VMAT Optimization: A Machine Learning Perspective

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Introduction

- VMAT is widely used clinically, but fundamental optimizer development remains limited by closed commercial systems.
- This study recasts VMAT direct aperture optimization as training a machine-learning model.
- MLC leaf positions and control-point weights are trainable parameters; dose deposition is a fixed linear map.
- Machine constraints are handled naturally as hard bounds and regularization terms.

Methods

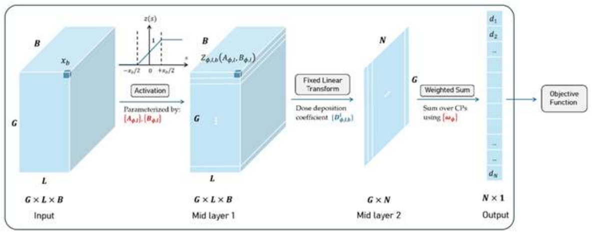

Figure 1: The neural network model for VMAT optimization. G: total number of control points. L: total leaf pairs. B: maximum beamlets per row. N: total voxels. Trainable parameters: $\{A_{\phi,l}\}, \{B_{\phi,l}\}, \{\omega_\phi\}$. Fixed, non-trainable parameters: $\{D^i_{\phi,l,b}\}$. The input layer is a stacking of x_b (x-coordinate in the 2D intensity map, grid resolution is 2.5mm) for all beamlets. It is connected to mid layer 1 through an activation given by the stepwise linear function $z(s)$. Mid layer 1 corresponds to $Z_{\phi,l,b}$ in equation 2. Mid layer 2 applies a fixed linear transformation using the dose deposition matrix. The output layer gives the voxel doses as a weighted sum over control points from mid layer 2. The entire forward pass is executed in parallel on GPU.

- Optimization objective: standard dose-volume terms plus machine-aware penalties (**regularization**).
- **Leaf motion**: maximum travel between neighboring control points.

$$C_1 = \alpha_1 \sum_{\phi,l} \left(|A_{\phi+1,l} - A_{\phi,l}| - s_{MLC}\right)_+^2 + \left(|B_{\phi+1,l} - B_{\phi,l}| - s_{MLC}\right)_+^2$$

- **Dose rate:** penalty for exceeding 600 MU/min nominal maximum.

$$C_2 = \alpha_2 \sum_{\phi} \left(\frac{MU * \omega_\phi}{\Delta\phi / v_g^{max}} - DR^{max}\right)_+^2$$

- **Smoothness:** discourages erratic back-and-forth leaf trajectories.

$$C_3 = \alpha_3 \sum_{\phi} \left(A_{\phi+1,l} - A_{\phi,l}\right)^2 + \left(B_{\phi+1} - B_{\phi,l}\right)^2$$

- Weights: sigmoid reparameterization maintains positive CP weights.
- Benchmarks: corresponding IMRT plans using the same objective and dose model.
- Implementation: PyTorch 2.1.2, L-BFGS optimizer, NVIDIA Quadro RTX 8000 GPU.
- Validation: optimized plans imported into Eclipse and delivered on TrueBeam without interlocks.

Results

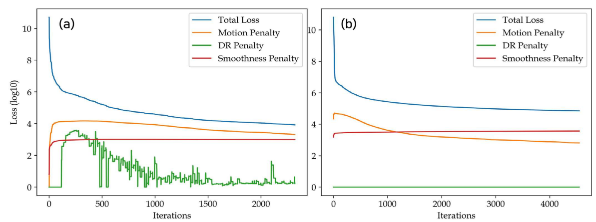

Figure 2: Total objective and regularization terms decrease stably for prostate and HN cases.

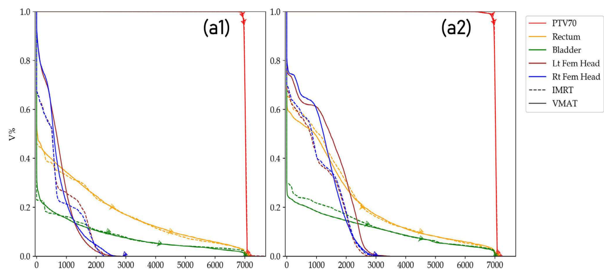

Figure 3: Prostate DVHs show two-arc VMAT plan quality comparable to benchmark IMRT

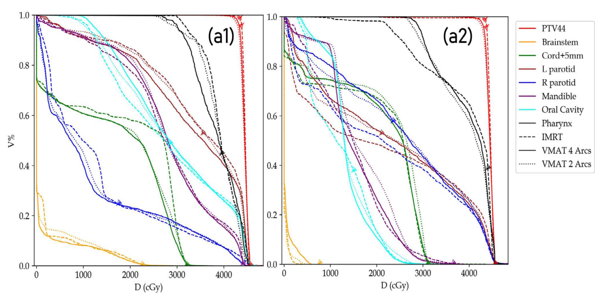

Figure 4: HN DVHs show four-arc VMAT improves target conformity and OAR sparing relative to two arcs.

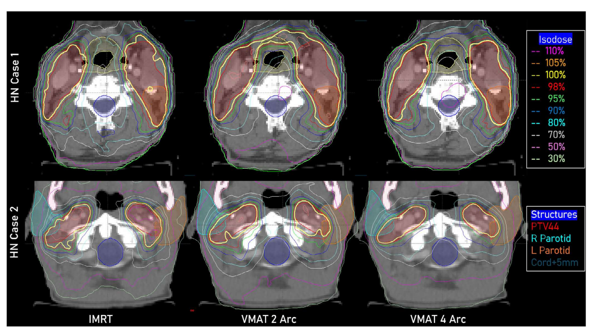

Figure 5: Dose distributions confirm smoother VMAT dose patterns and improved four-arc conformity in complex HN geometry.

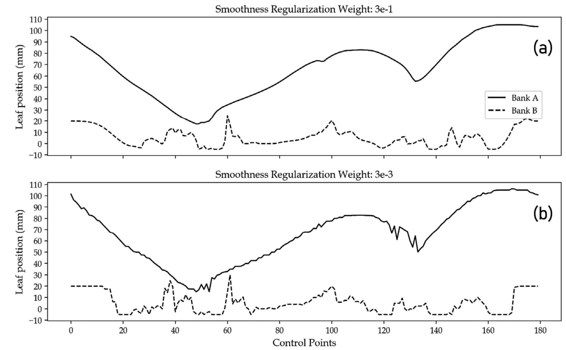

Figure 6: Stronger smoothness regularization reduces unnecessary leaf trajectory spikes.

- All VMAT optimizations converged successfully with stable objective reduction.
- For prostate cases, two-arc VMAT achieved PTV coverage and OAR sparing comparable to IMRT.
- For HN cases, four-arc VMAT consistently improved target conformity and OAR sparing versus two arcs.
- Machine-related penalties behaved as intended: dose-rate violations were limited and motion/smoothness terms guided deliverable trajectories.

Metric	Prostate (2-arc)	HN (4-arc)
Iterations	~ 3,000	~4,500
Total time	~40min	~140min
Peak GPU Usage	4-7 GB	19-22 GB

Conclusions

- VMAT optimization can be formulated as training a patient-specific ML model.
- The framework bridges ML optimization infrastructure with treatment planning physics.
- Plan quality was comparable to benchmark IMRT in tested cases, with four-arc HN VMAT improving over two-arc VMAT.
- The approach offers an extensible platform for future VMAT algorithm development.

References

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