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# Hard & Soft Fusion in Defence and Security – Discussion of Examples

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1. Tracking-derived Anomaly Detection
2. Extended Objects and Object Clusters
3. Fusion for Security Assistance Systems

**NATO LECTURE SERIES STO IST-155**

**ADVANCED ALGORITHMS FOR EFFECTIVELY  
FUSING HARD AND SOFT INFORMATION**

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# What is the methodological essence of *Multiple Source Object Tracking*?

Learn classified tracks of time-varying objects from uncertain data!

Which object properties are of interest?

Define an *object state* at varying time instants.

Which information is to be fused?

Time series of report data, context information

How to describe imprecise information?

E.g. functions of the state: pdfs, PHDs, intensities

What does “learning” from reports mean?

Iteratively calculate these functions (Bayes!)

What is required for the learning process?

Source and evolution models, data association

How to initiate/terminate object tracks?

Sequential decision making (implicitly, explicitly)

# Elements for Situation Pictures: Tracks of Time-varying Objects

Which object properties are of interest?  $\rightarrow$  **state**  $X_k$  **at time**  $t_k$

- road-moving vehicle: odometer count  $x_k$        $X_k = (x_k, \dot{x}_k)$
- position, speed, acceleration:       $X_k = (\mathbf{r}_k, \dot{\mathbf{r}}_k, \ddot{\mathbf{r}}_k)$
- joint state of several objects:       $X_k = (\mathbf{x}_k^1, \mathbf{x}_k^2, \dots)$
- attributes, e.g. radar cross section  $x_k \in \mathbb{R}^+$ :  $X_k = (\mathbf{x}_k, x_k)$
- maneuvering phase, object class  $i_k \in \mathbb{N}$ :       $X_k = (\mathbf{x}_k, i_k)$

# The general tracking equations

**Prediction**

$$p(X_k|Z^{k-1}) = \int dX_{k-1} \underbrace{p(X_k|X_{k-1})}_{\text{evolution}} \underbrace{p(X_{k-1}|Z^{k-1})}_{\text{filtering } t_{k-1}}$$

**filtering**

$$p(X_k|Z^k) = \frac{p(Z_k|X_k) p(X_k|Z^{k-1})}{\int dX_k \underbrace{p(Z_k|X_k)}_{\text{sensor model}} \underbrace{p(X_k|Z^{k-1})}_{\text{prediction}}}$$

**retrodition**

$$p(X_l|Z^k) = \int dX_{l+1} \frac{\underbrace{p(X_{l+1}|X_l)}_{\text{evolution}} \underbrace{p(X_l|Z^l)}_{\text{filtering } t_l}}{\underbrace{p(X_{l+1}|Z^l)}_{\text{prediction } t_{l+1}}} \underbrace{p(X_{l+1}|Z^k)}_{\text{retrodition } t_{l+1}}$$

# **Anomaly Detection: Part of Situational Awareness**

**Fusing incomplete and imperfect pieces of complementary sensor and context information to focus human decision makers / decision making systems to events requiring special attention or actions.**

**Fusion-based anomaly detection is either unobtainable otherwise or exceeds what can be obtained by single sources in accuracy, reliability, or cost.**

**Here: emphasis on intuitively clear examples; no more general theory on “anomalous behavior”.**

## Key observation in tracking-driven anomaly detection:

The methods of target tracking and data fusion have actually evolved to a mature key technology, but **their full potential** of enabling research and development in maritime situational awareness and anomaly detection **still waits to be realized**.

