Leveraging machine learning strategies for reduced uncertainty in small field dosimetry

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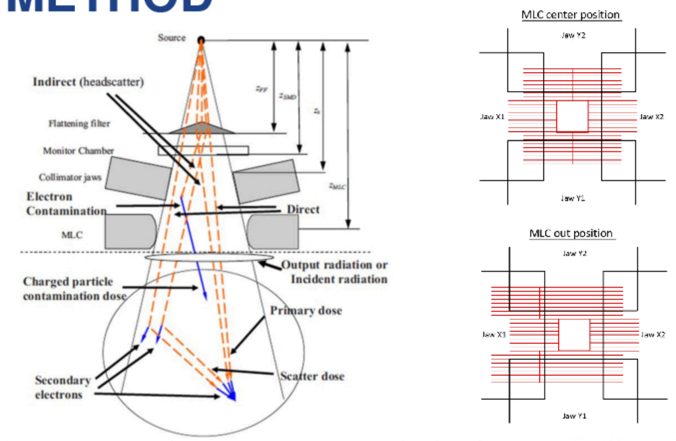
INTRODUCTION

The use of small fields in radiotherapy has increased substantially since the introduction and growing indications for intensity modulated radiation therapy and stereotactic body radiation therapy. However, small field dosimetry is complicated by a number of factors which are not seen in standard delivery of broad beams. Furthermore, modern treatment planning systems are not optimized for small field dose calculations and deviations between calculated and delivered dose can exceed 10%, which will have a high impact on the clinical outcome post treatment.

AIM

To overcome these issues and avoid the need for complicated and time-consuming physical measurements, we aim to propose a machine learning based approach for fast and accurate predictions of small field output factors to serve as a basis for dose calculations for increased accuracy and safety of patient treatments.

METHOD



Linac output factors at various multi-leaf collimator (MLC) positions, jaw positions, and with and without contribution from leaf-end transmission was collected from a Varian TrueBeam equipped with HD-MLC. The data was collected at a source-to-detector distance of 100cm at 10 cm depth with MLC defined fields. The datasets were split into training and testing data and there was no overlap between these two datasets. We formulated the small field output factor as an output of random forest regression problem, which was trained using a set of jaw and MLC settings together with corresponding output factors. 1200 sets of data were used to training and 350 datasets were used for testing the nonlinear regression model. For comparison, the small field output factors at various settings were also predicted using linear models trained with and without regularization. The predicted output factors were compared and evaluated using absolute percentage relative error (pRE).

RESULTS

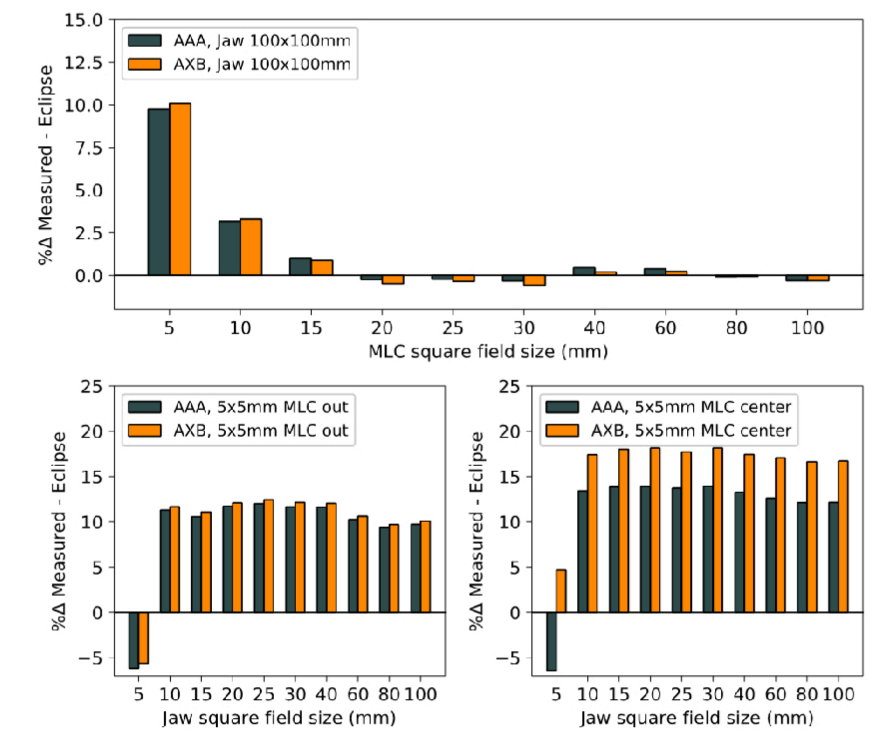


Figure 2. Large deviation between Eclipse calculated and measured output for small fields.

