Flexible-C^m GAN: Towards Precise 3D Dose Prediction in Radiotherapy

Riqiang Gao Bin Lou Zhoubing Xu Dorin Comaniciu Ali Kamen

Digital Technology and Innovation, Siemens Healthineers, Princeton NJ 08540

Introduction

- Previous deep methods are primarily limited to simple scenarios, e.g., a fixed planning type or a consistent beam angle configuration. This in fact limits the usability of such approaches and makes them not generalizable over a larger set of clinical scenarios.
- We propose a novel conditional generative model, Flexible-C^m GAN, utilizing additional information regarding planning types and various beam geometries. A shift-dose-volume loss is proposed to address clinical preference and a miss-consistency loss is introduced to help conditional GAN training.

Motivation

- Two key points need to be addressed for precise dose prediction: individualism and realism. individualism is required for the plan to be precise specifically in a heterogeneous set of conditions. Realism makes the subsequent tasks (e.g., fluence map prediction, deliverable dose) more manageable, as in Fig. 1.
- A simple conditional GAN can not satisfy our heterogeneous contexts since we need to handle (1) multi-level conditions with heterogeneous types and (2) missing conditions that may exist during training and testing.

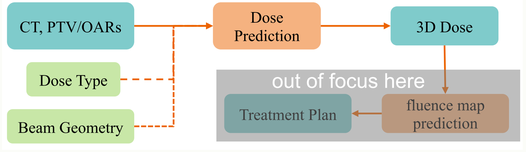


Fig. 1. Overview of a typical KBP pipeline. We focus on 3D dose prediction, the downstream fluence map prediction is out of scope of this study.

Dose Prediction Framework

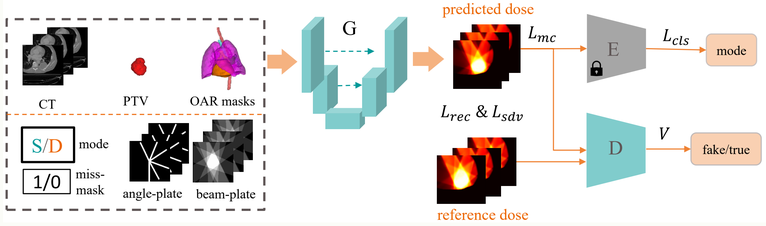


Fig. 2. Our model Flexible-C^m GAN for 3D dose prediction. CT, PTV/OAR masks, mode, angle/beam plates, and miss-mask are fed into a U-shape-based Generator (G) to predict dose maps. The loss functions are described in *Methodology*.

Methodology

- **Flexible-C^m GAN (FCGAN) Mechanism**

Given M conditions $\{C^i\}_{i=1}^{M}$ (i.e., $\boldsymbol{C}$) and their missing indicator $\boldsymbol{m}$ ($m^i = 0$ if i-th condition is missing, otherwise $m^i = 1$), our adversarial loss becomes:

$$V(D,G) = \mathrm{E}_{x\sim p_{data}}[\log D(x|\boldsymbol{C},\boldsymbol{m})] + \mathrm{E}_{z\sim p_z(z)}[\log(1 - D(G(z|\boldsymbol{C},\boldsymbol{m})))],$$

where G and D are generator and discriminator. To let the model be robust to the missing condition, we introduce a miss-consistency loss L_{mc} based on condition regularization loss L_{cr}:

$$L_{cr} = \sum_{i,m^i>0} L^i(E^i(G(z|\boldsymbol{C},\boldsymbol{m})),\cdot),$$

$$L_{mc} = \sum_{j\neq i,m^j>0} |E^j\left(G(\cdot\,|m^i=0,\cdot)\right) - E^j(G(\cdot))|,$$

where $E^i(\cdot)$ extracts feature from the prediction $G(\cdot)$ for the condition C^i. $L^i(\cdot,\cdot)$ measures the discrepancy between the prediction and the reference corresponding to C^i, and L_{mc} reflects how predictions related to observed condition j are consistent when another condition i is given versus the scenario in which it is missing. Experiments with face dataset can be found in the paper.

- **FCGAN Instantiation for 3D Dose Prediction**

Our overall framework for 3D dose prediction is illustrated in Fig. 2. For three-dimensional conditions (CT, PTV/OARs masks, angle/beam plates), the condition regularization terms of L_{cr} (related E^i is *Identity*) are jointly covered by a reconstruction loss L_{rec} and shift-dose-volume (SDV) loss L_{sdv}.

