From Monte Carlo to Neural Networks

Transforming Nuclear Medicine with GPUs

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Imaging in Nuclear Medicine

Imaging the 3D radioactivity distribution by detecting gamma photons

Axial level of sinogram

Alternative way of projecting the distribution onto the gamma camera with multiple pinholes

Reconstruction: calculate 3D distribution data from 2D projections

2D planar

projection

Sinogram

Gradually approximates the radioisotope distribution

Accuracy of Forward Projection is crucial

Physical processes has to be modelled precisely

Time constraint makes reconstruction dependent on computational performance

Parallelization of transport algorithms on GPU makes using Monte Carlo possible

Simulating single particle trajectory

1. Sampling source distribution

2. Simulating photon interactions with: collimation body tissues detector material

3. Registering counts in image matrix

Photon trajectories are independent: Each photon can be simulated on a single GPU thread

Problem:

Photon trajectories are random, threads can diverge

Iterative Reconstruction

Results of forward projections during the reconstruction of a bone SPECT

Benefits of Monte Carlo Superior resolution Lower scatter background Free of penetration background Can handle multiple isotopes Absolute quantitation: activity in Bq/ml or SUV

Conventional 2D reconstruction

Monte Carlo based 3D iterative reconstruction

Noise Reduction

Development goals in nuclear medicine:

Shorter examination time

Higher throughput

Increased patient comfort

Reduced movement artifacts

Lower amounts of radioisotope

Reduced radiation dose

Decreased costs

Decreased image statistics Higher noise levels

Development of noise reduction methods

Effect of reducing scan time on image quality:

Original U-Net architecture:

Neural Network Architecture

Following candidate architectures were implemented in TensorFlow:

Neural Network Strategy

Training:

1000 anonymized patient scan with standard statistics

Images with degraded statistics was generated from the original acquisitions using random binomial sampling

Degraded images was used as the input and the corresponding original image as the desired output

128 x 128 patches randomly selected

L1 (maximum value) loss was used

Learning rate:

Gradually decreased as 1/(1+C*iterations)

Through 400 epochs learning rate decreased one order of magnitude

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Evaluation:

Visual evaluation

Quantitative analysis of image quality based on artificially generated lesions

Preliminary clinical test performed on 30 patients (lesion evaluation blind test)

Performance (4 x GTX 1080 Ti):

Training time: 30 sec / epoch Inference time: 0.08 sec

Evaluation — Visual Examples

Evaluation – Visual Examples

Evaluation — Visual Examples

Stats:	unfiltered	filtered	unfiltered 1/	filtered	unfiltered 1/	filtered

Evaluation – Visual Examples

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	unfiltered	filtered	unfiltered	filtered	unfiltered	filtered
stats:	1/8		1/16		1/32	

Evaluation – Epochs

Quality of filtered images degraded to 1/16 statistics as a function of epochs

Difference images between the inferred images and the original

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Stats:

Evaluation – Lesion Generation

Difference images between the inferred images and the original

Preliminary clinical test was performed on 30 patient acquisitions (retrospective study).

From each original image, three additional images were generated with the following steps:

1. Degrade image to $\begin{bmatrix} 1/2 \\ 1/4 \end{bmatrix}$ 2. Filter images with NN $\begin{bmatrix} 2 \\ 3 \end{bmatrix}$ 3. Increase noise level according to original image 1/8

Noise level of the resulting images are indistinguishable Source of a given image cannot be easily guessed

Images were evaluated with a blind test

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Lesions were localized and labeled into 6 categories injection point / bladder / kidney / low risk / medium risk / high risk

Labels from the degraded images were compared with the labels from the original patient scan

False / True positives and negatives were counted on each image

Anterior

Posterior

A statistical analysis was performed on the lesions found on the different image types.

	Test Statistics ^a							
		PA_12.5 - PA_100	PA_50 - PA_100	PA_25 - PA_100				
	Z	-2,033 ^b	-,853 ^b	-1,754 ^b				
•	Asymp. Sig. (2-tailed)	,042	,393	,079				
	Exact Sig. (2-tailed)	,044	,408	,082				
	Exact Sig. (1-tailed)	,022	,204	,041				
	Point Probability	,003	,007	,002				

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

No significant difference was found between the original, the $\frac{1}{2}$ and the $\frac{1}{4}$ statistics.

1/8 statistics show significant difference in lesion detection.

"Usual" challenges of clinical evaluation: intra/inter-operator variability