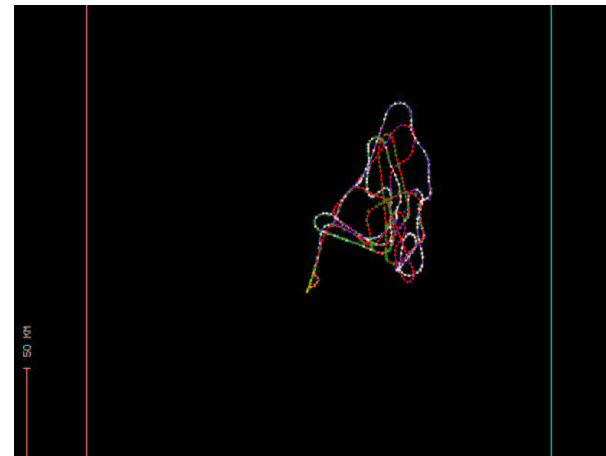
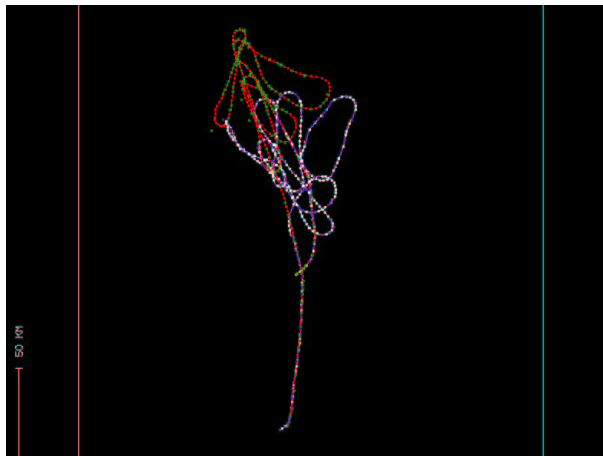
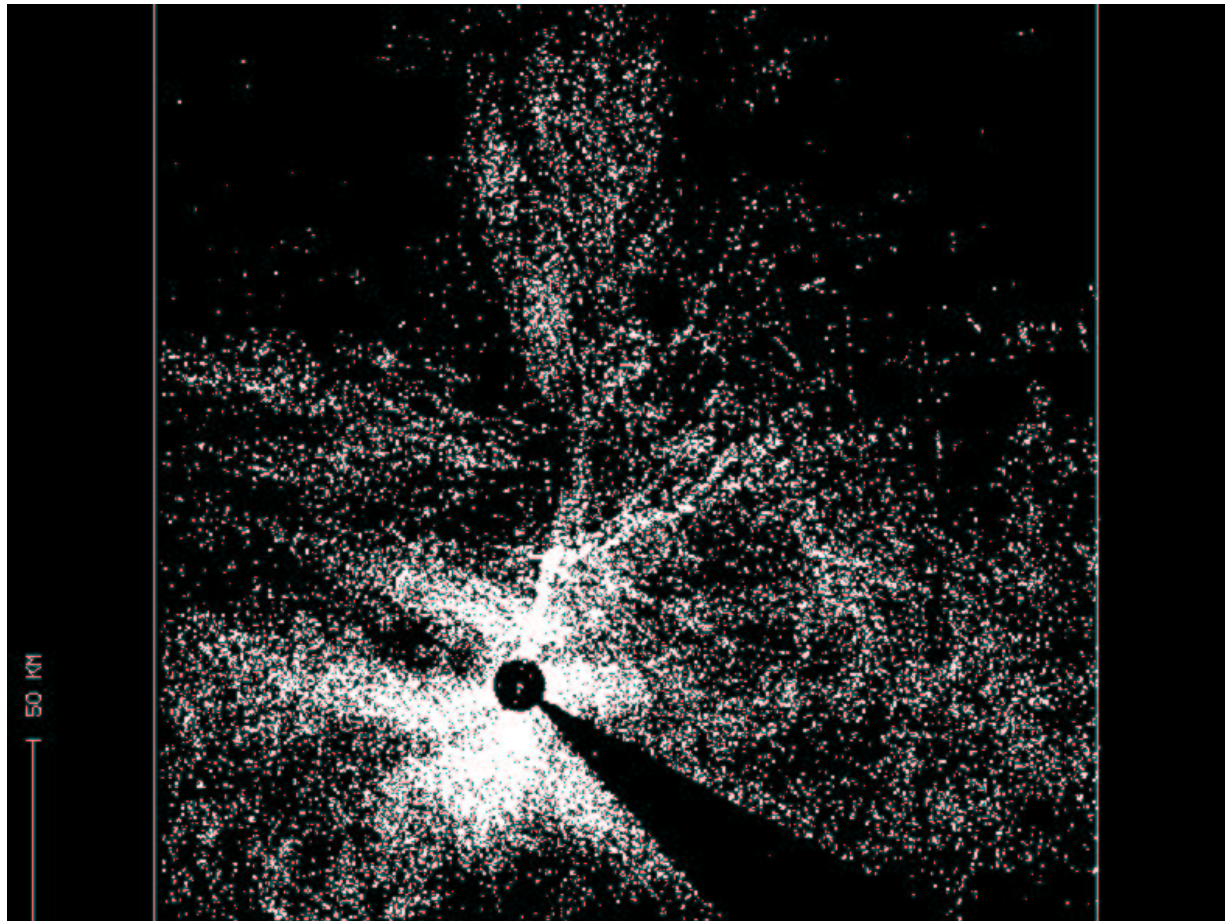
## Promising approach to anomaly detection:

