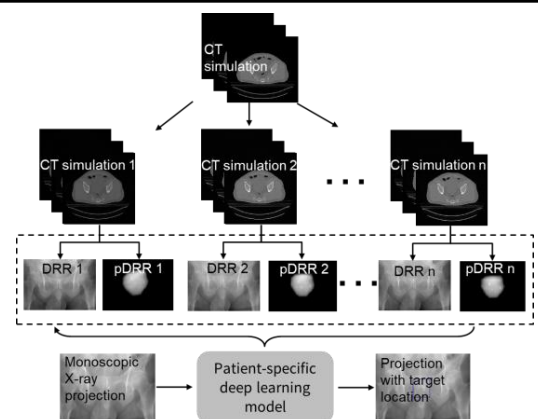


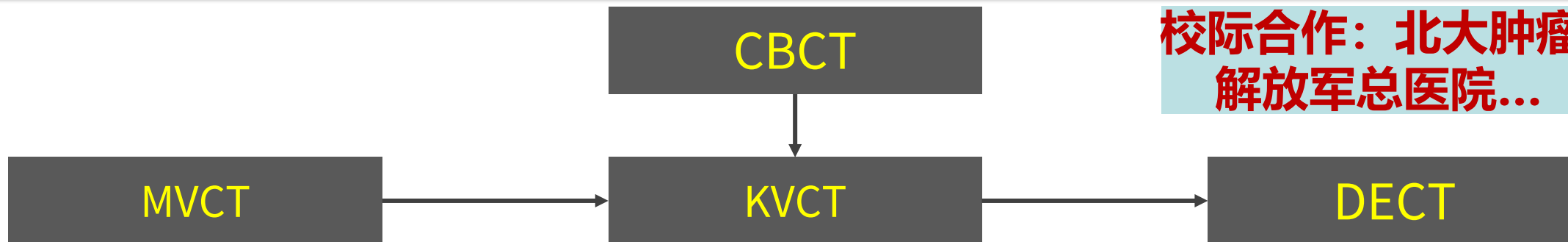
Proton Interaction Processing



Energy straggling Algorithm

无金标
图像引导
质子（重离子）
放疗





校际合作：北大肿瘤、解放军总医院...

