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Compton Camera Event Classification Using Artificial Neural Networks

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INTRODUCTION

Real-time imaging has potential to greatly increase the effectiveness of proton beam therapy for cancer treatment. One promising method of real-time imaging is the use of a Compton camera to detect prompt gamma rays, which are emitted by the beam, in order to reconstruct their origin. However, because of limitations in the Compton camera's ability to detect prompt gammas, the data are often ambiguous, making reconstructions based on them unusable for practical purposes. Deep learning's ability to detect subtleties in data that traditional models do not use make it one possible candidate for the improvement of classification of Compton camera data. We show that a suitably designed neural network can reduce false detections and misorderings of interactions, thereby improving reconstruction quality.

AIM

Assess the ability of a deep artificial neural network to classify and order Compton camera data to improve reconstruction quality.

METHOD

We used a validated simulation (Ref 2) to generate labeled Compton camera data produced by prompt-gammas emitted from a 150 MeV proton pencil beam incident on a HDPE phantom at 180 kMU/min. The possible event types can be doubles (2 interactions in an event), triples (3 interactions), doubles-to-triples (2 interactions from the same gamma plus an interaction from a different gamma) and false doubles or triples (all events from different gammas). Data is output in a random order, rather than the order in which they occurred. Interaction data (energy deposited, 3D position) was labeled based on actual event order (e.g. 123 is a properly ordered triple, 132 is an improperly ordered triple).

We used the taki supercomputer cluster at UMBC to train a fully connected network with the following parameters:

Input and output: dense 15 neuron layer. 1.36 million labeled events

Hidden: 25 dense neuron layers, fully connected, 4096 square dimensions, SeLU activation

Training: residual skip every 4 layers, 10^{-6} learning rate, batch size 8192, 1000 epochs.

For all data we performed simple back-projection image reconstructions on the available data, excluding data that was correctly labeled as false coincidence. Properly labeled data was reordered, and improperly labeled data was passed as-is into the reconstruction routine.

In addition to the current achievable classification accuracy (labeled nominal, details in Table 1) we generated data at artificial, uniform accuracies of 100% (perfect), 90% and 80%.

RESULTS

Event classification and sorting using a neural network is feasible to at least 80% average accuracy (range 64%-97%). This improves the good data (properly ordered and true coincidence) to bad (improperly ordered or false coincidence) ratios by 33X. This results in significant improvement of both reconstructed images and profiles. Additionally, the beam shape and range is readily visible even at our nominal classification accuracy once the data is classified by the neural network.

CONCLUSION

Deep neural networks offer a new method to improve both data quality and data quantity of Compton camera data. With classifications accuracies of greater than 80%, we were able to improve our good/bad coincidence ratio from 0.092 (uncorrected) to 3.04 (corrected), with a 1.9X increase in useable events.

The confusion matrix (below, Table 1) presents (input on left, output on top) the nominal classification accuracies of the presented neural network. The numbers indicate event types and output orders, with 1, 2, and 3 being the actual interaction orders contained within the event, and 4 being a spurious interaction. [123] permutations are triples, [124] and [214] are doubles, [444] is false doubles or triples, and all other cases are double-to-triple events. Properly classified events can be used for reconstruction, while incorrectly classified events contribute noise. False events can be rejected.

