

# Classification of Intensity-Modulated Proton Therapy Plans

L. Lima<sup>(1)</sup>, A. Liu<sup>(1)</sup>, S. Laub<sup>(2)</sup>, A. Panchal<sup>(2)</sup>, M. Pankuch<sup>(2)</sup>

## Introduction

### Proton Radiotherapy

Proton radiotherapy is a form of radiation treatment that uses energized protons to break DNA, leading to cell death and killing cancers.

### SFUD vs MFO

- Types of planning optimization methods for Pencil Beam scanning
- Single-Field Uniform Dose, SFUD, is composed of multiple fields, individually optimized at different locations to deliver a homogenous dose across a tumor (Fig. 3&4).
- Multi-Field Optimization, MFO, is used when a tumor is surrounded by healthy, vital organs and tissues that can be harmed by radiation. The beams in this plan are all optimized simultaneously, so that they can vary the intensity of radiation delivered at each voxel, working around organs at risk (Fig. 2&5).
- Fig 2&3 show differential Dose-Volume Histograms (dDVH), graphs displaying the percentage of full dosage delivered to every percentage of volume of structure, for a full SFUD and a full MFO plan.

### Hybrid

In practice, treatment plans are a combination of SFUD and MFO, or a hybrid plan. As shown in Fig. 6&7, each beam deposits varying intensities of dosage to different voxels, the MFO component. The two beams have the same intensity distributions, so they are doing the same thing, just coming in from different positions.



Fig. 1 (left): Gantry rotates 360° around the patient, delivering dose at any angle necessary.