对抗生成网络基于MVCT, CBCT合成伪kVCT

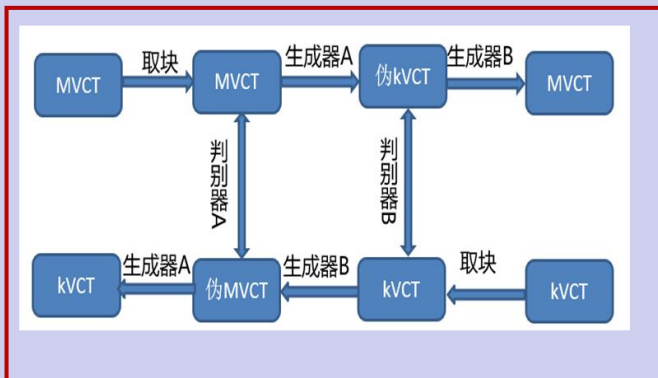
30名接受ToMo放疗的鼻咽癌患者

图像重采样

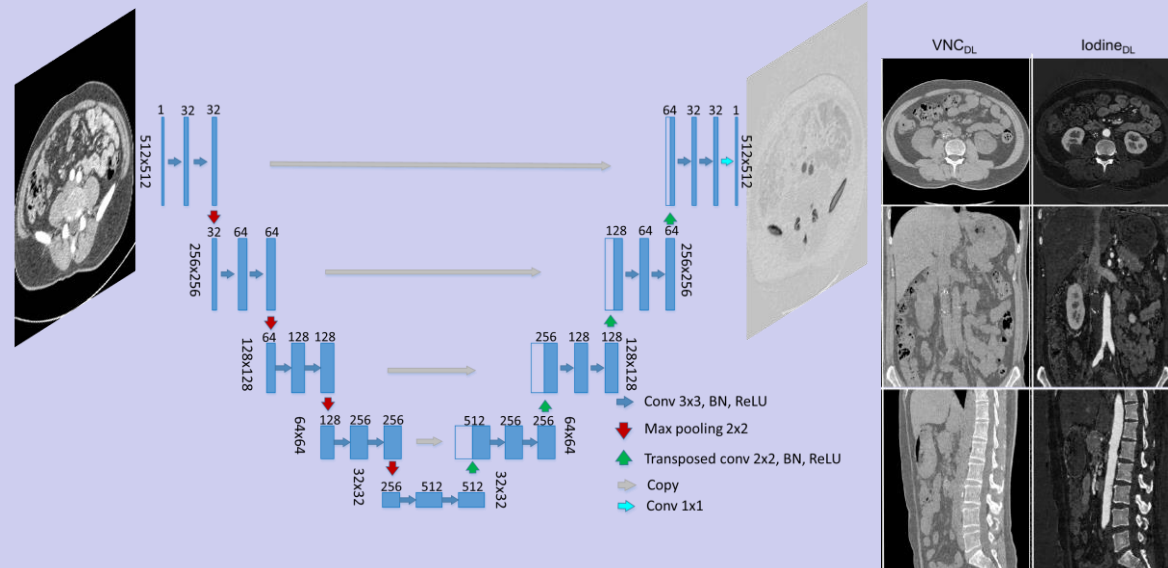
刚性配准

形变配准

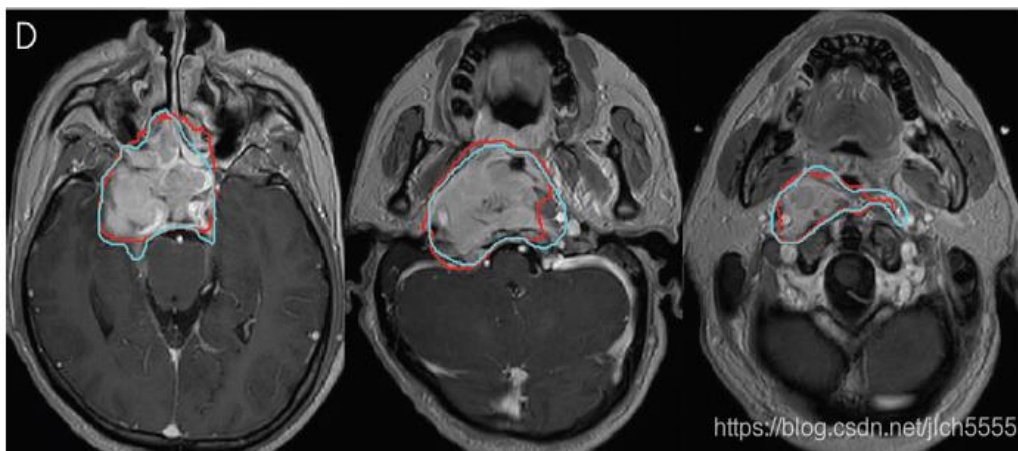
输入网络进行训练



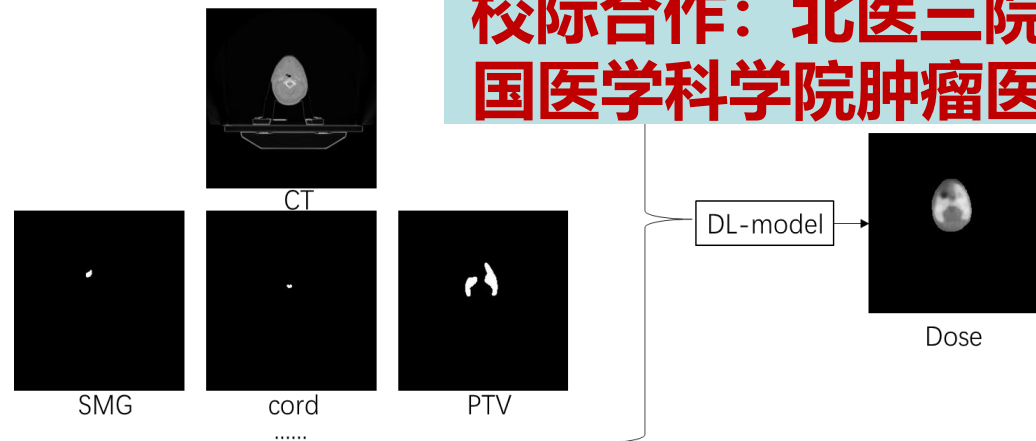
深度学习算法在能谱CT图像合成中的应用



研究方向3——自动放疗系统

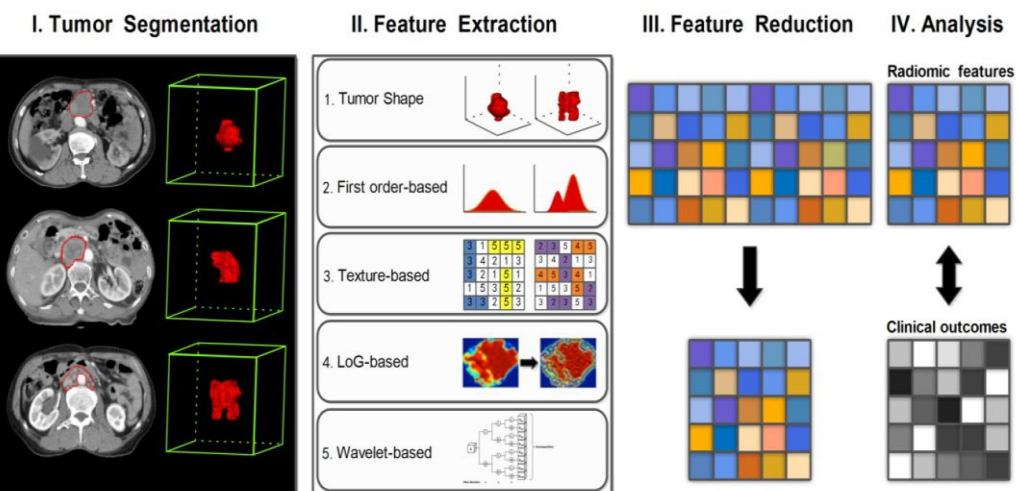


结构勾画：基于深度学习的头颈部肿瘤靶区勾画

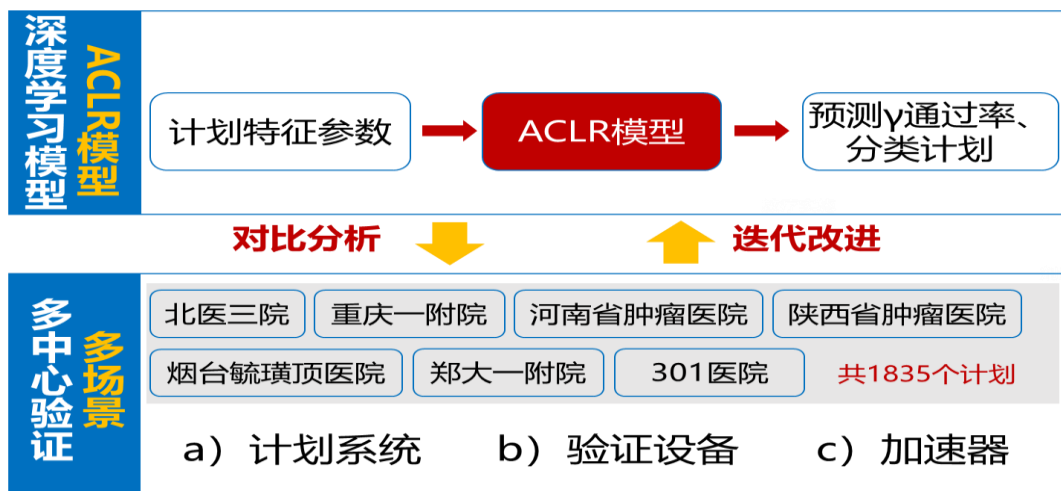


校际合作：北医三院、中国医学科学院肿瘤医院...

剂量预测：使用CT与ROI预测Tomotherapy治疗鼻咽癌患者的剂量分布



预后预测：基于影像组学的肺癌预后预测



剂量验证：基于深度学习的患者剂量验证方法的多中心验证

- 多中心验证 多场景
- 北医三院 重庆一附院 河南省肿瘤医院 陕西省肿瘤医院
 - 烟台毓璜顶医院 郑大一附院 301医院 共1835个计划
 - a) 计划系统 b) 验证设备 c) 加速器

2021年代表性成果



发表文章6篇

1. Ruijie Yang, Xueying Yang, Wang Le, et al. *Radiotherapy and Oncology* 2021; 161:230-240.
2. Liu X, Li KW, Yang R, Geng LS. *Front Oncol.* 2021; 11:717039.
3. Li KW, Fujiwara D, Haga A, Liu H, Geng LS. *Phys Med.* 2021; 89:182-192.
4. Li KW, Fujiwara D, Haga A, Liu H, Geng LS. *Br J Radiol.* 2021; 94(1128):20201236.
5. Zhao W, Shen L, Islam MT, et al. *Quant Imaging Med Surg.* 2021; 11(12): 4881-4894.
6. Liu B, Xiong T, Lu J, Li S, Bai X, Zhou F, Wu Q. *Med Phys.* 2021; 48(11):7493-7503

AAPM年会摘要3篇



Improvement of Volumetric Analytical Anisotropic Algorithm Dose Calculations Using an ROI Contour-Based Deep Learning Method

INTRODUCTION
Speed and accuracy are both critical factors in dose calculation for radiotherapy. By applying the AAPM dose calculation results to generate electron beam maps, we can reduce the AAPM dose calculation time and improve the accuracy of the AAPM dose calculation. In this study, we propose a novel deep learning method that can improve the accuracy of the AAPM dose calculation by using the AAPM dose calculation results to generate electron beam maps.

