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Original article

Beam orientation in stereotactic radiosurgery using an artificial neural network

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ABSTRACT

Background and purpose: To investigate the feasibility of using an artificial neural network (ANN) to generate beam orientations in stereotactic radiosurgery (SRS).
Material and methods: A dataset of 669 intracranial lesions was used to build, train, and validate three ANNs. In ANN1, Cartesian coordinates described the localization of the PTV and OARs. In ANN2, a genetic algorithm was used to optimize the model. In ANN3, vectors were used to define the distance between the PTV and OARs. In all ANNs, inputs consisted of the treatment plan parameters plus the patient's particular geometric parameters; outputs were beam and table angles. The ANN- and human-generated plans were then compared using dose–volume histograms, root-mean-square (RMS) and Gamma index methods.
Results: The mean volume of PTV covered by the 95% isodose was 99.2% in the MP's plan vs. 99.3%, 98.5% and 99.2% for ANN1, ANN2, and ANN3, respectively. No significant differences were observed between the plans. ANN1 showed the best agreement (Gamma index) with the human planner. While RMS errors in the three ANN models were comparable, ANN1 showed the lowest (best) values.
Conclusion: ANN models were able to determine beam orientation in SRS. ANN-generated treatment plans were comparable to human-designed plans.
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In recent years, stereotactic radiosurgery (SRS) has become a standard treatment option for many pathologies of the central nervous system, including metastases [1–6]. The number of beams needed and their arrangement are strictly related to the prescribed dose to the PTV and the location of nearby critical organs [7,8]. When a linear accelerator is used to perform SRS, optimal treatment plans are achieved when the plan consists of several coplanar and non-coplanar beams selected by the medical physicist (MP) [9–12].

Unlike other radiotherapy procedures, SRS uses multiple narrow beams whose number and orientation vary so much that the use of a standard template is less effective than in most other radiotherapy modalities; even so, standard templates are used in certain tumor locations [12]. Given that beam configuration in SRS always requires a compromise between target coverage and OAR sparing [13–16], numerous studies have evaluated algorithms that might support automated beam orientation selection [14] for both coplanar [17–19] and non-coplanar [15,19,20] beams.

The complexity inherent to the wide array of potential beam configurations provides an opportunity to apply an artificial intelligence support system [17,21,22]. Artificial neural networks (ANN) have an important advantage over conventional modeling methods in that the neural net requires no prior knowledge of the functional relationship between the various input values, nor between input and output parameters. For this reason, ANNs have been used in many medical applications, as an adjunct to standardized treatment planning [23,24], to adjust treatment planning parameters [17,22,25], to improve the treatment process [26], and to predict treatment outcomes [27,28].

The main aim of the present study was to determine whether an ANN could help accelerate and improve the process of SRS planning. To do this, we constructed three ANN models to predict SRS beam arrangement (gantry and table orientations) using various sets of inputs.

Material and methods

A total of 539 patients ranging in age from 16 to 85 years were treated with SRS for intracranial lesions at our clinic between November 2004 and November 2012 (for treatment planning

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details and inclusion criteria see Supplementary Material). Most patients (425) had only a single lesion (425 lesions), while 98 patients had two lesions (98 × 2 = 196 lesions), and 16 had three lesions (16 × 3 = 48 lesions). Therefore, a total of 669 lesions were included in the study; of these, 617 were used to train the ANNs while the remaining 52 were used for prospective validation. The ANN models architecture is described in the Supplementary Material.

A pilot study using multivariate analysis was performed to define the number and type of inputs needed. In that study, multiple linear regressions were performed to identify those parameters that provided non-relevant information. Such parameters were excluded from the model because they increased the processing time without providing any useful information.

The general inputs were obtained from the treatment planning system (TPS) and included the prescribed dose value, number of PTVs treated concomitantly (maximum three), and the volumes of the PTVs (PTV, PTV1 and PTV2) and the 6 OARs. Supplementary Table 1 (see in Supplementary Material) summarizes and presents the set of 12 general inputs (with their range and median values). Input parameter #12 (Region) describes the localization of the PTV in one of the eight brain sub-volumes defined by the authors in Table 1. This was done to define PTV localization in the brain and to separate intracranial lesions by location.

Two approaches to mapping patient geometric information to the corresponding set of input parameters were evaluated. Both sets of inputs were based on defining the position of the PTV and the geometric relationship between the PTV and other structures. The first approach used the Cartesian system defined by the TPS: each structure was mathematically reduced to three coordinates (x,y,z) of the middle point above structures. Supplementary Fig. 1a (in Supplementary Material) provides an example. Using this reduction scheme, each lesion could be reduced to just 27 geometric input parameters (3 for each of the 9 analyzed structures).