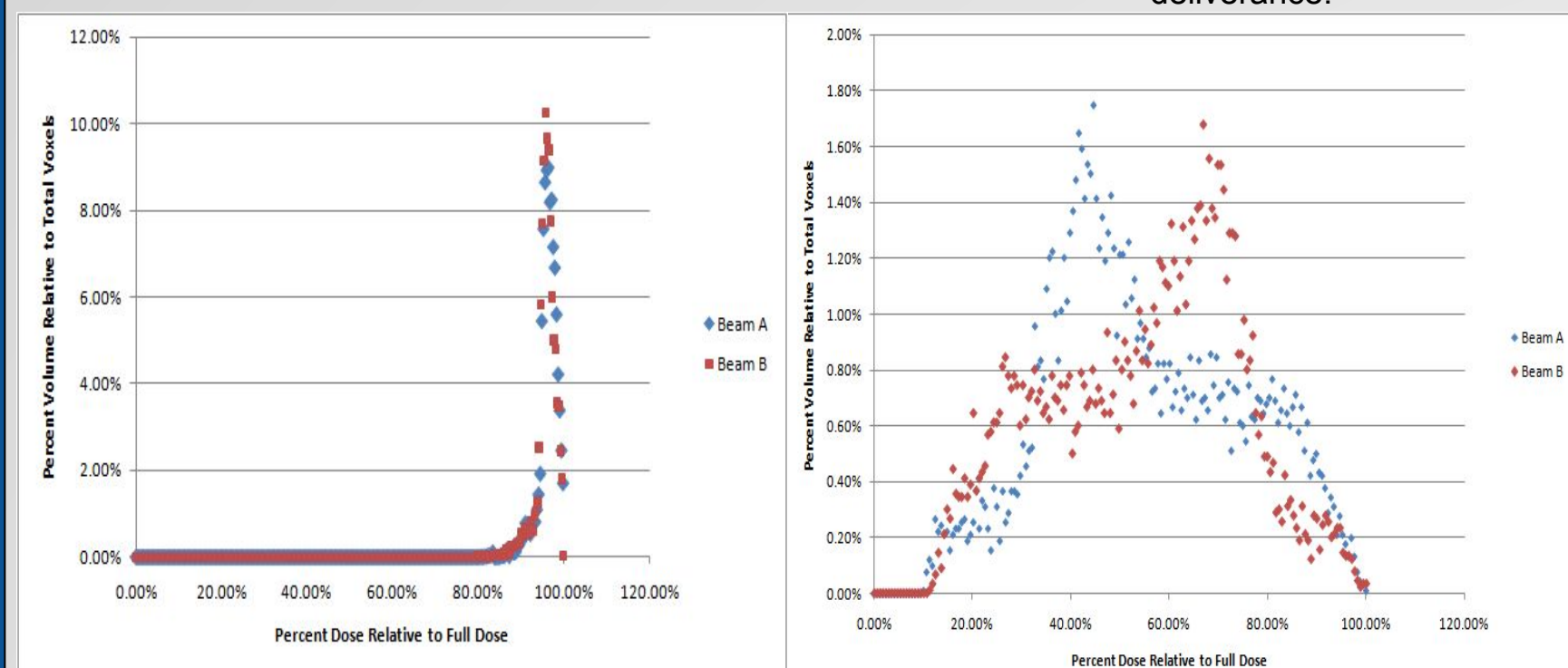


Fig. 2 (below): Differential DVH of MFO plan, shown by varied percent dose deliverance.

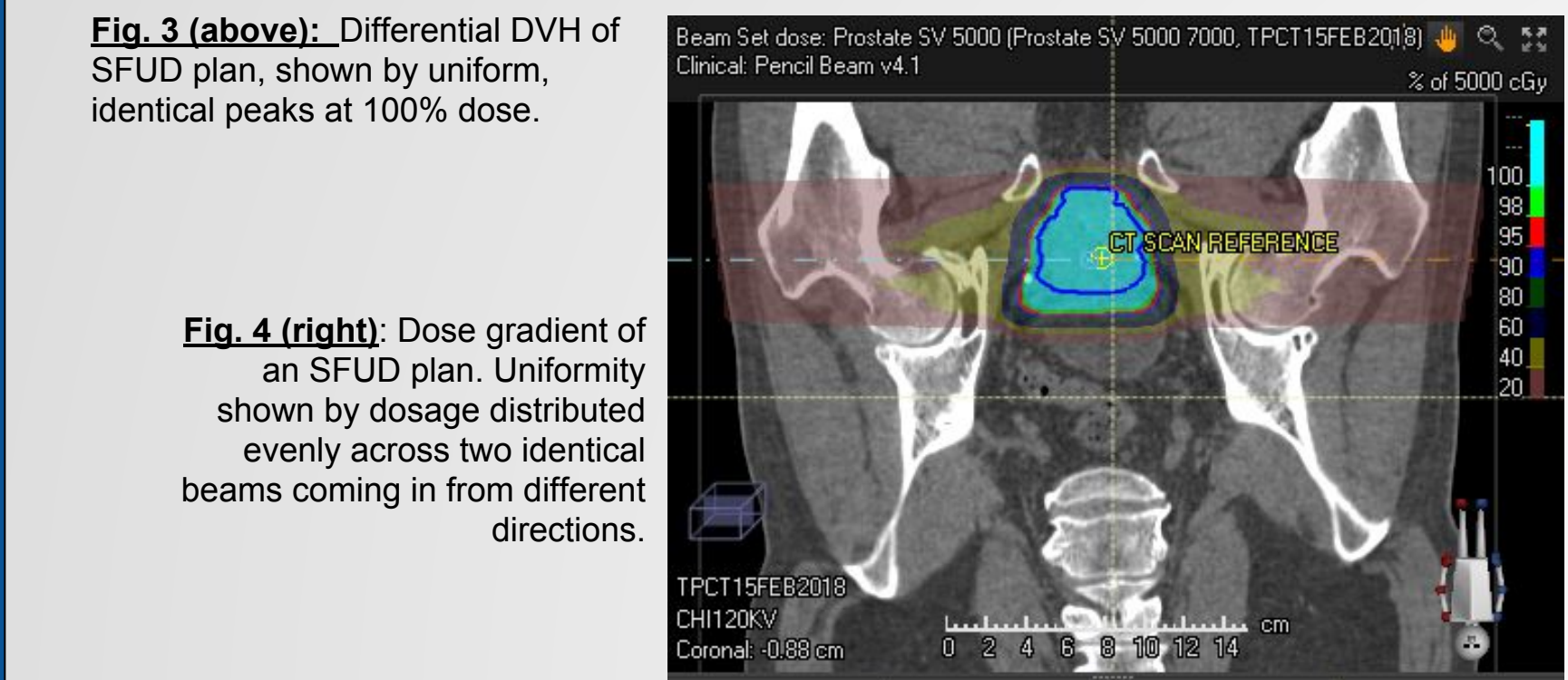


Fig. 3 (above): Differential DVH of SFUD plan, shown by uniform, identical peaks at 100% dose.