AIM
To improve the accuracy of the AAPM dose calculation, we propose a novel deep learning method that can improve the accuracy of the AAPM dose calculation by using the AAPM dose calculation results to generate electron beam maps.

METHOD
The AAPM dose calculation results were used to generate electron beam maps. The AAPM dose calculation results were used to generate electron beam maps. The AAPM dose calculation results were used to generate electron beam maps.

RESULTS
The AAPM dose calculation results were used to generate electron beam maps. The AAPM dose calculation results were used to generate electron beam maps. The AAPM dose calculation results were used to generate electron beam maps.

CONCLUSIONS
The AAPM dose calculation results were used to generate electron beam maps. The AAPM dose calculation results were used to generate electron beam maps. The AAPM dose calculation results were used to generate electron beam maps.

REFERENCES
1. Li KW, Fujiwara D, Haga A, Liu H, Geng LS. *Phys Med.* 2021; 89:182-192.

ACKNOWLEDGEMENTS
This work was supported by the National Natural Science Foundation of China (Grant No. 81873001).

CONTACT INFORMATION
Ruijie Yang, School of Physics, BUAA, Beijing 100191, China. Email: yangruijie@buaa.edu.cn



Dose prediction using three-dimensional convolutional neural network for nasopharyngeal carcinoma with Tomotherapy

INTRODUCTION
Tomotherapy is a novel radiotherapy technique that combines intensity-modulated radiation therapy (IMRT) and tomographic therapy. The dose prediction accuracy of Tomotherapy is a key factor in the treatment of nasopharyngeal carcinoma. In this study, we propose a novel deep learning method that can improve the accuracy of the Tomotherapy dose prediction by using the Tomotherapy dose prediction results to generate electron beam maps.

AIM
To improve the accuracy of the Tomotherapy dose prediction, we propose a novel deep learning method that can improve the accuracy of the Tomotherapy dose prediction by using the Tomotherapy dose prediction results to generate electron beam maps.

METHOD
The Tomotherapy dose prediction results were used to generate electron beam maps. The Tomotherapy dose prediction results were used to generate electron beam maps. The Tomotherapy dose prediction results were used to generate electron beam maps.

RESULTS
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CONCLUSIONS
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1. Li KW, Fujiwara D, Haga A, Liu H, Geng LS. *Phys Med.* 2021; 89:182-192.

ACKNOWLEDGEMENTS
This work was supported by the National Natural Science Foundation of China (Grant No. 81873001).

CONTACT INFORMATION
Ruijie Yang, School of Physics, BUAA, Beijing 100191, China. Email: yangruijie@buaa.edu.cn



Clinical Implementation of Deep Learning-Based VMAT Patient-Specific QA

INTRODUCTION
The clinical implementation of deep learning-based VMAT patient-specific QA is a key factor in the treatment of nasopharyngeal carcinoma. In this study, we propose a novel deep learning method that can improve the accuracy of the VMAT patient-specific QA by using the VMAT patient-specific QA results to generate electron beam maps.

AIM
To improve the accuracy of the VMAT patient-specific QA, we propose a novel deep learning method that can improve the accuracy of the VMAT patient-specific QA by using the VMAT patient-specific QA results to generate electron beam maps.

METHOD
The VMAT patient-specific QA results were used to generate electron beam maps. The VMAT patient-specific QA results were used to generate electron beam maps. The VMAT patient-specific QA results were used to generate electron beam maps.

RESULTS
The VMAT patient-specific QA results were used to generate electron beam maps. The VMAT patient-specific QA results were used to generate electron beam maps. The VMAT patient-specific QA results were used to generate electron beam maps.

CONCLUSIONS
The VMAT patient-specific QA results were used to generate electron beam maps. The VMAT patient-specific QA results were used to generate electron beam maps. The VMAT patient-specific QA results were used to generate electron beam maps.

REFERENCES
1. Li KW, Fujiwara D, Haga A, Liu H, Geng LS. *Phys Med.* 2021; 89:182-192.

ACKNOWLEDGEMENTS
This work was supported by the National Natural Science Foundation of China (Grant No. 81873001).

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Ruijie Yang, School of Physics, BUAA, Beijing 100191, China. Email: yangruijie@buaa.edu.cn



Radiotherapy and Oncology

Available online 21 June 2021

In Press, Journal Pre-proof



Original Article

Commissioning and clinical implementation of an Autoencoder based Classification-Regression model for VMAT patient-specific QA in a multi-institution scenario

Ruijie Yang^{a,1}, Xueying Yang^{b,1}, Le Wang^{c,d,1}, Dingjie Li^e, Yuxin Guo^f, Ying Li^g, Yumin Guan^h, Xiangyang Wuⁱ, Shouping Xu^j, Shuming Zhang^{a,k}, Maria Chan^l, Lisheng Geng^{b,m}, Jing Sui^{c,d}

REVIEW article

Front. Oncol., 08 July 2021 | <https://doi.org/10.3389/fonc.2021.717039>

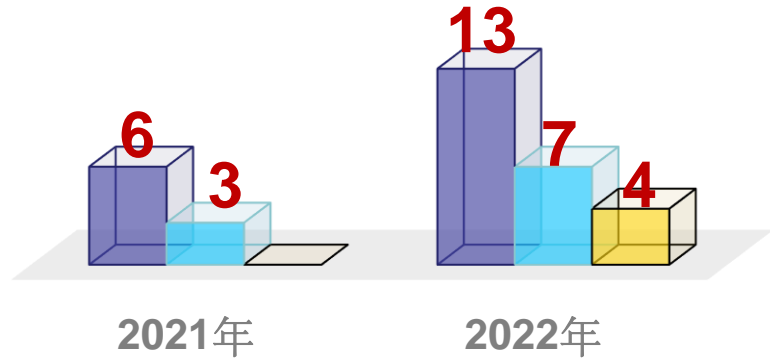
Review of Deep Learning Based Automatic Segmentation for Lung Cancer Radiotherapy

Xi Liu¹, Kai-Wen Li^{1,2}, Ruijie Yang^{3*} and Li-Sheng Geng^{1,2,4,5*}



2022年代表性成果

■ 已发表文章 ■ AAPM摘要 ■ 申请授权专利



2022年申请授权专利4篇

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100080
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发明创造名称: 基于深度学习算法的质子CT成像方法、装置和电子设备

2022AAPM年会4篇

2022年发表文章7篇

- Zhao W, Yang Y, Xing L, et al. Phys Med Biol. 2022, 67(15): 155019.
- Li Y, Zhao W. Springer, Cham, 2022: 150-158.
- Niu T, Tsui T, Zhao W. Seminars in Radiation Oncology, 2022, 32(4): 365-376.
- Fujiwara D, Shimomura T, Zhao W, Geng LS*, et al. Phys Med Biol. 2022, 67(15): 155008f.
- Peng Y, Liu Y, Chen Z, Zhang G, et al. Front Oncol. 2022; 12:808580.
- Yang B, Liu Y, Chen Z, Wang Z, Zhou Q, Qiu J. Int J Comput Assist Radiol Surg. 2023; 18(5):953-959.
- Qin Y, Zhu LH, Zhao W, Wang JJ, Wang H. Front Oncol. 2022; 12:913683.