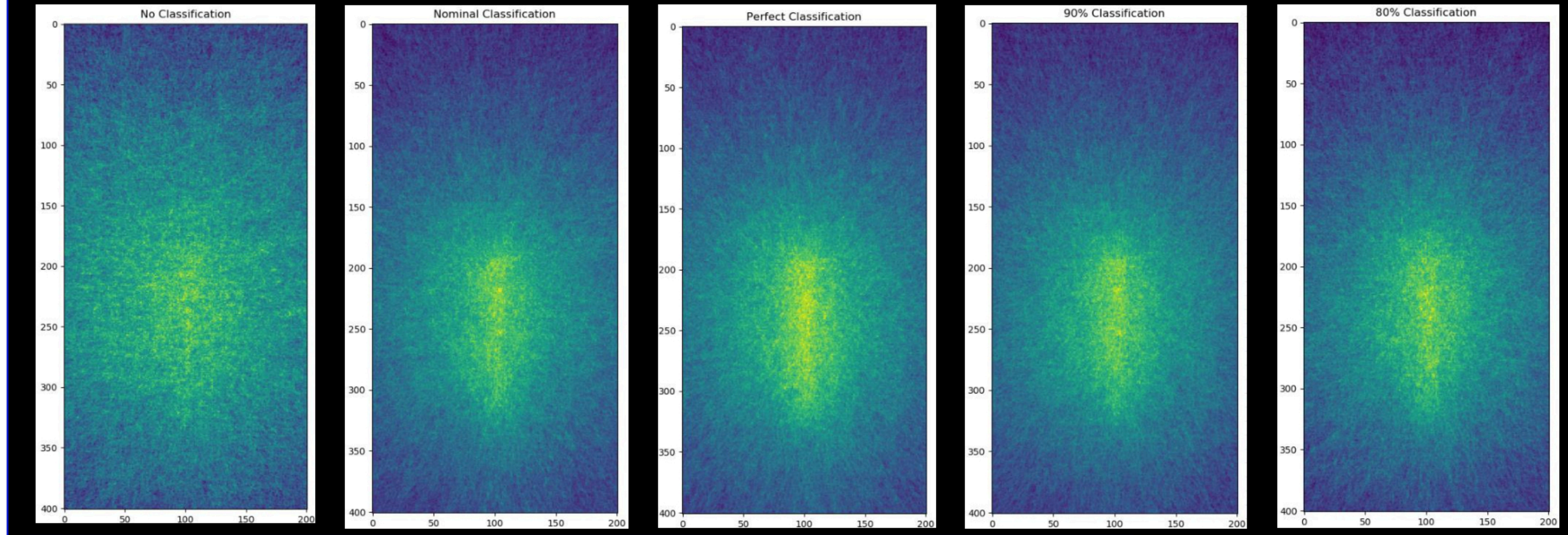

Table 1: *Confusion matrix of nominal event classification and sorting ability*

	123	132	213	231	312	321	124	214	412	421	134	314	234	324	444
123	0.6637	0.0601	0.0347	0.0378	0.0185	0.1019	0.0000	0.0000	0.0085	0.0119	0.0034	0.0039	0.0314	0.0220	0.0023
132	0.0618	0.6394	0.0309	0.0578	0.0551	0.0587	0.0000	0.0000	0.0048	0.0035	0.0131	0.0139	0.0257	0.0326	0.0027
213	0.0215	0.0180	0.7229	0.0686	0.0615	0.0382	0.0000	0.0000	0.0069	0.0130	0.0188	0.0165	0.0064	0.0045	0.0032
231	0.0197	0.0183	0.0515	0.7522	0.0261	0.0669	0.0000	0.0000	0.0136	0.0136	0.0098	0.0150	0.0041	0.0064	0.0027
312	0.0292	0.0515	0.0521	0.0358	0.6709	0.0757	0.0000	0.0000	0.0032	0.0047	0.0136	0.0229	0.0207	0.0177	0.0020
321	0.0439	0.0217	0.0298	0.0600	0.0196	0.7563	0.0000	0.0000	0.0082	0.0195	0.0022	0.0041	0.0129	0.0195	0.0023
124	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8200	0.1800	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
214	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2208	0.7792	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
412	0.0039	0.0023	0.0018	0.0053	0.0017	0.0048	0.0000	0.0000	0.9168	0.0567	0.0000	0.0000	0.0000	0.0000	0.0067
421	0.0026	0.0016	0.0028	0.0035	0.0035	0.0068	0.0000	0.0000	0.0000	0.9669	0.0036	0.0000	0.0000	0.0000	0.0087
134	0.0032	0.0032	0.0047	0.0034	0.0030	0.0024	0.0000	0.0000	0.0000	0.0059	0.9379	0.0256	0.0000	0.0000	0.0107
314	0.0020	0.0025	0.0040	0.0057	0.0060	0.0066	0.0000	0.0000	0.0000	0.0000	0.0574	0.9070	0.0000	0.0000	0.0089
234	0.0232	0.0134	0.0046	0.0029	0.0141	0.0243	0.0000	0.0000	0.0000	0.0000	0.0000	0.0197	0.8616	0.0178	0.0184
324	0.0083	0.0094	0.0028	0.0071	0.0047	0.0112	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0278	0.9173	0.0114
444	0.0044	0.0039	0.0051	0.0053	0.0046	0.0076	0.0000	0.0000	0.0423	0.0501	0.0432	0.0437	0.0415	0.0361	0.7121

Figure 1: *Simple back-projection reconstructions of Compton camera data at different classification and ordering accuracies. The confusion matrix for the nominal accuracy is given in Table 1. All units are in mm*

REFERENCES

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CONTACT INFORMATION

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