





October 28, 2015 ADSA13 Workshop

Amit Ashok College of Optical Sciences University of Arizona

> Mark Neifeld (PI) Ali Bilgin Eric Clarkson University of Arizona

> > *Michael Gehm Duke University*

This work is supported by Department of Homeland Security, Science and Technology Directorate, Explosives Division, BAA 13-05 (Contract # HSHQDC-14-C-B0010)





Physical interaction encodes "information" about object(s) into the measurement. Information embedded in the measurement determines the fundamental limit of threat detection.



Information Bottleneck

Key Observations:

- Measurements have cost (size, weight, power, latency, ...).
- Physical world represents more variables than we can *afford* to measure.
- Bottleneck demands judicious selection of measurements that convey most useful information relevant to task at hand.

Q: What is fundamental limit of a X-ray measurement (system) for threat detection ? A: Our information-theoretic system analysis framework quantifies this fundamental limit.

Q: What are the optimal measurements for X-ray threat detection ?

A: Our analysis framework allows rigorous "comparison" of competing measurement (system) designs and enables measurement (system) optimization.





Project structure

Our work products will be theory and related analysis/design so the "system concept" presented below is notional and intended to provide structure/context to our explorations.



Task 1.1

Thrust 1 – Application of Current TSI Tools

- Task 1.1 Signal and Task Priors
- Task 1.2 TSI Analysis and Design for Current Systems
- Task 1.3 Application of TSI to new Modalities
- Task 1.4 Exploration of Adaptive TSI Strategies

Thrust 2 – Extension of Current TSI Tools

- Task 2.1 Game Theoretic Approaches
- Task 2.2 Joint Detection and Estimation
- Task 2.3 TSI Optimal Fusion from Heterogeneous Data
- Task 2.4 TSI Optimal Measurements on Graphical Models





Staffing & Org Chart

Program Lead

Mark Neifeld–U. Arizona

Thrust 1 – Application of Current TSI Tools (Gehm)

Task 1.1 Signal and Task Priors *Amit Ashok*–U. Arizona

Task 1.2 TSI Analysis and Design for Current Systems Michael Gehm–Duke U.

Task 1.3 Application of TSI to new Modalities Michael Gehm–Duke U.

Task 1.4 Exploration of Adaptive TSI Strategies Mark Neifeld–U. Arizona Thrust 2 – Extension of Current TSI Tools (Ashok)

Task 2.1 Game Theoretic Approaches Amit Ashok–U. Arizona

Task 2.2 Joint Detection and Estimation *Eric Clarkson*–U. Arizona

Task 2.3 TSI Fusion from Heterogeneous Data *Ali Bilgin*–U. Arizona

Task 2.4 TSI Measurements on Graphical Models *Mark Neifeld*–U. Arizona

	THRUST I - Application of Current TSI Tools				ls	THRUST II - Extension of Current TSI Tools					
	1a	1b	1c	1d		2a	2b	2c	2d		
											Task Lead
Neifeld											Task Participation
Gehm											Interest
Ashok											
Bilgin											
Clarkson											





Information content is task/context dependent

Shape/material threats



Threat detection task: Probability of presence/absence = ½ Information content ≤ 1 bit

Threat detection/localization task: Probability of absence = $\frac{1}{2}$ Probability of occurrence in a region = 1/256 Information content ≤ 8 bits

Threat type (N types) classification task: Probability of each threat type = 1/N Information content ≤ log(N) bits





Task Specific Information (TSI) = Channel Capacity



Task-specific Information (TSI) can be defined as:

$$\begin{array}{l} \text{Mutual-information} & \longrightarrow & TSI \equiv I(X;R) \leq J(X) \leftarrow & \text{Upper-bounded by source} \\ \text{Algorithm and} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Algorithm agnostic,} \\ \text{Dependent} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Magorithm agnostic,} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Magorithm agnostic,} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Mutual-information} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leq I(X;R) \leftarrow & \text{Mutual-information} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Mutual-information} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Mutual-information} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Mutual-information} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Mutual-information} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Mutual-information} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & \text{Mutual-information} \\ \text{Mutual-information} & \longrightarrow & I(X;X_{est}) \leq I(X;Y_{est}) \leq I(X;R) \leftarrow & I(X;X_{est}) \leq I(X;X_{est})$$

- TSI is analogous to Shannon's channel capacity for communication channels
- Defines *fundamental limit* on information transfer via a channel/imager





Information-theoretic Analysis Framework Diagram



variation in system description produces parameter sweep or ultimately optimization.





Framework components

Radiography Forward model

• We had developed a ray-tracing-based forward model of transmission imaging that utilized high-performance graphics APIs to allow ultra-rapid measurement of simulated bags on arbitrary system configurations



Stochastic bag generator

 We had developed a tool for automatically creating large numbers of simulated bags—the *Stochastic Bag Generator (SBG)*. The SBG draws from object / material libraries and uses tunable heuristics to pack the bags.