AAPM 2022 JULY 10-14 | WASHINGTON DC | 64th ANNUAL MEETING & EXHIBITION

Exploration of one-step auto-planning Tomotherapy MLC sequence prediction adversarial network
Corresponding Author: Shouping Xu, xshouping_xu@bnu.edu.cn
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National Cancer Center/Cancer Hospital, Chinese Academy of Medical Sciences and Peking Union Medical College, Department of Radiation Oncology, Beijing, China.

PURPOSE/OBJECTIVES
In related treatment such as Tomotherapy, Multileaf Collimator (MLC) movement sequence is a critical component in individualizing (PT) plan and can significantly control patients' dose distribution. Our study attempted to predict MLC sequences from CTs by deep learning, which can directly get the RT plan.

MATERIAL & METHODS
This study made the attempt to build the correct MLC sequence and CTs relationship. The sequence of Tomotherapy used in our study has features, when the gantry rotates around the gantry will move 8.9cm (360°/40) each width, 0.5cm/2cm in head/direction, and 0.5 cm/1cm of control points are recorded. Each control point records 10 pairs (30x30°) images of MLC, including other corresponding gantry angle, gantry rotation angle, CT slice (0.5cm) center, and the identifier with 100°/20°/5°. Three input parameters were used: corresponding MLC sequence, gantry angle, and gantry rotation angle. The corresponding MLC sequence tested by Tomotherapy were verified in our study. 41 for training and 10 for testing. The encoder-decoder deep learning model MLCNet was built (one model input from 100°/20°/5° to 1°/1°, then to 5°/5cm, and MSE loss was selected).

RESULTS
Mean Square Error (MSE) and Structural Similarity (SSIM) was the selection method for MLC prediction accuracy. The original MLC sequence was tested on MLCNet using 400000 images, and the predicted MLC sequence was tested on all MLC units with the same format. MSE and SSIM of 10 test cases were 0.024/0.93 and 0.76/0.91.

CONCLUSIONS
Our study explored a method of directly predicting MLC sequence from CTs by Tomotherapy and predicted MLC has obtained lower MSE and higher similarity. MLC prediction is with the hope of generating auto-planning, and in the training stage, more corresponding technical methods and evaluations can be made in the future.

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Adaptive Radiotherapy Via Deep Learning-Based Quantitative Cone-Beam CT Imaging
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National Cancer Center/Cancer Hospital, Chinese Academy of Medical Sciences and Peking Union Medical College, Department of Radiation Oncology, Beijing, China.

INTRODUCTION
Deep learning-based adaptive radiotherapy (ART) is a novel approach to personalize treatment based on tumor shrinkage or growth throughout treatment and thereby a more effective way to improve patient outcomes. ART relies on up-to-date quantitative cone-beam CT (CBCT) images which are not easily available in routine practice. Our study explored a method to generate quantitative CBCT images using deep learning-based quantitative CBCTNet. This model can generate quantitative CBCT images from standard quality cone-beam CT (CBCT) images. The model was trained on a publicly available dataset and validated on a separate dataset. The model was trained on a publicly available dataset and validated on a separate dataset. The model was trained on a publicly available dataset and validated on a separate dataset.

RESULTS
The model was trained on a publicly available dataset and validated on a separate dataset. The model was trained on a publicly available dataset and validated on a separate dataset. The model was trained on a publicly available dataset and validated on a separate dataset.

CONCLUSIONS
Our study explored a method to generate quantitative CBCT images from standard quality CBCT images using deep learning-based quantitative CBCTNet. This model can generate quantitative CBCT images from standard quality CBCT images using deep learning-based quantitative CBCTNet.

AAPM 2022 JULY 10-14 | WASHINGTON DC | 64th ANNUAL MEETING & EXHIBITION

Abdominal CT-CBCT deformable image registration using Deep Learning with generative adversarial network
Yi Zhang*, Tingting Liu*, Li Lv*, Huanhuan Geng*, Wei Zhou*, Gaoping Zhang*, Shouping Xu*
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National Cancer Center/Cancer Hospital, Chinese Academy of Medical Sciences and Peking Union Medical College, Department of Radiation Oncology, Beijing, China.

INTRODUCTION
Conformal image-guided radiotherapy (IGRT) relies on the use of cone-beam CT (CBCT) and kV fluoroscopy (kV-F) images. However, CBCT and kV-F images are often blurry and noisy, which makes it difficult to accurately register the CBCT and kV-F images. In this study, we proposed a deep learning-based deformable image registration (DIR) method to register the CBCT and kV-F images. The proposed method is based on a generative adversarial network (GAN) and a deep learning-based registration network. The proposed method is based on a generative adversarial network (GAN) and a deep learning-based registration network.

RESULTS
The proposed method is based on a generative adversarial network (GAN) and a deep learning-based registration network. The proposed method is based on a generative adversarial network (GAN) and a deep learning-based registration network. The proposed method is based on a generative adversarial network (GAN) and a deep learning-based registration network.

CONCLUSIONS
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Attention Augmented Deep Learning-based Dual-energy CT Imaging Via Single-energy CT Data
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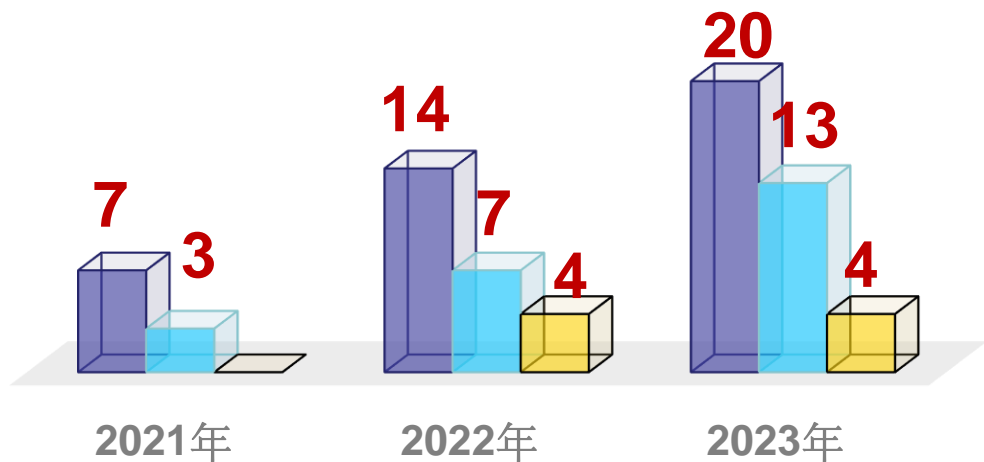
INTRODUCTION
Dual-energy CT (DECT) provides additional information compared to single-energy CT (SECT) by providing different energy images. However, DECT is often expensive and time-consuming. In this study, we proposed a deep learning-based method to generate DECT images from SECT data. The proposed method is based on an attention-augmented deep learning-based generative adversarial network (AAGAN). The proposed method is based on an attention-augmented deep learning-based generative adversarial network (AAGAN).