### Tracking-derived Situation Elements

1. Classification-based detection of anomalies
2. Violation of space-time regularity patterns

# Track-based inference of object properties

- **Velocity history:** vehicle, helicopter, plane
- **Acceleration history:** threat: no under-wing weapons
- **Rare events:** truck by night on dirt road near a border
- **Object interrelations:** resulting from formation, convoy
- **Object sources / sinks:** classification by origin / designation
- **Classification:** road-moving vehicle, 'on-road' → 'off-road'





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1. Classification-based detection of anomalies
2. **Violation of space-time regularity patterns**

# Using *time invariant* or *slowly changing* knowledge about the overall behavior

## Space-time regularity patterns: examples

- sea-/air-lanes as motion constraints
- planning information to be obeyed

## Benefit of space-time regularity patterns

- improved the track accuracy/continuity
- pattern violation: 'anomaly' detection

## Tracking-based motion pattern extraction

- generation of context knowledge
- fairly precise, timely information

# On Integrating Planning Information into Tracking

- **space-time waypoints  $\mathcal{W}$  to be passed at given times via particular lanes**
- **tolerances: known error covariance matrices for each waypoint / object**
- **impact of waypoints if plan is kept:  $p(\mathbf{x}_l | \mathcal{W}, \mathcal{Z}^k)$ , “artificial sensor data”**
- **treat sensor data with time stamps before waypoints as “out-of sequence”**
  - **if plan is kept: improved track accuracy / continuity, data association**

# Sequential Anomaly Detection: Pattern Violation

$h_1$ : The observed objects obey an underlying pattern.

$h_0$ : The pattern is not obeyed (e.g. off-lane, unplanned).

characterized by  $P(\text{accept } h_1|h_1)$ ,  $P(\text{accept } h_1|h_0)$ .

Consider the ratio: 
$$\frac{p(h_1|Z^k)}{p(h_0|Z^k)} = \frac{p(Z^k|h_1)}{\underbrace{p(Z^k|h_0)}_{=:LR(k)}} \frac{p(h_1)}{p(h_0)}.$$