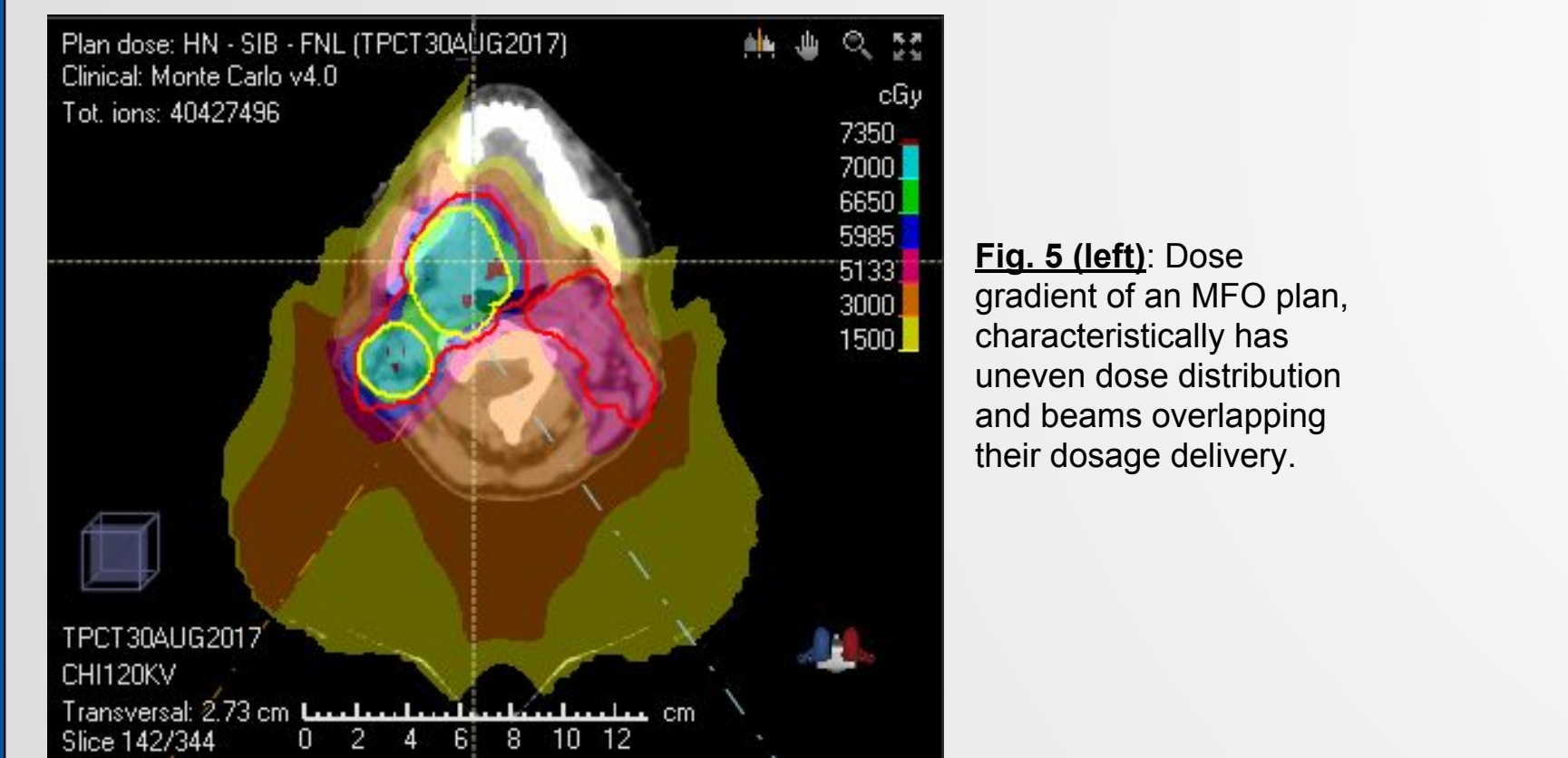


Fig. 4 (right): Dose gradient of an SFUD plan. Uniformity shown by dosage distributed evenly across two identical beams coming in from different directions.