RESULTS
The proposed method is based on an attention-augmented deep learning-based generative adversarial network (AAGAN). The proposed method is based on an attention-augmented deep learning-based generative adversarial network (AAGAN). The proposed method is based on an attention-augmented deep learning-based generative adversarial network (AAGAN).

CONCLUSIONS
The proposed method is based on an attention-augmented deep learning-based generative adversarial network (AAGAN). The proposed method is based on an attention-augmented deep learning-based generative adversarial network (AAGAN). The proposed method is based on an attention-augmented deep learning-based generative adversarial network (AAGAN).

2023年代表性成果

■ 已发表文章 ■ AAPM摘要 ■ 申请授权专利



发表文章6篇

1. Lv T, Xie C, Zhang Y, Liu Y, Zhang G, Qu B, Zhao W, Xu S. Med Phys. 2023 Jul 20.
2. Li, WG., Chang, C., Qin, Y. et al. Nucl Sci Tech 34, 77 (2023).
3. Liu Y, Shang X, Zhao W, et al. Phys Med Biol. 2023 Jul 21;68(15).
4. Wang Y, Liu Y, Bai Y, Zhou Q, Xu S, Pang X. Z Med Phys. 2023 Jan 9;S0939-3889(22)00100-3.
5. Yang X, Geng L, Huang D, Li K, Zhuang H, Cai J, Yang R. Chin Med J (Engl). 2023 Apr 20;136(8):998-1000.
6. Wan L, Jiang Y, Zhu X, Wu H, Zhao W. Med Phys. 2023 Sep 11.

2023AAPM年会6篇

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An ultra-speed planning method for Tomotherapy: MLC sequence prediction

Wang Jia-Lin^{1,2,3,4*}, Xie Ting^{1,2,3,4}, Zhang Guo^{1,2,3,4}, Qu Bin^{1,2,3,4}, Zhao Wen^{1,2,3,4}, Xu Si^{1,2,3,4}, Liu Yi^{1,2,3,4}, Zhang Geng^{1,2,3,4}, Shouping Xu^{1,2,3,4}

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PlanNet: Optimization Parameters Prediction with Deep Learning

Wang Jia-Lin^{1,2,3,4*}, Xie Ting^{1,2,3,4}, Zhang Guo^{1,2,3,4}, Qu Bin^{1,2,3,4}, Zhao Wen^{1,2,3,4}, Xu Si^{1,2,3,4}, Liu Yi^{1,2,3,4}, Zhang Geng^{1,2,3,4}, Shouping Xu^{1,2,3,4}

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Commissioning Dose Computation Model for Proton Source in Pencil Beam Scanning Therapy by Convolution Neural Network

Wang Jia-Lin^{1,2,3,4*}, Xie Ting^{1,2,3,4}, Zhang Guo^{1,2,3,4}, Qu Bin^{1,2,3,4}, Zhao Wen^{1,2,3,4}, Xu Si^{1,2,3,4}, Liu Yi^{1,2,3,4}, Zhang Geng^{1,2,3,4}, Shouping Xu^{1,2,3,4}

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Dose prediction of CyberKnife Monte Carlo plans for lung cancer patients based on deep learning: robust learning of beam configuration from heterogeneous tissue

Y. Xiao^{1,2,3,4*}, X. Gao^{1,2,3,4}, Y. Liu^{1,2,3,4}, G. Zhang^{1,2,3,4}

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A detailed method of building a Monte Carlo frame for proton therapy in pencil beam scanning

Wang Jia-Lin^{1,2,3,4*}, Xie Ting^{1,2,3,4}, Zhang Guo^{1,2,3,4}, Qu Bin^{1,2,3,4}, Zhao Wen^{1,2,3,4}, Xu Si^{1,2,3,4}, Liu Yi^{1,2,3,4}, Zhang Geng^{1,2,3,4}, Shouping Xu^{1,2,3,4}

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3D dose prediction based on deep CNNs for brain cancer in CyberKnife: Accurate beam modeling of homogeneous tissue

Y. Xiao^{1,2,3,4*}, R. Ge^{1,2,3,4}, C. Xie^{1,2,3,4}, D. Qu^{1,2,3,4}, Y. Liu^{1,2,3,4}, G. Zhang^{1,2,3,4}, S. Xu^{1,2,3,4}

¹ National Cancer Center/National Clinical Research Center for Cancer/Cancer Hospital, Chinese Academy of Medical Sciences and Peking Union Medical College, Beijing, China; ² Department of Radiation Oncology, the First Medical Center of PLA General Hospital, Beijing, China; ³ ACCURAY, China National Nuclear Corporation, Tianjin, China; ⁴ National Cancer Center/National Clinical Research Center for Cancer/Cancer Hospital, Chinese Academy of Medical Sciences and Peking Union Medical College, Beijing, China

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INTRODUCTION

Accurate beam modeling is essential for dose calculation in stereotactic radiation therapy (SBRT). In cases of CyberKnife treatment, however, the precise dose-learning methods only involve general empirical energy and detector models in training. And the major general focus on traditional Monte Carlo-based radiation therapy (RT) plans.

AIM

This work aims to develop a deep convolutional neural network (CNN)-based method for CyberKnife plan dose prediction about brain cancer patients. It utilizes modified beam information, target delineation, and patient anatomical information (CT image).

METHOD

This study proposes a method that adds beam information to predict brain cancer cases' dose distribution of CyberKnife. A retrospective dataset of 16 brain and head-and-neck cancer patients treated with the Ray-tracing algorithm of RT was performed. The datasets include patient anatomical information (CT image), energy models (energy at risk (EAR)) and targets, as well as the clinical plans (containing beam information). The datasets were randomly split into 05, 6 and 14 brain cases for training, validation and testing.

RESULTS

Four different methods, TB, CTB, CT+TB and CT+TB+R, were evaluated in the 14 brain cancer test cases. The letters represent different data fed into the network for training, such as TB target, TB brain, and R (range information).

- Based on the quantitative comparison of the four sets of experiments, as shown in Fig.2, we could see that regardless of the different training methods, the predicted dose distribution around the target area (mean maximum dose) was well matched. It indicated that our proposed beam modeling-based method exhibited good performance.
- Fig.2 shows the absolute differences in dose metrics about OARs and PTVs between the results of each model and ground truth. The maximum dose difference for OARs was within 1.0 Gy, and the mean dose difference was within 1.0 Gy (including standard deviation). The differences in key metrics in the target area were generally below 1.0 Gy (approximately a 3% difference relative to the prescription dose).
- Fig.3 shows the absolute differences in dose metrics about OARs and PTVs between the results of each model and ground truth.