• We had developed a number of methods for generating the surfaces in the object library.

Laser-scanned



Segmented from CT









Validation of transmission imaging forward model

Custom phantom



Delrin body; Variety of 'slug' sizes and materials

Experimental setup



2D integrating detector; Broadband tungsten conebeam source

Representative data





Dead pixels on array; Support table and spatial filter visible



No free parameters; Good qualitative agreement

Plotting [In(counts)]³ to better use dynamic range of display

When then took all experimental data (12 material configurations from 3 different views) and performed one best fit to extract an overall scale parameter (for ADC vs. photon counts, source uncertainty, etc.) and a DC offset for each configuration (for scatter background)

Representative results shown to right

Agreement now semi-quantitative (few percent)













Aluminum Delrin PVC Acrylic Water Methanol

Copper





Framework components

Information-theoretic metric: Cauchy-Schwartz Mutual Information

 Cauchy-Schwarz divergence based mutual information (CSMI) is computationally tractable and scalable



• Scalable CSMI implementation suitable for *Poisson mixture model* (shot noise limited model)

$$J_{CS} = D_{CS}(p(g, C), p(g) \cdot p(C))$$

Computational complexity
$$O(K^2N)$$

bags Measurement
dimensionality





Stochastic (Threat) Bag Ensembles

Two fundamentally different threat classes

- Shape-based (object geometry distinguishes from non-threat objects)
- Material-based (object composition distinguishes from non-threat objects)

Unrelated to screening guidelines

Currently, prohibit primary alarming based on shape.

Threat ensembles created via the stochastic bag generator (SBG)

Stochastic bag ensembles (SBEs)

Shape-based SBE

- 10k threat and 10k non-threat bags
- Threat/non-threat bags generated/arranged in pairs
- Threat bags are identical to non-threat partner, except 1-2 items replaced with threat objects
 Volume
 Volume

 Volume
- Threat objects: Gun, knife, wiring

Material-based SBE

- Multiple ensembles at differing threat volume ranges.
- At each volume, 10k threat and 10k non-threat bags
- Threat/non-threat bags arranged in pairs
- Threat bags are identical to non-threat partner, except a single object has had its material composition switched from a common false-alarm material to a true threat material
- Common false-alarm materials: Playdoh, peanut butter, NaCl, water/NaCl, water/sugar
- Threat materials: Gunpowder, AN, gasoline, H₂O₂, MEKP

Volume range (cm³)	Geometric mean (cm)				
1-8	1–2				
64–216	4–6				
512-1000	8–10				
1728–3375	12–15				
4913-8000	17–20				
	Volume range (cm ³) 1-8 64-216 512-1000 1728-3375 4913-8000				











Selected results





Study 2B—Energy-resolving retrofit (material threats)



10

10

Equivalent Baseline Source Radiant Intensity (photons/10⁻⁴Sr· s)

10

• Smallest threat volume is barely detectable















Study 4A—Multi-View Retrofit (Shape Threats)



Threat type: Shape

Variation from baseline system: Multiple (>2) views

Study variations: Number of views, simultaneous vs. sequential exposures, source brightness

Conclusions:

- Observe diversity/SNR tradeoff
 - Sequential: Results improve from 2 to 3 views and the deteriorate with more views
 - Simultaneous: results are uniformly worse than sequential measurement



Adding more view beyond 3 views does not yield improved detection for this AT geometry







Adding more views beyond 3 views does not yield improved detection for this AT geometry





Reduction in measurements with no loss of performance



- Spatially undersampled, energy-resolving system outperforms operational baseline system
- Spatial undersampling *reduces* measurements by 25x while energy-resolution *increases* measurements by 4x.
- Net reduction of measurement number is 25/4 = 6.25

Reduction in measurement number by > 5x while improving information-theoretic performance limit.



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$P_e/P_D/P_{FA}$ and ROC Analysis



 ROC analysis confirms the log[w/b] comparison between operational baseline and spatially undersampled, energy resolving system

Reduction in measurement number by > 5x while improving information-theoretic performance limit.





Joint Estimation/Detection Information (JEDI)



Estimation performance

- Our information-theoretic exploration of the fundamental performance of joint estimation/detection problems (such as image formation combined with threat detection) has revealed a striking fact
- The detection performance of an optimal system *must* decrease monotonically with increasing estimation performance
 - In other words, improving the image will necessarily *degrade* detection performance
 - There may be broad ranges of parameter space for which the degradation is minimal, but it must exist
- Conversely, if image improvement is observed to improve detection capability, the ATR algorithm *must* be non-optimal and is underachieving in detection given the information present in the measurements