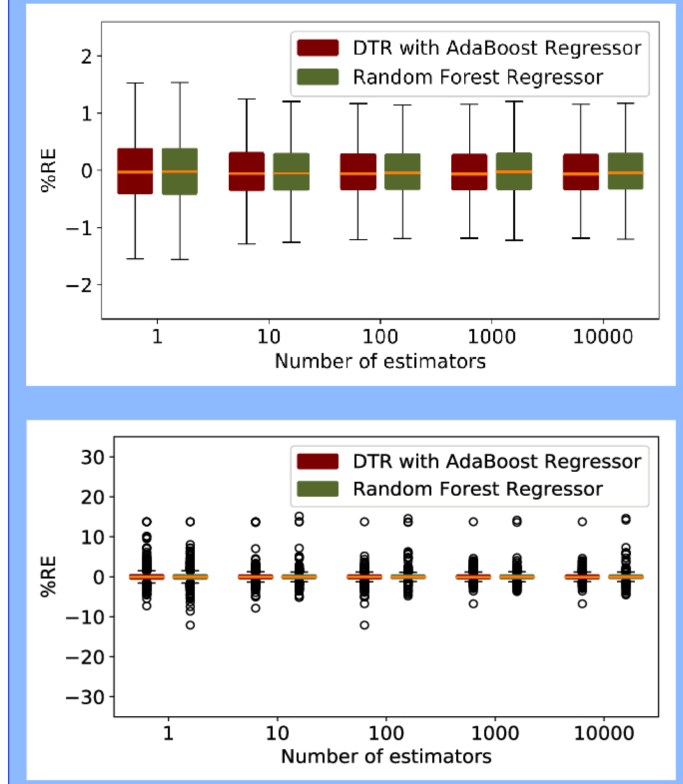


Figure 4. Robustness test with respect to the number of estimators. The results show Number of estimators had small impact on prediction accuracy.

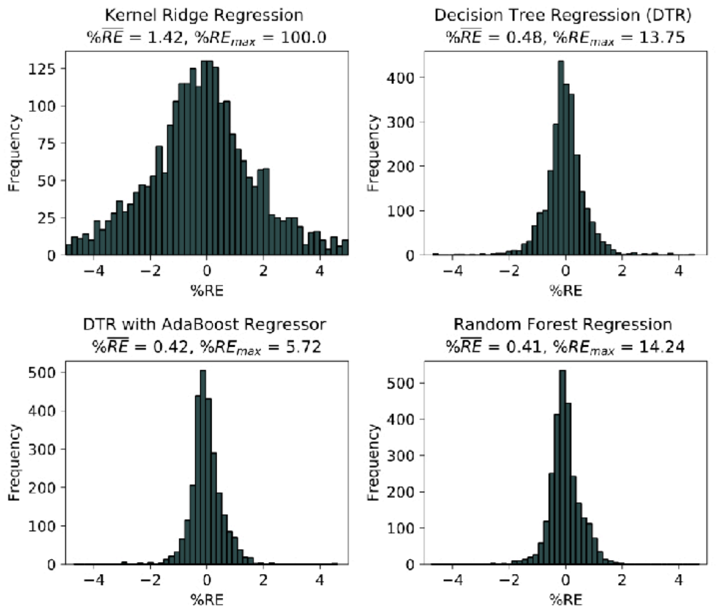


Figure 4. Results of the accuracy (relative percentage error, %RE) of the predicted output factors using different machine learning algorithms.