CONCLUSIONS

The preliminary results for selected 14 brain cancer cases suggest that accurate 3D dose prediction for brain cancer in CyberKnife treatment can be accomplished based on accurate beam modeling for homogeneous tissue. In further study, more patients and other cancer sites are needed to validate the proposed method fully.

With accurate beam modeling, the deep learning model can quickly generate the dose distribution for CyberKnife cases. This method accelerates the RT planning process, significantly improves the operational efficiency of RT planning and optimizes the RT process.

TABLE I The primary gross rates and critical incidence of the target area in brain cancer cases (Case 02)

Method	Criterion	TB	TBR	CT+TB	CT+TB+R
New	Accuracy	0.9254(0.019)	0.9254(0.019)	0.9254(0.019)	0.9254(0.019)
	Mean	0.9254(0.019)	0.9254(0.019)	0.9254(0.019)	0.9254(0.019)
PTV	Accuracy	0.9254(0.019)	0.9254(0.019)	0.9254(0.019)	0.9254(0.019)
	Mean	0.9254(0.019)	0.9254(0.019)	0.9254(0.019)	0.9254(0.019)

TABLE II The absolute difference of OARs in brain cancer cases (Case 02)

Method	Criterion	TB	TBR	CT+TB	CT+TB+R
G1	Max	1.0772(0.010)	1.110(0.007)	1.110(0.007)	1.110(0.007)
	Mean	1.2469(0.002)	1.2469(0.002)	1.2469(0.002)	1.2469(0.002)
G2	Max	1.0772(0.010)	1.110(0.007)	1.110(0.007)	1.110(0.007)
	Mean	1.2469(0.002)	1.2469(0.002)	1.2469(0.002)	1.2469(0.002)

FIG.2 The overall workflow of our beam modeling method dose prediction

FIG.3 Quantitative comparison of four groups of experiments

FIG.4 The absolute difference of dose metrics about OARs and PTVs between the predicted and ground truth

ACKNOWLEDGEMENTS
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浙江省基础公益研究计划项目任务书(2023年度) 第1页



浙江省基础公益研究计划 项目任务书

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项目名称: 智能虚拟平扫及虚拟单色CT成像方法及其临床应用研究
专项类别: 省自然科学基金
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□ 选拔临床和企业导师（双导师制），国际引智课程

● 引智课程



成为医学物理师：临床放疗剂量学课

黄英强 博士, DABR, CNYSMP

昆山杜克大学医学物理研究生项目教授, 驻校主任
美国斯隆凯特琳癌症中心前首席物理师/辐射安全师

时间: 3月8日起, 北京时间 每周四 上午 9:30 到 11:30

地点: 腾讯会议 (以发送邮件至 fenghn1996@163.com 方式申请加入)

课程计划表 (共 8 周):

第一周: 基本剂量学概念的回顾 (光子与物质的相互作用, 曝光量, 比释动能, 剂量, 直线加速器的主要作用);	第二周: 辐射的基本性质;
第三周: MU 计算 (I);	第四周: MU 计算 (II);
第五周: MU 计算 (III);	第六周: 治疗辅助设备;
第七周: 临床问题;	第八周: 治疗计划系统入门

本课程将为有志成为医学物理师的同學提供坚实的临床光子剂量学基础知识, 使他们能够顺利地展开临床活动和研究工作 (解决临床问题, 提高临床质量)。

本课程将从曝光量 (Exposure)、比释动能 (KERMA)、剂量 (Dose) 以及其他光子的基本特性和概念引入, 并从这些定义出发, 结合输出校准和基本光子特性建立 "MU-剂量 (MU-DOSE)" 关系。

课程还将介绍临床应用的辅助治疗的器械, 并将其纳入基本的 "MU-剂量" 公式中, 以解释这些器械对MU的实际影响, 从而建立一个更为完整的 "MU-剂量" 转换公式。此外, 我们将给出更多特殊的MU公式例子来说明如何将该公式应用到更多的领域。

为了进一步为有志之士在成为物理师的道路上提供更坚实的临床背景, 本课程还将涵盖另外两个重要主题: 临床问题 (Clinical Issues) 和治疗计划系统 (TPS, treatment planning system)。该议题将介绍医学物理师在临床实际需要面对的问题, 并提供常见的解决思路; 临床医学物理学家的主要工作之一是治疗方案设计, 那么如何设计一个最佳的治疗方案以满足医生的临床目标 (以规定的剂量精度目标, 并尽量减少对周围正常组织的剂量) 呢? 本课程将为大家提供前瞻性的指导建议。

北航前沿物理引智平台系列课程

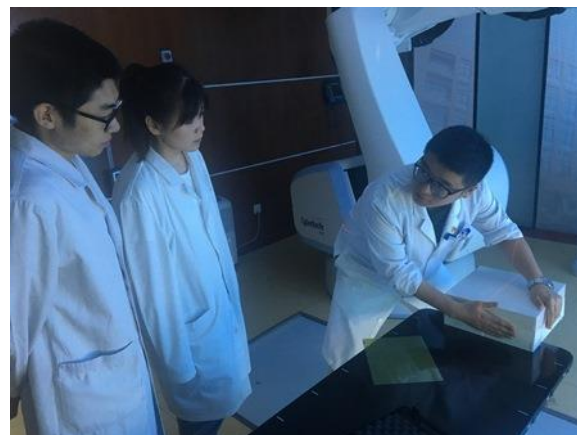
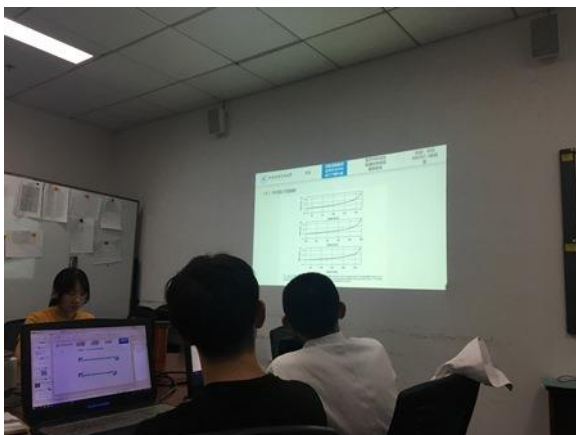
主办单位: 北京航空航天大学物理学院 联系人: 刘老师, Email: ruijiu@buaa.edu.cn

Supported by III Project (辐射物理与先进核能材料高等学校学科创新引智基地)

