Improved Prediction of MLC and Gantry Errors During VMAT Delivery Utilizing an Artificial Neural Network

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INTRODUCTION

Sculpted dose distributions characteristic of VMAT often require extensive fluence modulation and, thus, precise control over machine parameters is essential for accurate treatment delivery. In radiotherapy, the accurate delivery of radiation through the minimization of treatment errors is an important goal. By minimizing machine delivery errors, the dosimetric errors are also reduced. If machine errors can be predicted, then so too could the dosimetric errors. Predictive models may facilitate the generation of treatment plans robust to errors in gantry and MLC leaf positions, and, so doing, will aid in the assessment and prevention of dosimetric errors. The aim of this study is to demonstrate the utility of an artificial neural network (ANN) to predict MLC and gantry position errors occurring during VMAT delivery.

METHOD

Neural Network Construction

Errors in gantry and MLC leaf position were predicted using two separate ANN models: a gantry model composed of five dense hidden layers and an MLC model of three; both models utilizing 100 nodes/layer. The model was created using an in-house program coded in Python. The Rectified Linear Unit (ReLU) was used as the activation function and RMSProp was used for optimization. Data from 18 VMAT trajectory files representing various treatment sites were used to train and validate (90%/10%) the ANN model with 10 additional files serving as the test set, two of which were SBRT plans.

MLC and Gantry Model Features

Gantry and MLC leaf positions were predicted based on a variety of features. For both models, position, velocity, and acceleration were used. The trajectory file lists data in timepoints every 20ms apart. The number of this timepoint rather than the time itself was used, as it was only necessary to specify the relative time within the treatment duration. In order to incorporate the effects of past and future motion states, time point data (position, velocity, and acceleration) from ±10 and ±3 timepoints, for MLC and gantry respectively, were added to the feature vector.

MLC Model Specific Features

To describe the high complexity of MLC motion, the ANN was trained on additional MLC specific features. A 0 or 1 flag specified the size of the MLC (5mm or 10mm width), the direction the MLC is moving (toward or away from center), whether the MLC was moving or at rest, and whether the MLC was on carriage A or B. Each MLC was numbered from 1-60, specifying where it is located on the carriage relative to the other MLCs. Lastly, all previously mentioned features (except for timepoints) were added to the feature vector for the two neighboring leaves.

MLC Model Features		
Position	Velocity	Acceleration
Treatment Timepoint	MLC Size	Carriage
MLC Number	MLC Movement	MLC Direction
±10 Timepoints	Neighbor MLCs	
Gantry Model Features		
Position	Velocity	Acceleration
Treatment Timepoint	±3 Timepoints	

Table 1: Summary of MLC and gantry features used in the training of the ANN models.

Model Assessment

Model error was assessed by comparing predicted values with values recorded in the trajectory files. This error was compared with the error resulting from differences between treatment plan-derived and machine-reported component positioning.

RESULTS

Model Performance

Across the test set, the average root-mean-square error (RMSE) for predicting MLC positional errors was 0.006 mm (0.004-0.012 mm) using the ANN model compared to 0.032 mm (0.014-0.038 mm) using treatment planning values. The average RMSE for predicting gantry positional errors was 0.017° (0.008-0.026°) using the model compared to 0.048° (0.038-0.061°) with the plan.

Overall, the positional errors were small. The largest positional error seen in the MLC positions was ~0.08mm for the plan and ~0.02 for the prediction of non-SBRT plans. For the gantry, the largest error observed was ~0.2° for the plan and ~0.07° for the prediction.

MLC Model Observations

It was found that the planned positions generally lagged behind the actual positions during treatment as shown by the asymmetric, bi-modal distribution in Figure 1A. The spread of the planned positional errors tended to be large for the standard VMAT cases.

The predicted positional error spread was typically symmetric around zero, alluding to the accurate yet stochastic nature of the prediction. From Figure 3A, this pattern can be seen in the majority of typical VMAT cases.

