#### **Muon Tomography:** *Passive detection and imaging using cosmic ray muons*

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#### Nuclear smuggling is a clear and present danger



Los Alamos National Laboratory October 24, 2002

Stanford Nuclear Smuggling Database: Dynamics and Trends Over the Past Decade Lvudmila Zaitseva

Center for International Security and Cooperation, Stanford University Total = 1.13 IAEA "significant quantities"

(8 kg Pu or 25 kg of  $U^{235}$  in HEU)

# Active radiography is an established inspection technique

To date, radiography has depended on artificial sources of radiation, which bring with them a risk-benefit tradeoff

1895 First x-ray image (Mrs. Roentgen's hand)



#### 2001

Inspection of truck with American Science and Engineering backscatter x-ray system



#### Passive Source Radiography: Cosmic Radiation

No artificial radiation means:

- Cars and trucks inspection without evacuating the driver significant time factor
- 2. Deployment abroad without local regulatory complications Detection at point of origi
- No radiation signal to set off a salvage trigger
   Minimizes inspection risks.



- 1. Neutrons
- 2. Neutrinos
- 3. Electrons
- 4. Muons
- 5. Etc.

# **Cosmic Ray Muons**

- As cosmic rays strike upper atmosphere, are broken down into many particle components, dominated by muons.
- Muons have a large penetrating ability, go through tens of meters of rock with low absorption.
- Muons arrive at a rate of 10,000 per square meter per minute (at sea level).



# **Application: Truck Inspections**



- Penetrating interrogation with no artificial dose
- Prevent illicit movement of nuclear materials
- Used in concert with passive gamma / neutron detection.

# **Physics**

- Coulomb scattering changes the path of muons.
- Some particles are absorbed
- Variance of scattering depends on the material.





# **Absorption tomography**

- Hidden chambers in volcanos (Alvarez, 1970)
- Predicting volcanic
   erruptions (Tanaka,
   2003)

<text>



#### Shadowgrams (from scattering)



Possible to get shadowgrams from scattering instead of absorption

Proton radiography

# **Measuring the scattering**







- Tract individual muons
- Measure changes to the paths in and out

#### **Drift tubes and wire chambers**



#### (Idealized) Data

Incident ray:  $(x_0, \theta_0)$ Outgoing ray:  $(x_1, \theta_1)$ Strait line  $\phi(s)$  $\phi_{out}$ Dout x 0  $(x_0 + \sin(\theta_0)s, 1 - \cos(\theta_0)s)$ 1 Data (for each muon) x<sub>1</sub> 0  $\mathcal{D}_{\text{in}}$ • ¢<sub>in</sub>  $\Delta = \theta_1 - \theta_0$  $D = x_1 - x_0 - \tan \theta_0$ 

#### **Statistical Model**

 $Y = (\Delta, D)$  conditional on  $I = (\theta_0, x_0)$  is (approximatively) bivariate Gaussian with mean  $\mu(\varrho, \phi) = (0, \mu_d)$  and covariance  $\Sigma(\varrho, \phi)$  where

$$\mu_d(\varrho, \phi) = c(\theta_0) \int \|\phi(1) - \phi(s)\| \varrho(\phi(s)) ds$$
  

$$\Sigma_{11}(\varrho, \phi) = \mathbb{E}[\Delta^2] = \frac{1}{p} \int_0^1 \varrho(\phi(s)) ds$$
  

$$\Sigma_{12}(\varrho, \phi) = \mathbb{E}[\Delta D_{in}] = \frac{1}{p} \int_0^1 \|\phi(1) - \phi(s)\| \varrho(\phi(s)) ds$$
  

$$\Sigma_{22}(\varrho, \phi) = \mathbb{E}[D_{in}^2] = \frac{1}{p} \int_0^1 \|\phi(1) - \phi(s)\|^2 \varrho(\phi(s)) ds.$$

*ρ*: scattering density: parameter of interest *φ* path of muon (observed) *p*: momentum of the muon, unobserved

-approximation reasonable for  $|\theta_0| \leq \pi/3$ .

#### What we learn from the data

- Signal is (mainly) in the variance;
- To first order, weighted integrals along path  $\phi$ ;
- Sampling limited by geometry of detectors;

#### **Questions and Challenges:**

ESTIMATION: How well can we reconstruct  $\rho$ ?

DESIGN: What is the impact of the geometry? Change the difficulty of the inverse problem by changing the geometry.

COMPUTATION Computation in < 1 min; sequential method ok.

#### **Information extraction**

- Point of Closest Approach
- Maximum Likelihood
- Support vector (for detection of high-Z regions)

How Good?