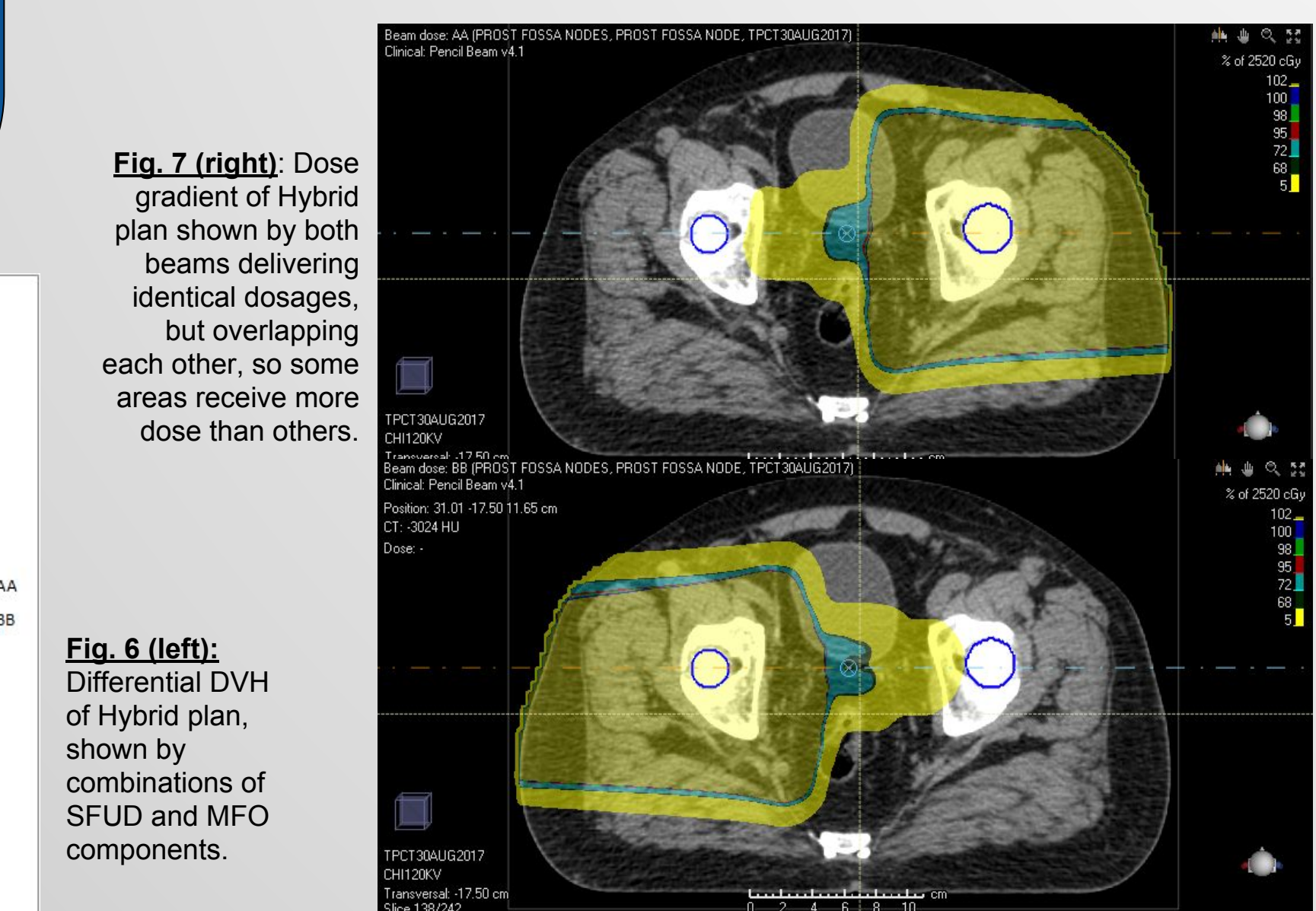


Fig. 5 (left): Dose gradient of an MFO plan, characteristically has uneven dose distribution and beams overlapping their dosage delivery.