学生培养：临床实习



北航物理学院
SCHOOL OF PHYSICS, BUAA



本科生及研究生的临床实习（解放军总医院、北京大学第三医院等）

在读博士生18人，硕士生31人



冯浩男
2020级博



秦贇
2021级博



尚栩莹
2021级博



谢传滨
2021级博



杨雪莹
2021级博



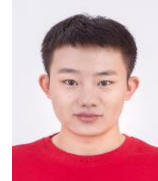
焦永旭
2021级硕



李瑞良
2021级硕



刘非凡
2021级硕



穆建东
2021级硕



屈瑞
2021级硕



宋喆祥
2021级硕



仵跃巍
2021级硕



张志磊
2021级硕



张文文
2021级博



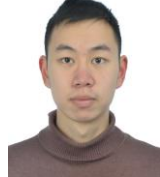
李伟光
2022级博



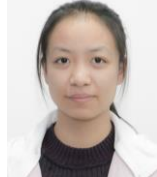
安嘉琳
2022级博



李琰
2022级博



向家兵
2022级博



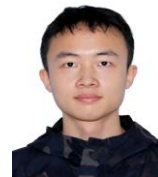
陈宇亭
2022级硕



李昊洋
2022级硕



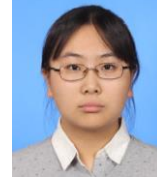
李林轩
2022级硕



李永清
2022级硕



李仲怡
2022级硕



林忻妍
2022级硕



齐浩天
2022级硕



王砚鑫
2022级硕



刘曦
2022级博



刘耀颖
2022级博



吕铁
2022级博



万鲁平
2022级博



程畅
2023级博



吴天宇
2022级硕



杨璐瑶
2022级硕



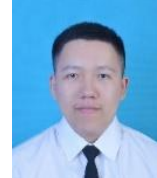
叶萍
2022级硕



张旭
2022级硕



张治杰
2022级硕



董佳舒
2023级硕



冀春君
2023级硕



李垚
2023级硕



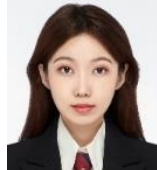
胡昕雨
2023级博



王诗佳
2023级博



尹宇莹
2023级博



刘昭阳
2023级硕



陆启坚
2023级硕



吕盛飞
2023级硕



王孝龙
2023级硕



王章逸
2023级硕



韦雯嘉
2023级硕



徐元昊
2023级硕

毕业生去向



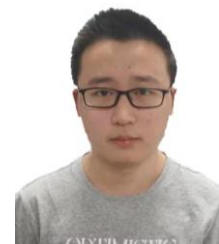
医院

冯朝阳 (2020级硕) 重庆大学附属肿瘤医院
苗余超 (2020级硕) 福建协和医院
张怡航 (2020级硕) 上海市第一人民医院



公司

孙小晴 (2019级硕) 联影深圳研究院
周子铖 (2020级硕) 上海联影医疗科技有限公司
韩加星 (2020级硕) 苏州光格科技有限公司



高校读博

姚庆龙 (2019级硕) 北航宇航学院图像处理中心
熊天宇 (2020级硕) 香港理工大学

2019级、2020级、2021级共11名硕士通过“硕转博”继续在北航物理学院攻读博士研究生



秦贇
2019级硕
2021级博



尚栩莹
2019级硕
2021级博



杨雪莹
2019级硕
2021级博



张文文
2019级硕
2021级博



刘曦
2020级硕
2022级博



刘耀颖
2020级硕
2022级博



吕铁
2020级硕
2022级博



万鲁平
2020级硕
2022级博



胡昕雨
2021级硕
2023级博



尹宇莹
2021级硕
2023级博



程畅
2021级硕
2023级博

硕士研究生培养方案



培养模式及学习年限

主要为一级学科内培养，结合**国际联合培养及校企联合培养**等模式。采用**课程学习、实践训练和学位论文相结合**的培养方式。实行**导师或联合导师负责制**，负责制订研究生个人培养计划、指导科学研究和学位论文。

遵循《北京航空航天大学研究生学籍管理规定》。学术型硕士研究生**学制为2.5年**。

学术型硕士研究生实行学分制，在攻读学位期间，要求在**申请硕士学位论文答辩前**，依据培养方案，获得知识和能力结构中所规定的各部分学分及总学分。鼓励研究生从入学起就开始学位论文相关的研究工作；学术学位研究生**文献综述与开题报告至申请学位论文答辩的时间一般不少于8个月**。

硕士研究生培养方案



知识和能力结构

	学位理论课程					综合实践环节		
	思政课程模块	基础及学科理论课程模块	专业理论课程模块	学术素养课程模块	跨学科课程模块	专业实践	学术报告	开题答辩
学分要求	3	≥12	≥4	≥3	≥3	≥4	1	1
		≥16						
学分合计	≥32							
申请答辩学分要求	需同时满足以上各模块学分及研究学分要求							

硕士研究生培养方案



知识和能力结构

基础及学科理论核心课	19112301	高等量子力学	64	4	≥ 8
	19112302	群论	64	4	
	19112303	高等统计物理	64	4	
	19112304	高等电动力学	64	4	
	19112305	量子场论	64	4	≥ 4
	19112306	固体理论	64	4	
	19112307	量子光学	64	4	
	19112308	等离子体理论	64	4	
	19112309	计算物理	64	4	
	19112310	粒子物理与原子核物理探测与分析	64	4	

核心课程



专业理论核心课	19113101	广义相对论	64	4	≥4
	19113102	量子多体理论	64	4	
	19113103	凝聚态物理导论	64	4	
	19113104	介观物理	64	4	
	19113105	高等光学	64	4	
	19113106	非线性光学	64	4	
	19113107	等离子体实验与诊断	64	4	
	19113108	粒子物理基础	64	4	
	19113109	原子核理论	64	4	
	19113110Y	当代临床放疗物理学	48	3	
	19113111Y	肿瘤放疗物理学	48	3	
19113112Y	医学影像物理学	32	2		
综合实践环节及学分要求	19116101	现代物理实验	64	4	≥4
	19116102	临床技能训练	64	4	
	19117201	开题答辩 (硕)		1	1
	19117202	学术报告 (硕)		1	1



特殊规定

- 医学物理方向的硕士生经学院和导师同意后，可以选修专业理论核心课程组的19113110Y-19113112Y课程通过认定获得基础及学科理论核心课程组19112301-19112304课程的4学分。
- 医学物理方向的硕士生可以选修北京大学医学部64学时的临床技能训练。



培养目标

坚持党的基本路线，热爱祖国，遵纪守法，品行端正，诚实守信，身心健康，具有良好的科研道德和敬业精神。

适应科技进步和社会发展的需要，在本学科上掌握坚实宽广的基础理论和系统深入的专门知识；熟练掌握一门外语；**具有独立地、创造性地从事科学研究工作的能力；具有良好的综合素质和主持较大型科研与技术开发项目的能力。**

在科学或专门技术上做出创造性的成果。

博士研究生培养方案



培养模式及学习年限

主要为一级学科内培养，结合**跨学科培养、国际联合培养及校企联合培养**等模式。**实行导师或联合导师负责制**，负责制订研究生个人培养计划、指导科学研究和学位论文。

