Automatic detection of scintillation light splashes using conventional and deep learning methods

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Introduction

The portable Hybrid Gamma Camera (HGC) [1] is one example of the use of low profile high energy detectors for intraoperative imaging and radiation source detection in 3D space.

Figure 1: Simulation of the HGC in clinical use (thyroid scanning).

The HGC's gamma detector is a 1.5mm thick CsI:Tl scintillator coupled to an EMCCD. Each gamma interaction in the scintillator produces a light splash on the EMCCD. By locating these light splashes, a gamma image can be built up over a number of image frames.

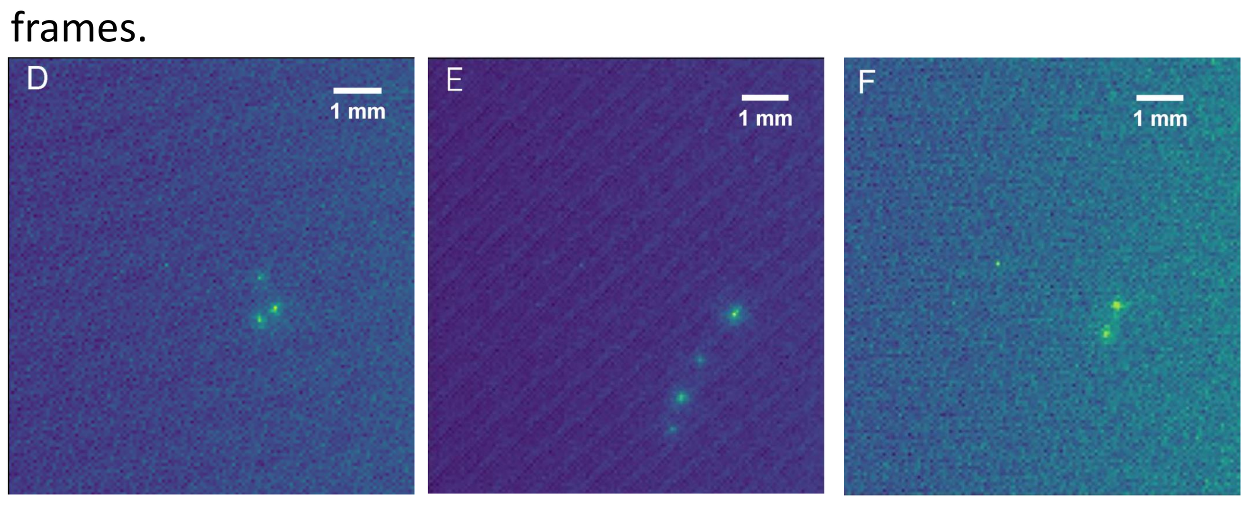

Figure 2: Example image frames (figure D-F) from radiation sources of Cd109, Co57, Am241 respectively. Each light splash is a single gamma interaction.

The current light splash identification algorithm used in the HGC is automatic scale selection [2]. There are some limitations with this technique;

1) It over-detects some background pixels as light splashes, but can also miss lower energy light splashes.
2) It does not predict the scale (size) of the light splashes well.
3) It is too slow for frames with >10 events, decreasing the HGC frame rate or count rate capability.
4) It's performance is strongly dependant on the noise thresholding value chosen.

The poster investigates alternative techniques for reconstructing HGC gamma events in real-time.

Methods

Six automatic detection algorithms are applied to simulated HGC data. These are:

1. LoG_1: The current automatic scale selection method used by the HGC.
2. LoG_2: A different implementation of the Laplacian of Gaussian technique [3], from the Python scikit-image library [4].
3. DoG: A Difference of Gaussian (DoG) algorithm [5] from the scikit-image library.
4. DoH: A Determinant of Hessian (DoH) algorithm [6] from the scikit-image library.
5. Faster RCNN based on VGG16: An implementation of the faster Region-Based Convolutional Neural Network (RCNN) [7] based on a pre-trained VGG16 [8], training with the simulated image frame dataset.
6. ResNet-101 based faster RCNN: An implementation of the faster RCNN based on a pre-trained ResNet-101 [9], training with the same simulated image frame dataset.

These algorithms are compared for **performance** in identifying light splashes, their size and total energy, and **speed**.

Results

All new tested models showed an improvement over LoG_1. For splash localisation, LoG_2 gives the best performance with the highest F1-score of 98.21%, the biggest PR AUC. For the blob scale and energy prediction task, faster RCNN based on the VGG16 model performed best. Therefore, LoG_2 and the faster RCNN based VGG16 model can improve the current light splashes identification of the HGC.