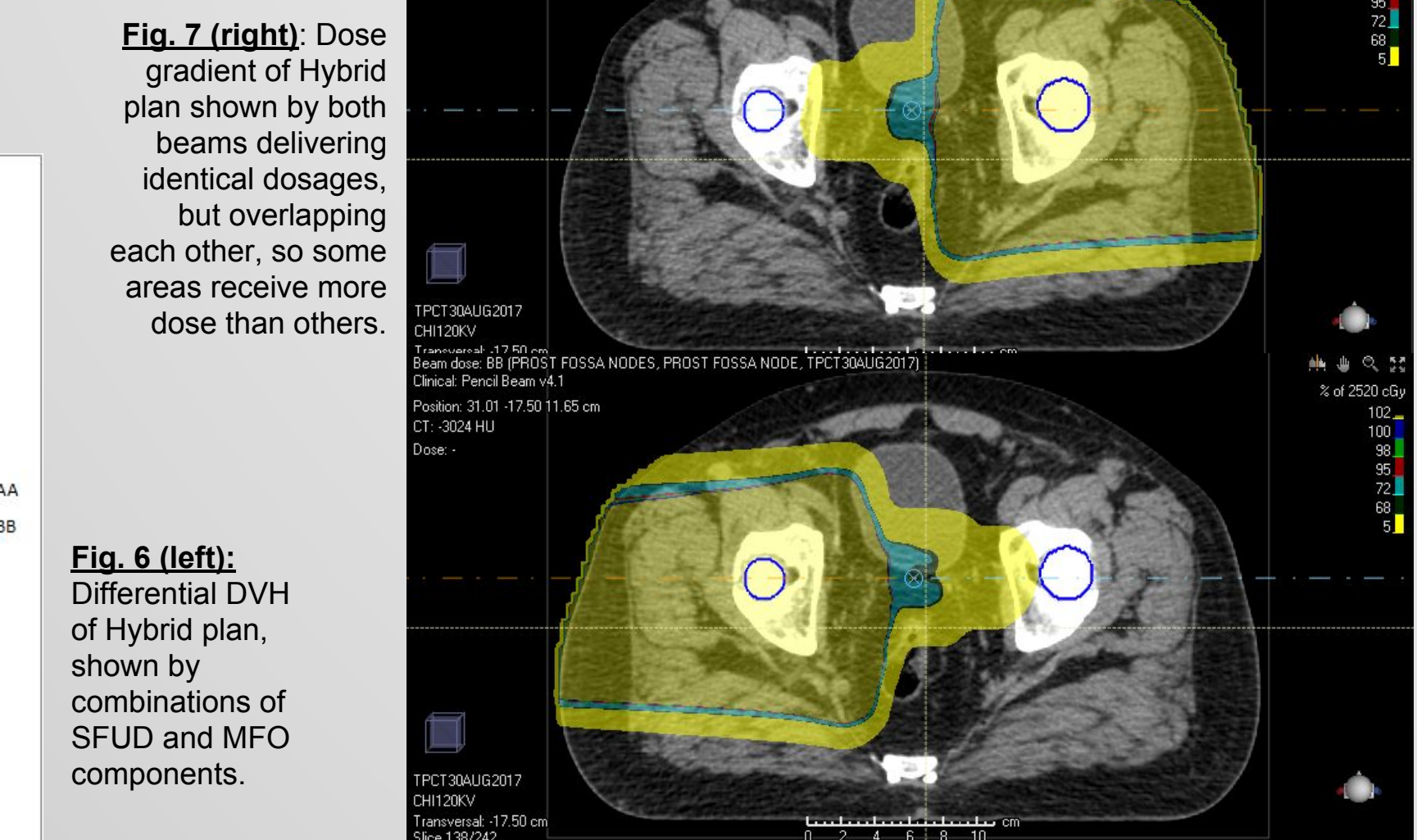


Fig. 6 (left): Differential DVH of Hybrid plan, shown by combinations of SFUD and MFO components.



Fig. 7 (right): Dose gradient of Hybrid plan shown by both beams delivering identical dosages, but overlapping each other, so some areas receive more dose than others.

## Methods

### Research

Our research revolves around analyzing the beam distributions represented in the dDVH graphs of each treatment plan, and creating a robust procedure to classify them on a spectrum of how uniform they are, from full SFUD to full MFO. With this, we would be able to identify when it is or is not necessary to turn on the MFO setting.

### Analysis

To analyze and classify the treatment plans into the SFUD-MFO spectrum, we created a python procedure that goes through five weighted factors in the dDVH graphs to classify the type of plan being used (Fig. 8&9). These factors are based off of the uniformity of the graph considering that SFUD always has a single, tall, narrow peak delivering 100% of the dose, while an MFO has multiple uneven peaks.