遵循《北京航空航天大学研究生学籍管理规定》。**直接攻博研究生学制为4年；其它类型博士研究生学制为3年，实行弹性学习年限。**

■博士研究生**实行学分制**，在攻读学位期间，要求在申请博士学位论文答辩前，依据培养方案，获得知识和能力结构中所规定的各部分学分及总学分。

■鼓励研究生从入学起就开始学位论文相关的研究工作；博士研究生文献综述与开题报告至申请学位论文答辩的时间**一般不少于1年。**

博士研究生培养方案



知识和能力结构

博士（不含直博）学位知识和能力结构及学分要求

结构类型	学位理论课程				综合实践环节		
	公共课	基础及学科理论课	跨学科课	选修课	学术交流	学术报告	文献综述与开题报告
学分小计	≥4	≥7	≥2	≥0	1	1	1
总学分	≥16 （需同时满足各类学分小计和总学分要求）						

直接攻读博士学位知识和能力结构及学分要求

结构类型	学位理论课程					综合实践环节		
	公共课	基础及学科理论课	跨学科课	专业课	专业实验	学术交流	学术报告	文献综述与开题报告
学分小计	≥5	≥13	≥4	≥8	≥6	1	1	1
总学分	≥39 （需同时满足各类学分小计和总学分要求）							



课程设置及学分要求

学位必修课、学位必修环节和学位选修课

学位必修课：

公共必修课：思想政治理论、第一外国语、专题课等。

学科必修课：基础及学科理论课和专业课

跨学科课：在导师指导下跨一级学科选课

学位必修环节：专业实验(直博生)、学术交流、学术报告、文献综述与开题报告。

学位选修课：

不做最低学分要求，导师可根据博士研究生知识背景情况及课题研究需要**指定选修**公共课、本专业课或跨专业课。**第一外国语为非英语**（德、日、法等）的博士研究生**必须选修英语作为二外**；若在硕士阶段已修二外，可免修；对**缺少本学科本科层次专业基础**的跨学科硕士研究生，应在导师指导下将2-3门本学科本科核心课程作为选修课程，所修课程记录成绩，不计入总学分。

博士研究生培养方案



博士(不含直博)公共课(≥4)

课程名称	学时	学分	备注
中国马克思社会主义理论与当代	36	2	必修
英语一外(博)	60	2	必修1门
研究生日语	90	2	
研究生俄语	90	2	

直博公共课(≥5)

课程名称	学时	学分	备注
中国马克思社会主义理论与当代	36	2	必修
英语一外(博)	60	2	必修1门
研究生日语	90	2	
研究生俄语	90	2	
人文(或科技)专题课	16	1	必修1门



博士(不含直博)学位理论课程	基础及学科理论课 (≥7)	课程名称	学时	学分
		高等量子力学	48	3
		高等统计物理	48	3
		物理学中近代数学方法(博)	48	3
		加速器原理与粒子探测技术	32	2
		核技术及应用	32	2
		数字信号处理	48	3
		物理学科综合课	48	3
		科学写作与报告	16	1
		核辐射物理及探测	48	3
		肿瘤放射物理学	48	3
		辐射剂量与防护	32	2
		医学影像物理学	32	2
		辐射生物学	32	2
		医学物理前沿	32	2
		临床放射肿瘤学	32	2
		生理学	32	2
		影像解剖学	32	2
		诊断学	32	2
	高等核物理实验	48	3	
辐射物理实验	48	3		
医学物理实验	48	3		
跨学科课 (≥2)	导师指导下跨一级学科选必修课	必修		
综合实践环节 (3)	文献综述与开题报告(博)		1	
	学术报告(博)		1	
	学术交流		1	
学位选修课(一外非英语必修)	英语二外	60	2	

直博士学位理论课程 ≥33

基础及学科理论课 (≥13)	课程名称		学时	学分	
	数值分析A		48	3	
	矩阵理论A		48	3	
	数理统计A		48	3	
	高新技术中的物理学基础		48	3	
	高等量子力学		48	3	
	高等统计物理		48	3	
	数字信号处理		48	3	
	现代物理测量原理与技术		48	3	
	物理学中近代数学方法(博)		48	3	
	学科综合课(博)		48	3	
	科学写作与报告		16	1	
	辐射剂量与防护		32	2	
	核辐射物理及探测		48	3	
	肿瘤放射物理学		48	3	
	生理学		32	2	
	影像解剖学		32	2	
	诊断学		32	2	
	专业课 (≥8)	计算物理		32	2
		加速器原理与粒子探测技术		32	2
核技术及应用			32	2	
医学影像物理学			32	2	
辐射生物学			32	2	
医学物理前沿			32	2	
临床放射肿瘤学			32	2	
放射性同位素技术与安全			16	1	
保健物理学			16	1	
跨学科课(≥4)		导师指导下跨一级学科选必修课	必修		
综合实践环节 (≥9)	医学物理实验(必修)		48	3	
	高等核物理实验	必修1门	48	3	
	辐射物理实验		48	3	
	文献综述与开题报告(博)			1	
	学术报告(博)			1	
学术交流				1	

博士研究生培养方案



学分要求

硕博连读生：硕博连读研究生应**同时满足**学术硕士学位课程的学分要求，对硕士学术报告及硕士开题学分不做要求。

博士研究生：根据导师的安排一般在2年内（直博生3年内）完成课程学习。

培养环节及基本要求

个人培养计划：由导师或指导小组与研究生本人共同制定研究生的个人培养计划。包括**课程学习计划和学位论文研究计划**。课程学习计划应在研究生**入学后2周内制定**，研究生据此计划在网上办理选课手续。博士研究生的学位论文研究计划应在开题报告中详细描述。

研究生个人培养计划确定后不应随意变更。

学术交流：申请论文答辩前参加**不少于8次**的学术交流与讨论，其中本人作报告不少于2次，提交《博士研究生学术交流记录表》、《博士研究生学术交流考核表》、本人2次报告内容和其它各次交流提纲，由导师负责考核，通过者获得1学分，由学院研究生教务审核后记载成绩。

学术报告：要求选听学术报告**总数不少于20次**，提交《博士研究生学术报告考核表》并附总结报告，由导师负责考核，**通过者取得1学分**。由学院研究生教务审核后记载成绩。



学位论文

文献综述与开题报告：

- 大量调研、查阅国内外相关文献的基础上，掌握本领域学科前沿与发展趋势，撰写出综述报告
- 开题报告内容：**学位论文选题依据、学位论文研究方案、预期达到的目标、预期的研究成果；学位论文详细工作进度安排和主要参考文献等。
- 要求**直博生在3年内、其他博士生一般2年内**完成文献综述与开题报告。
- 文献综述与开题报告至申请学位论文答辩的时间**一般不少于1年**。

中期检查：依据《北京航空航天大学研究生院关于博士研究生培养工作的基本规定》及本学科相关规定执行。

论文标准与答辩：执行《北京航空航天大学学位授予暂行实施细则》

成果与发表论文：执行《北京航空航天大学关于研究生申请学位发表论文的规定》

终止培养：执行《北京航空航天大学研究生院关于博士研究生培养工作的基本规定》

面向人民生命健康、面向国家重大需求
探索医学物理教研的校际合作模式与互利互惠
培养一流医学物理人才，做出一流创新成果

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