Algorithm	Accuracy	Sensitivity	Specificity	Precision	F1-score	PR AUC	Correlation coefficient r_s between scales	Correlation coefficient r_e between energies	Speed (seconds/frame)
LoG_1	99.96%	78.54%	99.97%	59.73%	67.86%	0.691	0.737	0.934	0.366
LoG_2	100%	98.60%	100%	97.86%	98.21%	0.982	0.897	0.922	0.024
DoG	99.99%	93.26%	100%	93.75%	93.51%	0.935	0.851	0.873	0.023
DoH	99.92%	32.81%	99.96%	31.87%	32.33%	0.324	0.564	0.405	0.070
Faster RCNN based on ResNet-101	99.99%	87.57%	100%	93.95%	90.65%	0.907	0.981	0.962	0.072
Faster RCNN based on VGG16	99.99%	88.15%	100%	93.94%	90.95%	0.915	0.982	0.964	0.057

Figure 3: Evaluation of each light splash identification algorithm.

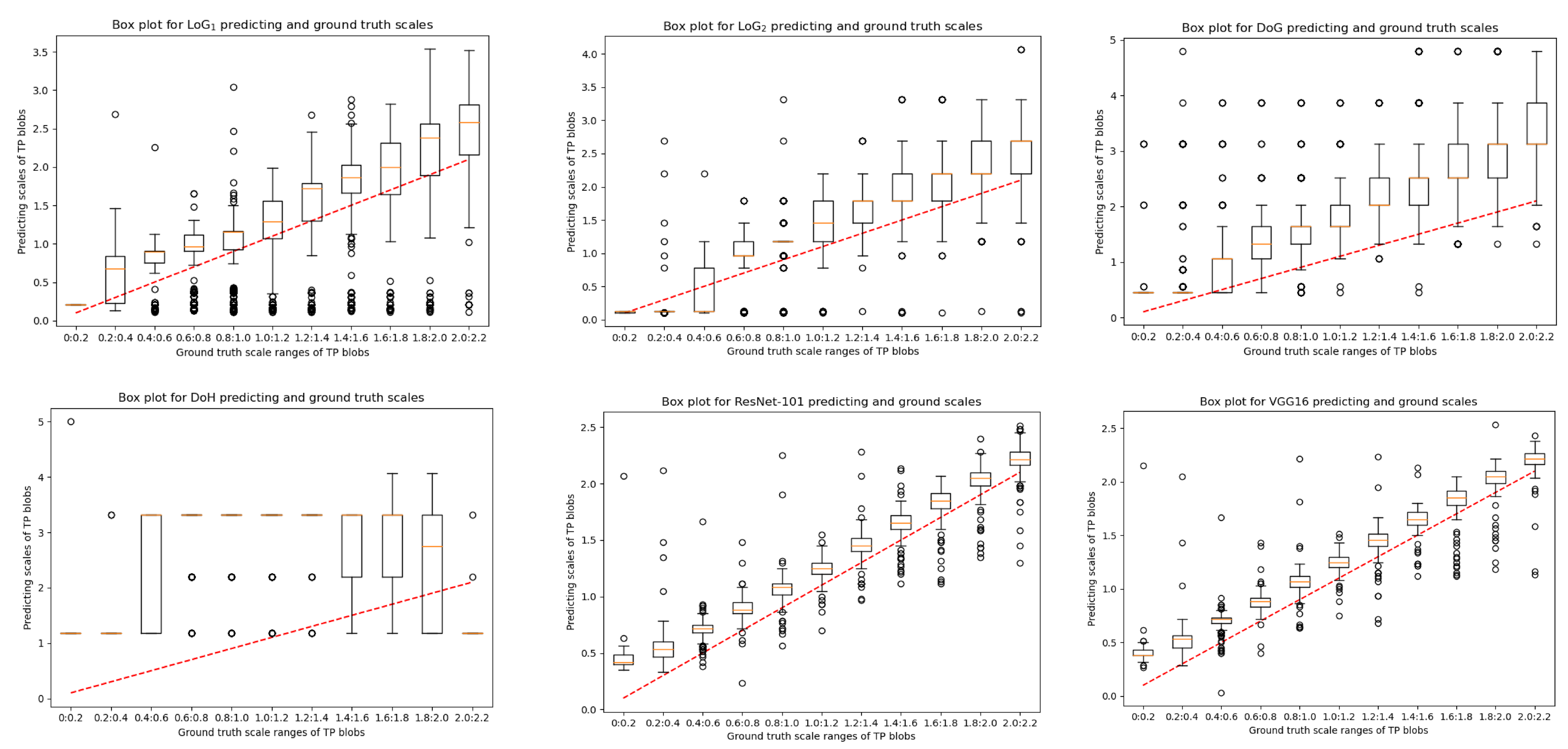

Figure 4: Box plots comparing the performance of each algorithm. The red line represents an ideal scale predicator.

Conclusion

The LoG_2 and faster RCNNs can mitigate the light splash over-detection problem. The faster RCNN-based VGG16 shows the best correlation coefficients in scale and energy predictions. Moreover, the detection speed of LoG_2 and faster RCNNs are suitable for real-time imaging. Faster RCNNs do not require pre-processing thresholding. Based on these results, the faster RCNN based VGG16 will be implemented in future iterations of the HGC.