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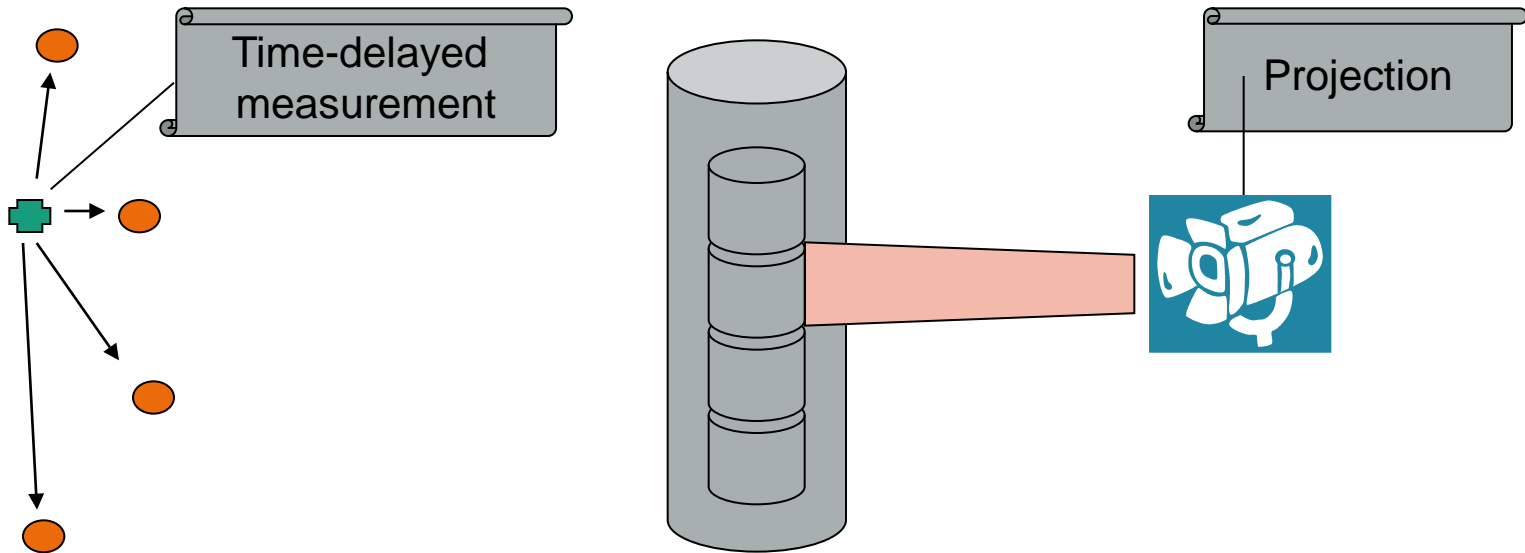
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Calculate  $LR(k)$  iteratively using evolution / sensor models:

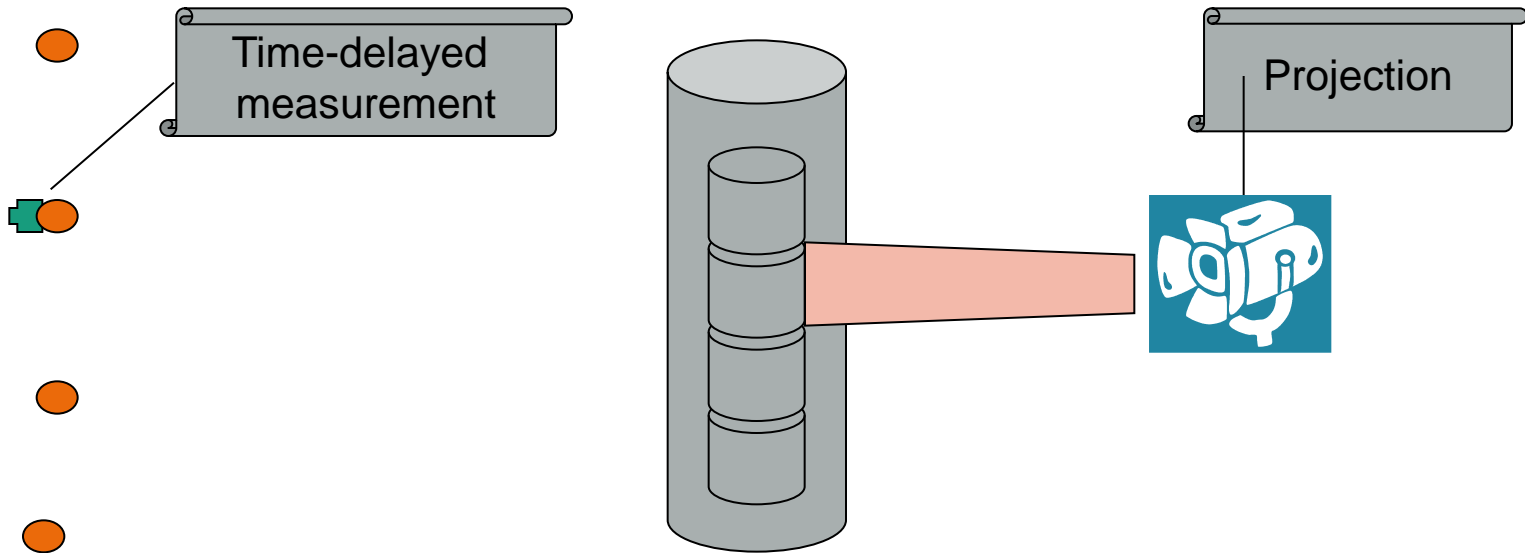
$$LR(k) = \frac{\int d\mathbf{x}_k \overbrace{p(Z_k, m_k|\mathbf{x}_k)}^{\text{likelihood}} \overbrace{p(\mathbf{x}_k|Z^{k-1}, h_1)}^{\text{prediction}}}{\int d\mathbf{x}_k p(Z_k, m_k|\mathbf{x}_k) \underbrace{p(\mathbf{x}_k|Z^{k-1}, h_0)}_{\text{no pattern assumed}}} LR(k-1).$$