The L_{rec} of N samples is the mean absolute error (MAE) of the reference dose $\boldsymbol{Y}_i$ and its prediction $\widehat{\boldsymbol{Y}}_i$: $L_{rec} = \frac{1}{N}\sum_{i=1}^{N}\left\|\boldsymbol{Y}_i - \widehat{\boldsymbol{Y}}_i\right\|_1$. We introduce the cross-entropy loss to instantiate L_{cr} for the planning mode condition C^m:

$$L_{cls} = \frac{1}{N}\sum_{i=1}^{N} -C_i^m \log(\hat{p}_i) - (1 - C_i^m)\log(1 - \hat{p}_i).$$

The proposed L_{sdv} is derived from DVH definition to close address clinical preference. Given S ROIs masked by $\{\boldsymbol{M}_i^s\}$ for i-th patient, we have

$$L_{sdv} = \frac{1}{N}\sum_{i=1}^{N}\sum_{s=1}^{S}\lambda_s\left\|\boldsymbol{Y}_i \odot (\boldsymbol{Y}_i - \widehat{\boldsymbol{Y}}_i) \odot \boldsymbol{M}_i^s\right\|_1.$$

The detailed mathematical derivation, properties of L_{sdv} can be found in the paper.

Experiment Design

- Our experiments are conducted on heterogeneous lung cancer, including both IMRT and VMAT plans.
- Five recently proposed dose prediction baselines are compared.
- Four different evaluation metrics are included to compare models.
- Ablation studies of different components (e.g., the proposed losses) are included.
- A demonstration of user intervention inference is included.

Experiment Results

Models	SDE (↓)	DDE(↓)	MAE(↓)	CEL(↓)
Barragan et al. [7]	7.30	1.95	3.14	2.10
DoseGAN [33]	7.43	1.81	3.33	<u>0.91</u>
DeepDoseNet [55]	<u>6.26</u>	1.60	3.11	2.07
Wang et al. [58]	6.41	<u>1.58</u>	<u>2.71</u>	1.30
Jhanwar et al. [27]	6.78	1.62	3.09	2.02
FCGAN (ours)	**5.80**	**1.48**	**2.64**	**0.05**

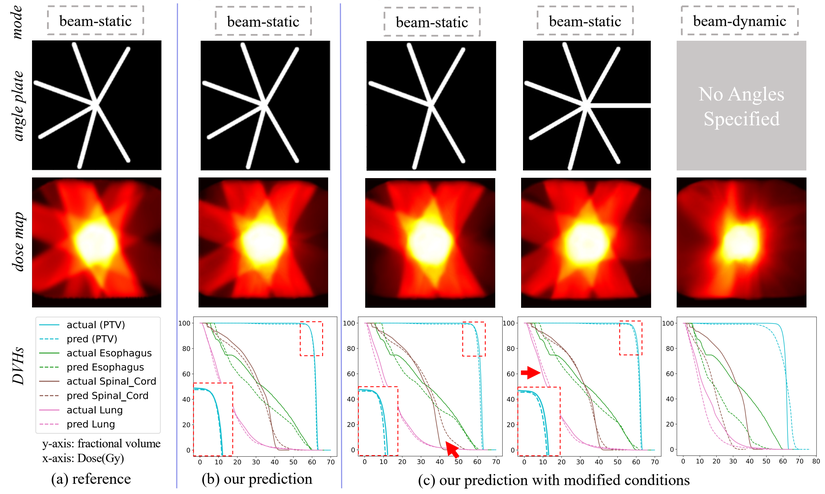
Tab. 1. Comparison with state-of-the-art baselines. Our model achieves the best performance in all four metrics. Best are shown in **bold**.

Models	SDE (↓)	DDE(↓)	MAE(↓)	CEL (↓)
DRUNet	7.01	1.75	3.12	1.12
FCGAN$^{(-2)}$	6.81	1.84	2.72	0.06
FCGAN$^{(-1)}$	<u>6.10</u>	<u>1.57</u>	<u>2.71</u>	**0.04**
FCGAN	**5.80**	**1.48**	**2.64**	<u>0.05</u>

FCGAN$^{(-2)}$ has no L_{mc} and no L_{sdv}. FCGAN$^{(-1)}$ has no L_{mc}.

Tab. 2. Ablation studies of the proposed GAN mechanism and loss functions, which indicate each proposed item makes contribution to the dose prediction task.

- *User Intervention Inference to get instant feedback*



Main References:

[1] Mirza et al. Conditional Generative Adversarial Nets. *arXiv:1411.1784*, 2014.

[2] Drzymala et al. DOSE-VOLUME HISTOGRAMS. *Inr. J. Radrarion Oncology Biol. Phys*, 1991.

[3] Ronneberger et al. U-net: Convolutional networks for biomedical image segmentation. In *MICCAI*, 2015.

Acknowledgement: We thank all the contributors to the REQUITE project, including the patients, clinicians and nurse. The core REQUITE consortium consists of David Azria, Erik Briers, Jenny Chang-Claude, Alison M. Dunning, Rebecca M. Elliott, Corinne Faivre-Finn, Sara Gutiérrez-Enríquez, Kerstie Johnson, Zoe Lingard, Tiziana Rancati, Tim Rattay, Barry S. Rosenstein, Dirk De Ruysscher, Petra Seibold, Elena Sperk, R. Paul Symonds, Hilary Stobart, Christopher Talbot, Ana Vega, Liv Veldeman, Tim Ward, Adam Webb and Catharine M.L. West. **Disclaimers:** The information in this poster is based on research results that are not commercially available. Future commercial availability cannot be guaranteed.