### Important Factors

- Number of Peaks**  
Any more than a single peak per beam is an MFO component
- Distance/Slope/Midwidth**  
the smaller the distance from the peak to the end and midwidth and the steeper the slope, the more SFUD it is.
- Difference**  
As seen in Fig. 2, the peaks in each of the two beams are almost identical in an SFUD plan as opposed to an MFO (Fig. 2&3). This means that the greater the difference is between the peaks of the beams, the more MFO the plan is.

```
ranking = 100.0
if (avgBeamPeak > 1):
    ranking = ranking - (25*(1-.5**(avgBeamPeak-1))/.5)
    print("ranking after peak count: " + str(ranking))
if (avgDist >= 40):
    ranking = ranking - 40
else:
    ranking = ranking - avgDist
    print("ranking after distance: " + str(ranking))
ranking = ranking - avgMidWidth
print("ranking after midwidth: " + str(ranking))
if (avgAbsDiff >= 1):
    ranking = ranking - 25
else:
    ranking = ranking - avgAbsDiff*25
    print("ranking after diff: " + str(ranking))
ranking = ranking - avgSlope/2
print("ranking after slope: " + str(ranking))
if (ranking > 100):
    ranking = 100
if (ranking < 0):
    ranking = 0
```

Fig. 9 (above): Python code calculating rank of each treatment plan based on the five weighted factors.

Patient Number	Rank	Peak	Slope	MW	DIE	DIF
1	0.000%	3	-1.32	9.17%	35.14%	57.74%
14	10.50%	4	-1.73	1.58%	28.72%	58.92%
34	20.88%	2	-6.09	2.95%	38.30%	51.82%
52	33.34%	1.5	-1.4	6.23%	35.12%	20.76%
60	43.93%	1	-3.15	4.03%	8.26%	165.29%
65	50.31%	1.5	-1.67	3.94%	19.88%	32.46%
78	61.21	1	-2.46	5.17%	18.99%	42.74%
92	70.69%	1	-2.11	5.71%	11.11%	31.31%
129	81.12%	1	-3.40	4.01%	11.21%	5.36%
175	90.74%	1	-3.55	2.29%	5.62%	3.33%
236	100%	1	-28.86	0.83%	2.15%	1.44%

Fig. 11 (above): 11 example patients of the 236 we tested. One patient from every 10% rank to show distribution of factors. Graphs on the right (from left to right and up to down) correspond to the patients in the table (from up to down).

## Ranking

We scaled all data from 100% (SFUD) down to 0% (MFO). Each plan started at 100% SFUD, and based on if each metric represented SFUD or MFO, we added or subtracted from that initial value. In addition, as we have an order of most-to-least important metrics, there were limits to make sure less important metrics would not influence the ranking more than metrics above it (Fig. 9).

## Efficiency

Fig. 10 shows the accuracy of our rankings. For each of the five metrics, as the rank increases towards SFUD, the value of each of the features decrease almost linearly, with the exception of a few outliers. This shows that our rank is efficient in classifying the patients' treatment plans.



Fig. 10 (above): Graph showing distribution of each of the five factors of a treatment plan according to the rank it was given 0%-100%.

## Results

We analyzed 236 patients in total. The table in Fig. 11 shows each of the 5 metrics used for the final rank of each patient. The table and graphs show that as the ranks of the patients increase, the graph becomes more uniform until they are completely single-field uniform dose.

## Conclusions

The rankings presented trends about the uniformity of certain treatments as seen in Fig. 12. These trends can help dosimetrists more readily identify the most efficient treatment plan to use for future patients and the program allows them to confirm that they have the safest and most efficient plan before applying it to the patient.

Ranking Range	Treatment Area
55-65%	Prostate & Lymph Nodes
70-80%	Brain
~80%	Neck
90-100%	Prostate

Fig. 12 (above): Table showing most common area treated with each range of ranks. Treatment areas closer to 100% rank would more likely receive an SFUD plan, while areas with a lower rank would receive more MFO components.

## Problem

- Treatment plans are created with one of two settings: SFUD, creating a completely uniform plan, or MFO, where the computer optimizes the beams in the most efficient way. If there are vital organs to work around, the computer will create a truly multi-field plan. However, if multi-field is not necessary, the computer will create a SFUD plan under a MFO setting, or it can combine parts of each setting. The word Hybrid is used for any plan composed of a combination of the two, however, each of these have varying degrees of each plan, currently unidentifiable.
- In addition, although MFO is more precise, this precision also causes it to be more sensitive to variations and sources of error, increasing the risk associated with it. Therefore, the MFO setting should only be used when absolutely necessary.