Restart: re-confirm “normality” or to detect a violation at last.

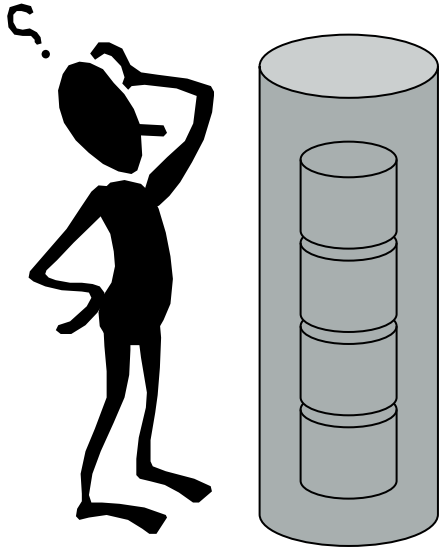
# Accumulated state densities (ASD)



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# ASD – A Joint PDF



In order to calculate the posterior of the joint pdf

$$p(\mathbf{x}_k, \dots, \mathbf{x}_n | Z^k)$$

we define the ASD state as

$$\mathbf{x}_{k:n} = (\mathbf{x}_k, \dots, \mathbf{x}_n)$$

Goal: find a recursive formulation. Let's see ..



$$p(\mathbf{x}_{k:n} | Z^k) = \frac{p(\mathbf{z}_k | \mathbf{x}_{k:n}) p(\mathbf{x}_{k:n} | Z^{k-1})}{\int d\mathbf{x}_{k:n} p(\mathbf{z}_k | \mathbf{x}_{k:n}) p(\mathbf{x}_{k:n} | Z^{k-1})}$$