#### **Penalized Loglikelihood**

Estimator:

$$\hat{\varrho} = \arg\max_{\varrho} - \sum_{i=1}^{n} \log |\Sigma(\varrho, \phi_i)| - Y_i^t \Sigma^{-1}(\varrho, \phi_i) Y_i - \lambda \|\varrho\|^2$$

**Difficulty:** Infinite dimensional optimization problem. **Solution:** Reduce it to a finite dimensional one.

Theorem. If

$$\int \|\phi_i(1) - \phi_i(s)\|^j \varrho(\phi_i(s)) ds = \int L_{i,j}(s) \varrho(s) ds$$

bounded linear functionals of  $\rho$ , then

$$\hat{\varrho} \in \text{span} \{ L_{i,j}, \ i = 1, \dots, n \ j = 0, 1, 2 \}$$

### **Approximate Linear Functionals**

 $K_h$  kernel, bandwidth hApproximate linear functionals:

$$\int \|\phi_i(1) - \phi_i(s)\|^j \varrho(\varphi_i(s)) ds$$
  
=  $\int_0^1 \|\phi_i(1) - \phi_i(s)\|^j \int \varrho(u) K_h(u - \varphi_i(s)) du ds + o(1)$   
=  $\int \varrho(u) \left\{ \int_0^1 \|\phi_i(1) - \phi_i(s)\|^j K_h(u - \varphi_i(s)) ds \right\} du + o(1)$ 

Define:

$$L_{i,j} = \int_0^1 \|\phi_i(1) - \phi_i(s)\|^j K_h(u - \varphi_i(s)) ds.$$

**Example of**  $L_{i,0}(s)$ 



example of linear functionals 8 rays

#### **Reproducing Kernel Approach**

Impose "regularity" on  $\rho$ , lies essentially in a compact set.  $\rho$  belongs to a r.k.h.s. if exists K(s,t) such that

$$\varrho(s) = \int K(s,t)\varrho(t)dt$$

$$\int \|\phi_i(1) - \phi(s)\|^j \varrho(\phi_i(s)) ds$$
  
=  $\int \|\phi_i(1) - \phi_i(s)\|^j \left\{ \int \mathbb{K}(\phi_i(s), u) \varrho(u) du \right\} ds$   
=  $\int \varrho(u) \cdot \left\{ \int \|\phi_i(1) - \phi_i(s)\|^j \mathbb{K}(\phi_i(s), u) ds \right\} du.$ 

$$L_{i,j}(u) = \int \|\phi_i(1) - \phi_i(s)\|^j \mathbb{K}(\phi_i(s), u) ds.$$

#### Example

Assume  $\rho$  in space of pixels (piecewise constant) Basis functions:

$$\varphi_{i,j}(u) = \begin{cases} 1 & \text{if } u \text{ in voxel } i, j \\ 0 & otherwise. \end{cases}$$

Mercer's Theorem: Reproducing kernel is

$$K(u,v) = \sum_{i,j} \varphi_{i,j}(u) \varphi_{i,j}(v)$$

#### **Example** — continued

Linear functional  $L_{i,j}(u)$  for pixel example:



Observe how "upper part better" determiner. Feature, not bug.

#### What can we learn from this?

Solution lies in  $\mathbb{V}_n = \text{span}\{L_{i,j}(u) \ i = 1, ..., n \ j = 0, 1, 2\}$ 

$$\hat{\varrho}(u) = \sum_{i=1}^{n} \sum_{j=0}^{2} \alpha_{i,j} L_{i,j}(u)$$

Negative result:

The part of  $\rho$  orthogonal to  $\mathbb{V}_n$  CAN NOT BE ESTIMATED.

Pre-data collection analysis.

Can compare estimates using change in angle alone with those using change in angle and displacement.

Study  $\mathbb{V}_n$  and statistical information.

#### **Information and natural basis**

- Want to find basis for span $\{L_{ij}(u)\}$  in increasing difficulty of estimation
- Use characterization to parametrize scattering density  $\rho(u|\alpha) = \sum_{ij} \alpha_{ij} L_{ij}(u)$
- Fisher Information
- Singular value decomposition

## **Reconstruction using pixels**

25 x 25 pixelization Uniform incidence angle

Maximal angle:  $[-\pi/4, \pi/4]$ 



## **Dictionary (angle alone) 1-9**





1

2.59









2.76



3.71



2.17



2.91



# **Dictionary (angle alone) 10-18**



3.89



4.76





Angle only





4.9



5.25



4.53

5.1 18

1.0

0.8

0.6

0.4

0.2

0.0

 $0.0 \quad 0.2 \quad 0.4 \quad 0.6 \quad 0.8 \quad 1.0$ 

# **Dictionary (angle alone) 19-27**



5.68



6.21





6







6.63



6.16

#### **Dictionary (full data) 1-9**



1



2.22





1.4







1.83







#### Dictionary (full data) 10-18



3.5



4.11















3.91



4.51



#### **ML Estimation of GEANT Simulation**









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#### **Real Example**

#### Radiograph of another object



#### **Real Example — reconstruction**

#### Clamp in z-projections



#### Conclusions

Can do nonparametric reconstructions

- Limitation in incidence angle should be avoided
- Value in using all the data
- Can answer: "What can we not recover" and "what is easy to recover" from a given experiment
- Can "see" effective pixel size
- Find dictionary

#### **Thank You**