## Important Factors

- Number of "peaks"
- Distance to end of beam
- Absolute difference
- Width at half-height
- Slope

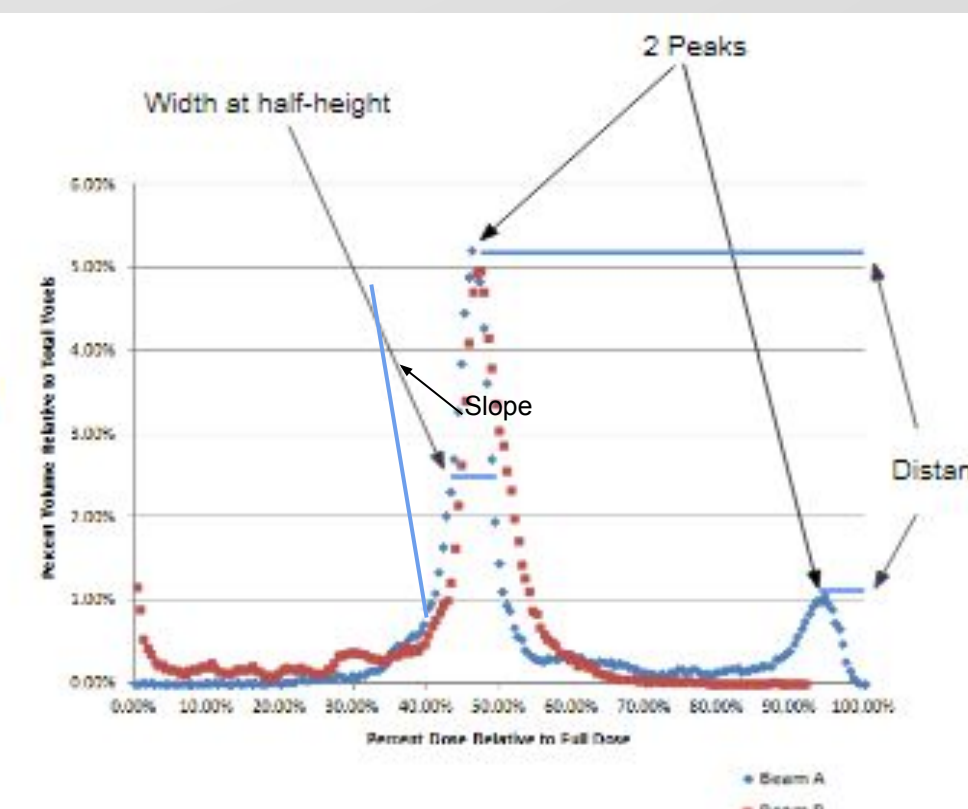


Fig. 8 (left): List of the five factors used to analyze a differential DVH to categorize the treatment plan. Four of the five are shown in the graph. The 5th, difference, is calculated by subtracting the two Ys for a given X.

## Future

In the coming months, we plan to integrate artificial intelligence into our program, so that it can evaluate the dosage data of previous patients and discover the most efficient weightings for each of our five metrics.

### References

- A Brief History of CT. (May, 2013). Retrieved from <http://www.impactscan.org/CTHistory.htm>
- Computed Tomography. (Dec. 15, 2017). Retrieved from <https://www.fda.gov/radiation-emittingproducts/radiationemittingproductsandprocedures/medicalimaging/medical-abx-rays/ucm115317.htm>
- Drzymala, R. E., Mohan, R., Brewster, L., Chu, J., Goitein, M., Harms, W., & Urie, M. (1991). Dose-Volume Histograms. Int. J. Radiation Oncology Biol. Phys. 21, 71-78. Retrieved January 2, 2018.
- Journal of the ICRU Report 78. International Commission on Radiation Units and Measurements, 7(2), 5-139.
- Liu, W., Zhang, X., Li, Y., Mohan, R., (2012). Robust Optimization of Intensity Modulated Proton Therapy. American Association of Physicists in Medicine, Vol. 39(2), pp. 1079-1091.