Using Deep Learning to Enhance Compton Camera Based Prompt Gamma Image Reconstruction Data for Proton Radiotherapy

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Proton beam radiotherapy is a cancer treatment method that uses proton beams to irradiate cancerous tissue while simultaneously sparing doses to healthy tissue. In order to optimize radiational doses to the tumor and ensure that healthy tissue is spared, many researchers have suggested verifying the treatment delivery through real-time imaging. One promising method of real-time imaging is through a Compton camera, which can image prompt gamma rays emitted along the beam's path through the patient. However, the images reconstructed with modern reconstruction algorithms are often noisy and unusable for verifying proton treatment delivery due to limitations with the camera. This paper demonstrates the ability of deep learning for removing false prompt gamma couplings and correcting the improperly ordered gamma interactions within the data for the case of Triples and Doubles-to-Triple events.

1 Introduction

Proton beams' primary advantage in cancer treatment as compared to other forms of radiation therapy, such as x-rays, is their finite range. The radiation delivered by the beam reaches its maximum, known as the Bragg peak, at the very end of the beam's range. Little to no radiation is delivered beyond this point. By exploiting the properties of the Bragg peak, it is possible to only irradiate cancerous tissues, avoiding any damage to the healthy surrounding tissues [1]. However, without some way to image proton beams in real time, limitations exist in our ability to take full advantage of the dose delivery properties of the proton Bragg peak. This is due to uncertainties in the beam's position in the body relative to important organs that should not be irradiated.

Therefore, whenever using proton beams, a safety margin must be added to the position of the Bragg peak in order to fully irradiate the tumor. This rules out certain beam trajectories that would otherwise minimize damage to healthy tissue. Figure 1 compares two possible beam trajectories through a cross-section of the chest [1]. In this case, the heart, outlined in purple is positioned at the top-center of the figure and a tumor, outlined in green is located next to it. The optimal trajectory, shown in the left image, uses a single beam, which is represented as the space between the dashed white lines, to fully irradiate the tumor while stopping before reaching the heart. However, due to uncertainty in the exact location that the Bragg peak occurs (and the beam stops), a safety margin is added to the end of the optimal beam path to ensure the tumor always receives the prescribed dose even in the presence of day-to-day changes in patient setup and patient internal anatomy. Therefore, in practice, the optimal trajectory is not used for treatment and instead the trajectory in the right image with two separate beams is used. Using two beams reduces the dose to the heart, but is considered suboptimal as these beams result in more radiation being delivered to a larger amount of healthy lung tissue. With proper real-time monitoring of the proton beam delivery, the optimal single beam treatment shown in Figure 1 (a) could be used without delivering high radiation doses to the heart while minimizing radiation to the lungs.

The Compton camera is one method for real-time imaging, which works by detecting prompt gamma rays emitted along the path of the beam. By analyzing how prompt gamma rays scatter through the camera, it is possible to reconstruct their origin. However, the raw data that the Compton camera outputs does not explicitly record the sequential order of the interaction data, which represents scatterings of a single prompt gamma ray. In addition, it often records false events, which mislabel scatterings of distinct prompt gamma rays as originating from a single ray. The order of interactions is directly connected to the path the prompt gamma took from the origin point. If the order of the interactions is shuffled then the origin point of the prompt gamma will change and no longer be representative of proton beam. These problems make reconstructions based on Compton camera data unusable for practical purposes [1].

We approach these problems by leveraging deep learning techniques. We use neural networks, which, in general, represent data transformations. The network is trained by passing data through it, then updating it systematically so as to reduce the loss of its output compared with some desired output. Doing this properly can create a model that exploits subtleties in the data which traditional models are unable to use. We show how this can be done in the following section. Additional discussion about the impact of the approach on the application area can be found in [2].

