Detecting presence of low SNR emission sources Analysis and "analysis" vs deep learning

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References

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- F. Terzioglu, P. Kuchment, L. Kunyansky, Compton camera imaging and the cone transform: a brief overview, *Inverse Problems*, **34** (2018), 054002
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Emission imaging and detection

Goal: Imaging/detection of presence of emission sources.
SPECT medical imaging, border crossings and harbors detection.

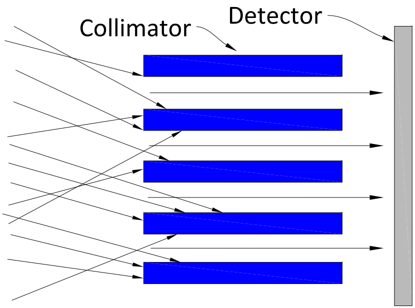


Direction sensitive sensors are needed.

Issue: Low, up to extremely low (1%, .1%, or even less) SNR.

Anger camera

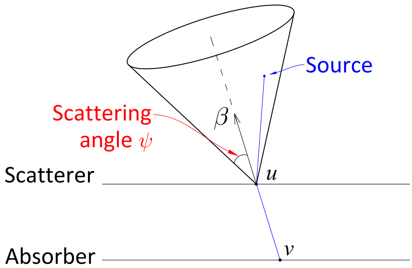
Standard collimated (Anger) γ-camera



Kills the signal when SNR is low!

Compton cameras & analogues

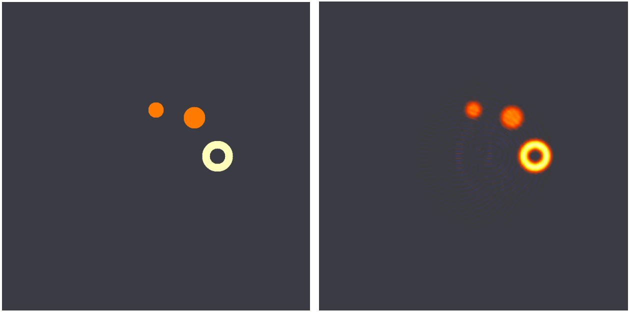
Compton γ-camera



Measures integrals over cones (a lie when the counts are low).
Analogs for neutron detectors.

Cone transforms, their properties and inversions

Overdetermined problem - GREAT!



Beautiful (not fully completed) analysis: uniqueness, inversion, stability, microlocal, ...).

Problem formulation

For HS problems the SNR is extremely low. Integral geometry formulations are wrong. Inversion formulas thus are also wrong. Silver lining: one does not need an image, just DETECTION of presence (YES or NO).

Goal: Detect presence of a low SNR γ- or neutron source using Compton-type data.

Possible approaches:

1. Using apriori information and math+stat processing. The backprojection technique below.

Works for SNR down to .1% **for a sufficiently long observation**.

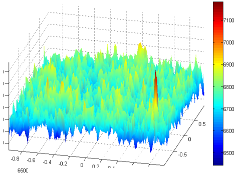
Too long for neutrons.

2. Bayesian technique

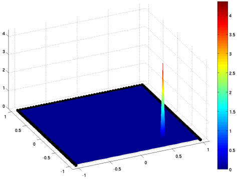
3. Deep learning technique without any prior math processing

Statistical backprojection approach

1. Assume small size of the source.
2. Backproject the (conical) data.
3. Subtract the mean



4. Find statistically significant local accumulations.



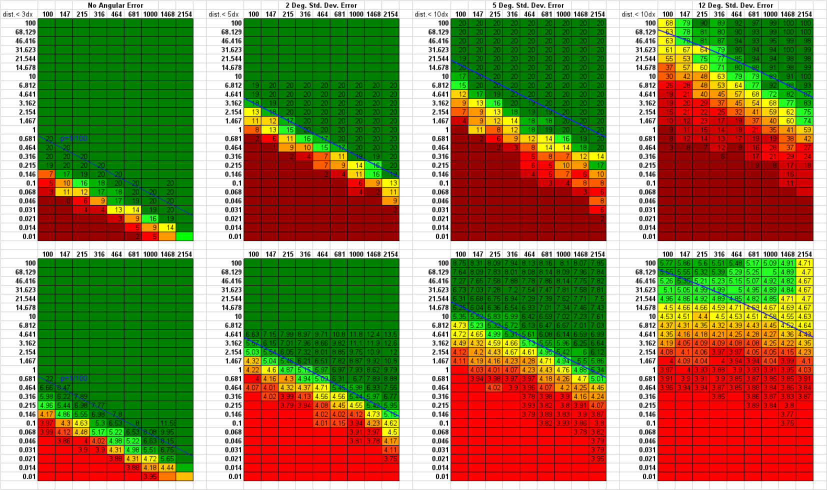
Details of the backprojection approach

N - the number of the background particles.
n - number of ballistic particles from the source.
$SNR := n/N$. $T := N + n$
p the (relative to the cargo hold) size of the source.
Apply (incorrectly, but justified by numerics) a CLT to get the detectability estimate

$$T \sim \left(\frac{8}{SNR}\right)^2 p(1-p)$$

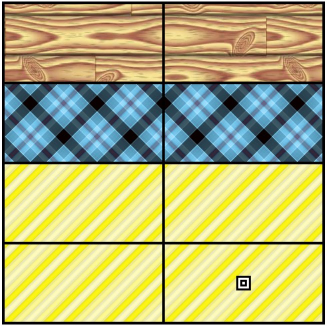
Results are similar with Bayesian techniques (with no location detection).