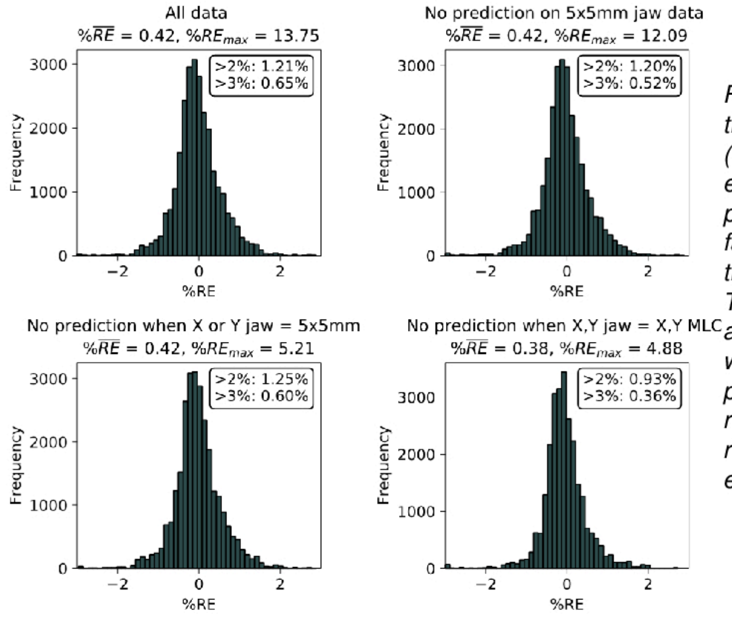


Figure 4. Results of the accuracy (relative percentage error, %RE) of the predicted output factors at different training scenarios. The results suggest avoiding predictions when Jaw and MLC position overlapped resulted in reduction of extreme errors.

CONCLUSIONS

The small field output factors were accurately predicted at different field sizes, independent of jaw and MLC position. The pRE for predictions of field sizes from 5×5 mm2 to 40×40 mm2 was less than 0.80%, with an overall mean pRE of 0.15%. independent of contribution from leaf-end transmission. For model trained using linear model with and without regularization, the overall mean pRE was increased to 4.23% and 9.93%, respectively. For model training with nonlinear random forest regression model, data augmentation showed a 10% improvement in pRE.

We propose a fast and accurate machine learning-based method to generate small field output factors for routine radiation therapy. With this method, small field output factors can be accurately generated using previous acquired output factors at different linac settings, which negates the need for time consuming and complicated measurements without affecting the accuracy of the data. The predictions may serve as input for dose calculation to overcome the limitations of modern TPSs in calculating dose for small fields, or as a secondary verification tool for use in the quality assurance process.

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REFERENCES

1. Benedict SH, Yenice KM, Followill D, Galvin JM, Hinson W, Kavanagh B, Keall P, Lovelock M, Meeks S, Papiez L, Purdie T. Stereotactic body radiation therapy: the report of AAPM Task Group 101. Medical physics. 2010 Aug;37(8):4078-101.
2. Dieterich S, Cavedon C, Chuang CF, Cohen AB, Garrett JA, Lee CL, Lowenstein JR, d'Souza MF, Taylor Jr DD, Wu X, Yu C. Report of AAPM TG 135: quality assurance for robotic radiosurgery. Medical physics. 2011 Jun;38(6Part1):2914-36.
3. Palmans H, Andreo P, Huq MS, Seuntjens J, Christaki KE, Meghzifene A. Dosimetry of small static fields used in external photon beam radiotherapy: Summary of TRS-483, the IAEA–AAPM international Code of Practice for reference and relative dose determination. Medical physics. 2018 Nov;45(11):e1123-45.
4. Fogliata A, Lobefalo F, Reggiori G, Stravato A, Tomatis S, Scorsetti M, Cozzi L. Evaluation of the dose calculation accuracy for small fields defined by jaw or MLC for AAA and Acuros XB algorithms. Medical physics. 2016 Oct;43(10):5685-94.
5. Tyler MK, Liu PZ, Lee C, McKenzie DR, Suchowerska N. Small field detector correction factors: effects of the flattening filter for Elekta and Varian linear accelerators. Journal of applied clinical medical physics. 2016 May;17(3):223-35.
6. Andreo P. The physics of small megavoltage photon beam dosimetry. Radiotherapy and Oncology. 2018 Feb 1;126(2):205-13.

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