Gantry Model Observations

As with the MLCs, the planned gantry positions lagged behind the actual treated positions, although, in this case, the distribution was systematically shifted. In Figures 1B and 2B, the planned positional error peak (blue) is negatively shifted from zero.

Again, the predicted positional errors were symmetric around zero. However, the ability of both the plan and the prediction in representing the actual gantry positions was far less consistent than for MLC positions. Figure 3B shows that the spread of the predicted gantry positions appear to be a function of the spread of the planned gantry positions.

SBRT Prediction

The MLC model was less accurate in predicting the MLC position error for the two SBRT plans that were included in the test set (pt. 3 and pt. 8). This is visualized in Figure 2A, in which the prediction peak is slightly shifted off zero and the spread of the values is larger. It can also be noted that the planned MLC positions for these two plans was a better representation of the actual positions than in the standard VMAT plans. These observations are seen with patient 8 to a larger degree. The performance of the gantry model prediction for these two patients was consistent with the other eight.

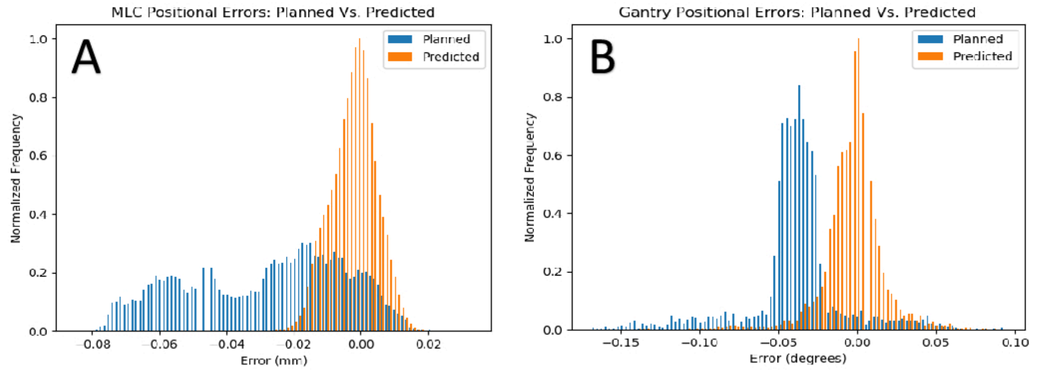

Figure 1: MLC and gantry positional errors for a single standard VMAT patient plan (Pt. 10 in Figure 4). The errors are relative to the direction of motion. Planned: Difference between treatment plan-derived and machine-reported component positioning. Predicted: Difference between ANN model predicted and machine-reported component positioning.

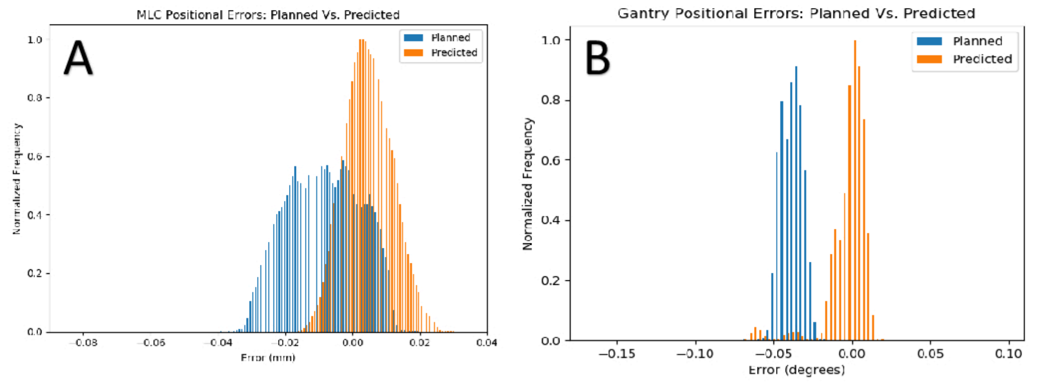

Figure 2: MLC and gantry positional errors for a single SBRT patient plan (Pt. 3 in Figure 4). The errors are relative to the direction of motion. Planned: Difference between treatment plan-derived and machine-reported component positioning. Predicted: Difference between ANN model predicted and machine-reported component positioning.