# Elementary Operations

Elementary operations on this product lead to

$$\begin{aligned} p(\mathbf{x}_{k:n}|Z^k) &= \prod_{l=n}^k \mathcal{N}(\mathbf{\Pi}_l \mathbf{x}_{k:n}; \mathbf{\Pi}_l \mathbf{x}_{k:n|k}, \mathbf{U}_{l|k}) \\ &\propto \prod_{l=n}^k e^{-\frac{1}{2}(\mathbf{\Pi}_l \mathbf{x}_{k:n} - \mathbf{\Pi}_l \mathbf{x}_{k:n|k})^\top \mathbf{U}_{l|k}^{-1} (\mathbf{\Pi}_l \mathbf{x}_{k:n} - \mathbf{\Pi}_l \mathbf{x}_{k:n|k})} \\ &= e^{-\frac{1}{2}(\mathbf{x}_{k:n} - \mathbf{x}_{k:n|k})^\top \left( \sum_{l=n}^k \mathbf{\Pi}_l^\top \mathbf{U}_{l|k}^{-1} \mathbf{\Pi}_l \right) (\mathbf{x}_{k:n} - \mathbf{x}_{k:n|k})} \\ &= \mathcal{N}(\mathbf{x}_{k:n}; \mathbf{x}_{k:n|k}, \mathbf{P}_{k:n|k}) \end{aligned}$$

with an ASD covariance matrix

$$\mathbf{P}_{k:n|k} = \left( \sum_{l=n}^k \mathbf{\Pi}_l^\top \mathbf{U}_{l|k}^{-1} \mathbf{\Pi}_l \right)^{-1}.$$

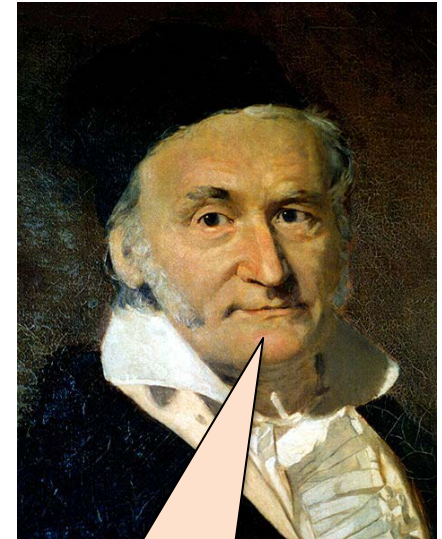
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A Gaussian.  
I knew it.

# The Inverse ASD Covariance Matrix

Summing up yields the inverse covariance matrix:

$$\mathbf{P}_{k:n|k}^{-1} = \begin{pmatrix} \mathbf{T}_{k|k} & -\mathbf{W}_{k-1|k}^\top \mathbf{U}_{k-1|k}^{-1} & \mathbf{O} & \cdots & \mathbf{O} \\ -\mathbf{U}_{k-1|k}^{-1} \mathbf{W}_{k-1|k} & \mathbf{T}_{k-1|k} & -\mathbf{W}_{k-2|k}^\top \mathbf{U}_{k-2|k}^{-1} & \ddots & \vdots \\ \mathbf{O} & -\mathbf{U}_{k-2|k}^{-1} \mathbf{W}_{k-2|k} & \ddots & \ddots & \mathbf{O} \\ \vdots & \ddots & \ddots & \mathbf{T}_{n+1|k} & -\mathbf{W}_{n|k}^\top \mathbf{U}_{n|k} \\ \mathbf{O} & \cdots & \mathbf{O} & -\mathbf{U}_{n|k} \mathbf{W}_{n|k} & \mathbf{T}_{n|k} \end{pmatrix}$$

where

$$\mathbf{T}_{l|k} = \begin{cases} \mathbf{P}_{k|k}^{-1} + \mathbf{W}_{l-1|l}^\top \mathbf{U}_{l-1|k}^{-1} \mathbf{W}_{l-1|l} & \text{for } l = k \\ \mathbf{U}_{l|k}^{-1} + \mathbf{W}_{l-1|l}^\top \mathbf{U}_{l-1|k}^{-1} \mathbf{W}_{l-1|l} & \text{for } n < l < k . \\ \mathbf{U}_{n|k}^{-1} & \text{for } l = n \end{cases}$$

Are we done now?

Not yet – we “only” have to invert this accumulated information matrix.