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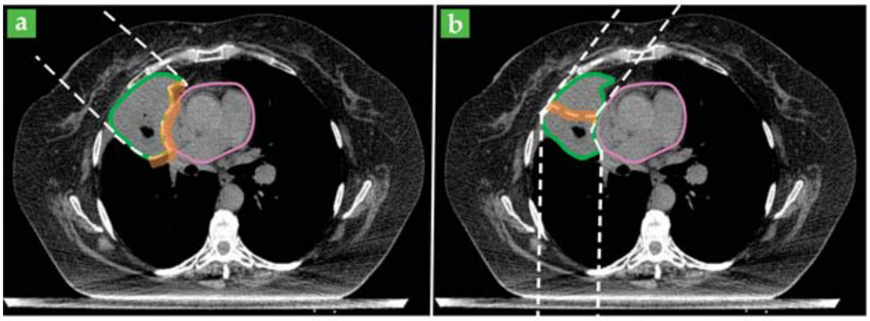

Fig. 1: (a) Optimal proton beam trajectory. (b) Suboptimal trajectory necessary to protect heart.

2 Results

We used Tensorflow 2.5 with the bundled Keras module for our neural network backbone. The network design is built on the fully connected residual blocks described in [3] and [4]. The architecture starts with an input layer with 15 neurons. The hidden layers are comprised of 64 fully connected residual blocks. Each block is made up of 8 layers, each consisting of 256 neurons with Leaky ReLU serving as the inter-layer activation function for the hidden layers. This gives us 256 hidden layers in total. Lastly, the output layer to the model consists of 12 neurons with a softmax activation function. Additional training information, hyperparamter configurations, and hardware data can be found in [3].

Figure 2 is a confusion matrix of classification accuracies from the neural network described in Section 1. The leftmost column of a row is the known input class and the proceeding columns represent the percentage of events which were classified under the class at the top of the column. We can see that the dominant classification for all classes are the classes themselves which shows that the network is correctly classifying between 70% and 80% of all events correctly. For all orderings of triples the second high prediction is the double to triple variant of the triple. This means that the network was unsure if the third event actually belonged but was still confident in the ordering presence of the other two. For the doubles to triples the second highest prediction is actually a reversed double ordering. This means that the network is confident in which of the three interaction does not belong but still struggles with correctly ordering the remaining events.

The neural network was moderately successful in determining the correct ordering for triples and double to triples. It was event capable of determining the single which had been falsely coupled to their associated double by the Compton camera. The accuracy is fairly high ranging from 70% to 80% but still needs improvements. Though an improvement of 10% to 20% per class would be needed for live treatment management, the results here show the ability of deep learning to enable the successful real-time image reconstruction of Compton camera data.

	123	132	213	231	312	321	124	214	134	314	234	324
123	76.2	3.2	1.4	3.2	2.3	1.9	6.4	0.2	0.4	0.0	4.0	0.8
132	2.2	76.5	2.5	2.2	1.2	2.1	0.4	0.2	7.3	0.7	1.4	3.4
213	1.5	2.7	75.6	3.9	1.2	1.9	0.3	7.1	4.0	1.5	0.2	0.1
231	2.2	1.6	2.8	72.9	3.6	2.2	0.2	0.2	1.6	5.2	7.1	0.5
312	2.9	2.5	1.6	1.9	75.5	3.0	3.6	1.8	0.8	6.2	0.0	0.2
321	1.5	2.9	3.5	1.9	3.4	70.9	1.3	4.2	0.2	0.2	1.2	8.8
124	3.5	0.0	0.4	0.1	2.5	1.1	80.2	8.0	1.1	0.6	0.8	1.8
214	0.4	0.1	3.9	0.1	1.4	2.1	8.1	79.9	0.6	1.9	1.1	0.6
134	0.6	4.4	2.7	1.3	0.9	0.1	1.6	0.5	78.2	7.6	1.7	0.4
314	0.1	0.5	1.1	2.6	4.5	0.3	0.9	1.4	7.9	78.8	0.6	1.4
234	3.1	1.1	0.5	4.8	0.1	0.2	0.4	1.4	1.6	0.4	78.7	7.9
324	1.0	3.1	0.1	0.7	0.4	3.7	1.7	0.3	0.7	0.9	8.1	79.3

Fig. 2: A confusion matrix for the 100kMU Triples and Doubles-to-Triples validation data set with each cell value being a percent classification. Cells are colored proportional to the table maximum.

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