Data simulation and preparation

Light splashes were simulated as 2D Gaussians with size and intensity distributions from experimental data. Poisson noise and background were added to create 2720 simulated data frames containing 28582 simulated light splashes. KS testing showed that both Gaussian and Laplacian distributions were equally reasonable fits to the experimental data.

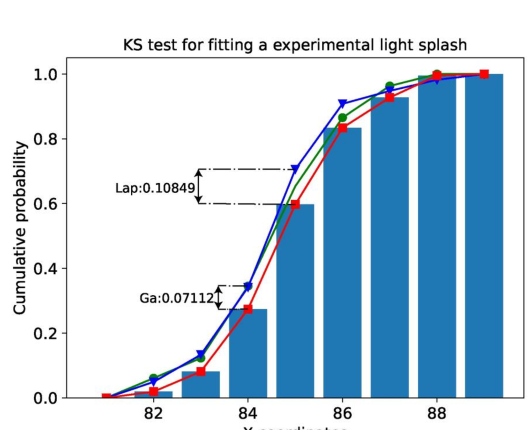

Figure 5: Kolmogorov-Smirnov test for an experimental light splash.

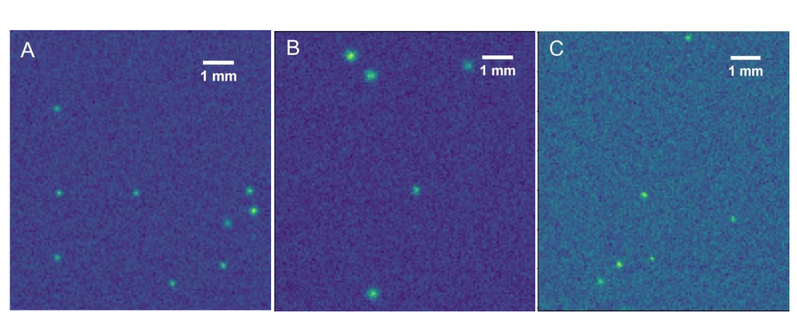

Figure 6: Three simulated date frames.

Dataset	Number of frames	Number of blob centre pixels (Positive cases)	Number of background pixels (Negative cases)
Training	2000	21000	37467000
Validation	360	3784	6744056
Testing	360	3798	6744042

Figure 7: Description of generated frames.

For RCNN techniques, images were converted to a PASCAL Visual Object Classes (VOC) format [10] for applying faster RCNNs.

Evaluation metrics

1. TP: true positive, a detected light splash with centre is ≤ 2 pixels away from a ground truth splash's centre.
2. FP: false positive, the detection algorithm misclassifies a background pixel as a splash centre.
3. FN: false negative, a ground truth splash with no associated detection.
4. TN: true negative, all other pixels
5. Sensitivity = TP/(TP + FN)
6. Specificity = TN/ (FP + TN)
7. Precision = TP/(TP+FP)
8. Accuracy = (TP+TN)/(TP + TN + FP + FN)
9. F1-score = 2*((Precision*Sensitivity)/(Precision+Sensitivity)), which is the harmonic mean of precision and sensitivity.
10. PR curve is a curve that shows the relationship between recall (sensitivity) and precision. The x axis is sensitivity, and the y axis is precision.
11. PR AUC can be assumed as an approximation of the average of precisions [11].

REFERENCES

[[1] J. E. Lees, S. L. Bugby, M. S. Alqahtani, L. K. Jambi, N. S. Dawood, W. R. McKnight, A. H. Ng, and A. C. Perkins, "A multimodality hybrid gamma-optical camera for intraoperative imaging," Sensors, vol. 17, no. 3, 2017.

[2] D. J. Hall, A. Holland, and D. R. Smith, "The use of automatic scale selection to improve the spatial and spectral resolution of a scintillator-coupled emccd," Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, vol. 604,no. 1-2, pp. 207–210, 2009

[3] T. Lindeberg, "Scale selection properties of generalized scale-space interest point detectors," Journal of Mathematical Imaging and vision, vol. 46, no. 2, pp. 177–210, 2013.

[4] S. Van der Walt, J. L. Schonberger, J. Nunez-Iglesias, F. Boulogne, J. D. Warner, N. Yager, E. Gouillart, and T. Yu, "scikit-image: image processing in python," PeerJ, vol. 2, p. e453, 2014.

[5] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," International journal of computer vision, vol. 60, no. 2, pp. 91–110, 2004.

[6] H. Bay, T. Tuytelaars, and L. Van Gool, "Surf: Speeded up robust features," in European conference on computer vision, pp. 404–417, Springer, 2006.

[7] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards real-time object detection with region proposal networks," arXiv preprint arXiv:1506.01497, 2015.

[8] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv preprint arXiv:1409.1556, 2014.

[9] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770–778, 2016.

[10] M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman, "The pascal visual object classes (voc) challenge," International journal of computer vision, vol. 88, no. 2, pp. 303–338, 2010.

[11] K. Boyd, K. H. Eng, and C. D. Page, "Area under the precision-recall curve: point estimates and confidence intervals," in Joint 618 European conference on machine learning and knowledge discovery in database

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