Experiments



Cargo effects

In the case of γ detection, presence of complex cargo causes problems



The SNR (for ballistic source particles) drops to undetectable by the backprojection methods levels.

However,

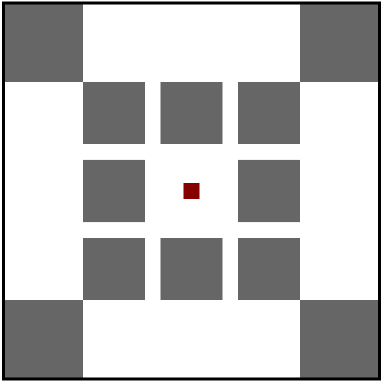
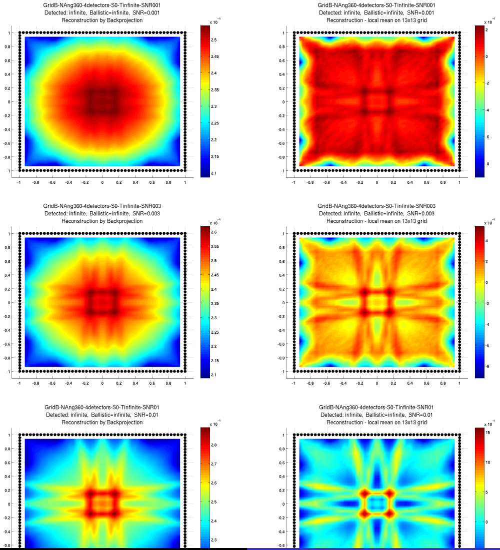
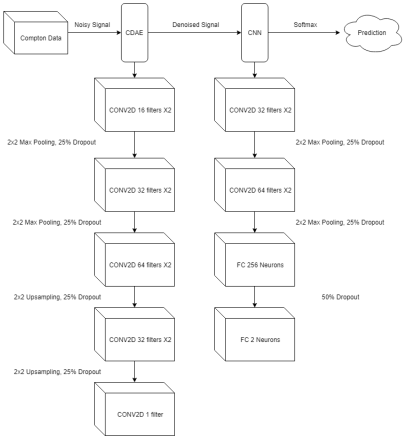


Figure: Material Arrangment

Is there some information?



Could deep learning help?



Results comparisons - no cargo

Bkgnd Cnt	Sensitivity	Specificity
10000	.960/.909	.998/.644
5000	.949/.725	.882/.528
2000	.732/.530	.519/.510

Neural Network Performance SNR 2% / 1%

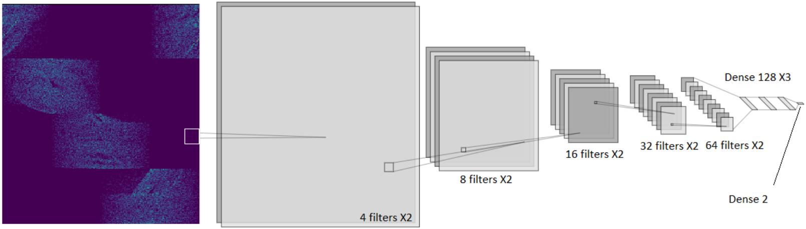
Bkgnd Cnt	Sensitivity	Specificity
10000	.06/.00	1.0/1.0
5000	.06/.00	1.0/1.0
2000	.02/.02	1.0/1.0

Back Projection Performance SNR 2% / 1%

Deep learning with cargo

- Convolutional Neural Network (CNN) is trained on 750 simulated media configurations with randomly placed source. Architecture is shown in Fig. below.
- Outputs a probability measure $\mathbb{P}$ on $\{0,1\}$, a source is determined to be present if $\mathbb{P}(x=1) > 0.5$.
- High Exposure Network (HEN) is trained on simulations corresponding to higher exposure time. Low Exposure Network (LEN) is trained on simulations corresponding to lower exposure time.

Architecture



CNN architecture used for source detection. The left-most cell shows an example of the detector data input to the CNN.

Forward simulations

Radiative transfer equation (RTE):

$$\hat{u} \cdot \nabla\psi(\vec{r}, \hat{u}) + \sigma_t(\vec{r})\psi(\vec{r}, \hat{u}) = \frac{\sigma_s(\vec{r})}{4\pi} \int_{\mathbb{S}^2} \psi(\vec{r}, \hat{u}') \cdot d\hat{u}' + \frac{Q(\vec{r})}{4\pi} \tag{1}$$

ψ – angular flux, Q – volumetric source term, σ_t and σ_s - the total cross section and scattering cross section respectively (isotropic).

Results comparisons - randomly generated cargo

Exposure Time (s)	Sensitivity	Specificity
30	1.00/.96	.97/.77
20	.97/.65	.99/.86
10	.69/.66	1.00/.86

Performance at 1% SNR.(HEN / LEN)

The end


STOP
WRONG WAY


THANK
YOU
GRACIAS
ARIGATO
SHUKURIA
TASHAKKUR ATU
DANKSCHEEN
BIYAN
SUKSAMA
GRAZIE
MEHRBANI
JUSPAXAR
BOLZÏN
MERCI