In the second approach, patient geometric structures were defined by 8 vectors that described the distances [in cm] between the middle points of the PTV and the other structures. The (x,y,z) coordinate inputs for the PTV were retained as shown in Supplementary Fig. 1b (in Supplementary Material). The second approach reduced the number of inputs to only 11 input parameters (8 vectors + 3 coordinates $[x,y,z]$ of the middle of the PTV).

Linear accelerator-based SRS treatment plans typically have more than a dozen beams [9,10,12]. In our study, the largest number of beams was 14. For each beam, two separate nets were constructed to account for the gantry and table angles as the outputs of the neural networks.

ANN design, training, testing and validation

The ANNs were built with data from 617 lesions based on a back propagation algorithm with 0.01 learning coefficient. The neural network was trained for approximately 10,000 iterations until the expected decrease in performance due to overtraining was observed. The errors for the nets were 0.001. The number of epochs ranged from 1000 to 3000. The lesions were randomly stratified to either training (517 lesions) or testing (100 lesions) by a random resampling technique (cross-validation).

Each input parameter was converted to numerical form (normalized according to the maximal value) and assigned a 10 digit code, which corresponded to 10 neurons. To illustrate this coding system, it is best to provide an example: for the 1st general input (i.e., the prescribed dose) doses could range from 6 to 24 Gy, thus a dose of 18 Gy was coded in binary form as 0000001000.

Output parameters were represented by 73 digits, which corresponded to 73 neurons, and converted to a 72-digit number (360/5° = 72; 5° accuracy) plus the 37th position with 0 for presence and 1 for absence of the particular angle. For example, a 30° angle was presented as 0010000000.....0 (all digits following the third digit were "0", including the 37th digit).

During the validation phase of the study, we used a set of clinical data (the inputs) for 40 consecutive patients (28 with one lesion and 12 with two lesions) that were unknown to the ANN models. These 52 (28 + 24 [12 × 2]) lesions were located in each of the eight brain regions: 11 lesions in region 1, and 8, 9, 6, 2, 3, 3, 10 lesions, respectively.

The datasets for each ANN model were extracted from the TPS and converted into binary form. Because the maximum number of beams was 14 and each beam orientation was defined by both gantry and table angles, a total of 28 neural nets (14 × 2) were needed.

The MP used ANN-generated beam orientations to prepare a total of 156 new treatment plans in the TPS. The other treatment plan parameters were the same as those used in the original treatment plans. To reduce bias, all plans were created at the same time.

Table 1
Eight regions of the brain (sub-volumes) defined by the authors. Patients were divided into 8 subgroups according to the PTV localization in the brain. The number of PTVs in each particular region with its anatomical localization is presented in the table.

Index	Anatomical localization	Number of PTVs
R1	Right cranial anterior	71
R2	Left cranial anterior	95
R3	Right cranial posterior	100
R4	Left cranial posterior	102
R5	Right caudal anterior	40
R6	Left caudal anterior	27
R7	Right caudal posterior	89
R8	Left caudal posterior	93

Methods of plans comparison

Dose values and dose distribution were used to compare the ANN-generated plans to the plan prepared by the MP. Both the MP and ANN-generated plans were required to fulfill the criteria for target coverage [30]. The comparison was performed in three steps in order to choose the best ANN model.

In the first comparison, the maximal doses to the OARs and maximal and minimal dose to PTV for the MP-designed plans and the three ANN-generated were compared for all lesions from the validation group. All doses were read from the respective dose–volume histograms (DVH). In the second comparison, root-mean-square (RMS) discrepancies between the MP-designed and ANN-generated plans were calculated for the number of beams (NB), maximal and minimal doses (D_{max}, D_{min},) in selected OARs, volume of PTV receiving 95% of the prescribed dose ($V_{95\%}$), and conformity index (CI 95%). The RMS error was defined as follows: RMS = square root (sum $(P_{MP} - P_{ANN})$), where parameters P were: NB, D_{max}, D_{min}, CI 95%, $V_{95\%}$.

In the third comparison, we used a dedicated program (OmnioPro IMRT v.1.6; IBA Dosimetry GmbH, Germany) to apply the Gamma index method proposed by Low et al. [34]. Agreement between the MP-derived plans and those predicted by the three ANN models was checked for the areas encompassed by the 60%, 80%, 90%, 95% and 99% threshold isodose levels. The areas considered were located at the reference transversal scan (intersecting isocenter). For each isodose level, we calculated the percentage of points with a gamma index below 1 ($\gamma < 1$) and the percentage of the field areas (%FA) that passed the agreement criteria (dose difference [DD] = 2%, dose to agreement [DTA] = 2 mm).

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