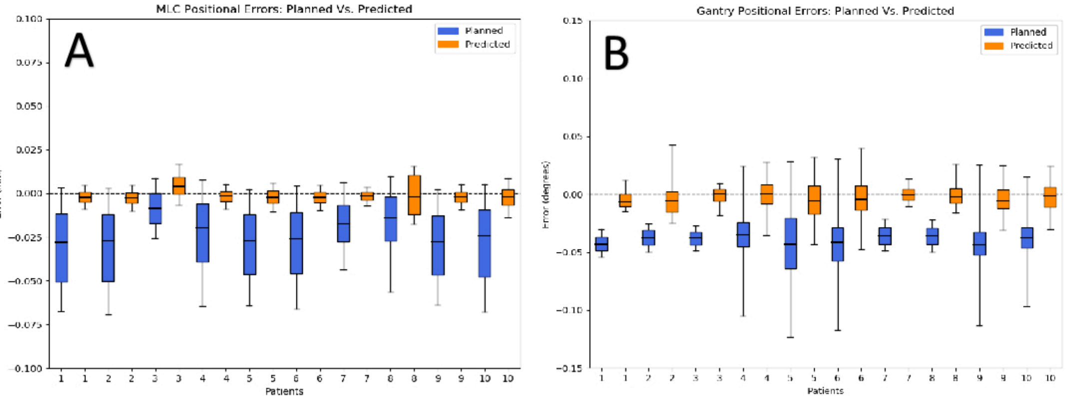

Figure 3: MLC and gantry positional errors for 10 unique patient plans. The errors are relative to the direction of motion. Planned: Difference between treatment plan-derived and machine-reported component positioning. Predicted: Difference between ANN model predicted and machine-reported component positioning.

DISCUSSION

Both the MLC and gantry models created in this study have shown to accurately predict positional errors during VMAT delivery. This model provides valuable information that can be used to evaluate the robustness of a VMAT plan, enabling informed decision making before the initiation of the treatment course. This information, available directly from the treatment plan, can also be used to provide a more meaningful approach to patient-specific and machine quality assurance.

Model Improvements

While highly accurate, the prediction was not a perfect representation of the actual VMAT delivery due to the stochastic nature of the predictive model. The model could potentially be improved further by investigating different neural network architectures and hyperparameters. This would include changing the number of hidden layers and nodes/layer, and using different activation functions and optimizers.

Typically, adding more training data would increase the accuracy of an ANN model. In this case, adding additional trajectory file data for standard VMAT plans, past the 18 used in this study, did not improve the accuracy of the MLC model. On the other hand, due to there being less gantry data per trajectory file compared to MLC data, the gantry model could possibly be improved with additional data.

None of the 18 trajectory files used to train the models included SBRT plans. While SBRT plans are a specific type of VMAT plan, they have unique characteristics that make them different. The inclusion of SBRT plans to the training data could improve the predictive accuracy of the MLC model for this technique. However, this could have the effect of diminishing the predictive accuracy for non-SBRT plans. Another option is to create separate non-SBRT and SBRT models which only use training data from their respective techniques.

Future Direction

Investigation into the dosimetric impact of the predicted positions compared to the planned positions is the next logical step since the main reason for preventing machine delivery errors is to prevent dosimetric errors.

Another avenue of investigation involves the creation of predictive models for other radiotherapy delivery equipment. Different machines, across multiple vendors, incorporate unique designs into their equipment that have varying magnitudes of delivery error. These machines would require their own models in order to achieve the optimal predictive accuracy.

CONCLUSIONS

MLC and gantry positions reported by trajectory files were closer to the positions predicted by our models than to those expected according to the plan. Predicting MLC and gantry positions allow for preemptive assessment of treatment plan deliverability. This approach may be used to develop robust treatment plans as well as to develop meaningful plan-specific and periodic machine quality assurance assessments.

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