# ASD Covariance Matrix

Elementary matrix operations yield

$$\mathbf{P}_{k:n|k} = \begin{pmatrix} \mathbf{P}_{k|k} & \mathbf{P}_{k|k} \mathbf{W}_{k-1|k}^\top & \mathbf{P}_{k|k} \mathbf{W}_{k-2|k}^\top & \cdots & \mathbf{P}_{k|k} \mathbf{W}_{n|k}^\top \\ \mathbf{W}_{k-1|k} \mathbf{P}_{k|k} & \mathbf{P}_{k-1|k} & \mathbf{P}_{k-1|k} \mathbf{W}_{k-2|k-1}^\top & * & \mathbf{P}_{k-1|k} \mathbf{W}_{n|k-1}^\top \\ \mathbf{W}_{k-2|k} \mathbf{P}_{k|k} & \mathbf{W}_{k-2|k-1} \mathbf{P}_{k-1|k} & \mathbf{P}_{k-2|k} & * & \vdots \\ \vdots & * & * & * & \mathbf{P}_{n+1|k} \mathbf{W}_{n|n+1}^\top \\ \mathbf{W}_{n|k} \mathbf{P}_{k|k} & \mathbf{W}_{n|k-1} \mathbf{P}_{k-1|k} & \cdots & \mathbf{W}_{n|n+1} \mathbf{P}_{n+1|k} & \mathbf{P}_{n|k} \end{pmatrix}$$

where

$$\mathbf{W}_{l|k} = \prod_{\lambda=l}^{k-1} \mathbf{W}_{\lambda|\lambda+1}$$

# What are the Parameters?

The updated track state is given by

$$\begin{aligned}\mathbf{x}_{k:m:n|k,m} &= \mathbf{x}_{k:m:n|k} + \mathbf{W}_{k:m:n}(\mathbf{z}_m - \mathbf{H}_m \mathbf{\Pi}_m \mathbf{x}_{k:m:n|k}) \\ \mathbf{P}_{k:m:n|k,m} &= \mathbf{P}_{k:m:n|k} - \mathbf{W}_{k:m:n} \mathbf{S}_{k:m:n} \mathbf{W}_{k:m:n}^\top,\end{aligned}$$

where

$$\begin{aligned}\mathbf{S}_{k:m:n} &= \mathbf{H}_m \mathbf{\Pi}_m \mathbf{P}_{k:m:n|k} \mathbf{\Pi}_m^\top \mathbf{H}_m^\top + \mathbf{R}_m \\ \mathbf{W}_{k:m:n} &= \mathbf{P}_{k:m:n|k} \mathbf{\Pi}_m^\top \mathbf{H}_m^\top \mathbf{S}_{k:m:n}^{-1}.\end{aligned}$$

That is the updated state. Finally.



Rudolph E. Kalman

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# **modeling: sensor data produced by extended objects**

- **actual measurement errors of individual scattering centers unimportant**
- **the ‘message’ of individual plots is dominated by the object extension**
- **individual plots to be interpreted as measurements of the object center**
- **related ‘measurement error’ proportional to extension *to be estimated***

# Elements for Situation Pictures: Tracks of Time-varying Objects

Which object properties are of interest?  $\rightarrow$  **state**  $X_k$  **at time**  $t_k$

- road-moving vehicle: odometer count  $x_k$        $X_k = (x_k, \dot{x}_k)$
- position, speed, acceleration:       $X_k = (\mathbf{r}_k, \dot{\mathbf{r}}_k, \ddot{\mathbf{r}}_k)$
- joint state of several objects:       $X_k = (\mathbf{x}_k^1, \mathbf{x}_k^2, \dots)$
- attributes, e.g. radar cross section  $x_k \in \mathbb{R}^+$ :  $X_k = (\mathbf{x}_k, x_k)$
- maneuvering phase, object class  $i_k \in \mathbb{N}$ :       $X_k = (\mathbf{x}_k, i_k)$
- object shape: SPD random matrices  $\mathbf{X}_k$        $X_k = (\mathbf{x}_k, \mathbf{X}_k)$



# extended objects: simplified description

- **kinematical state** at time  $t_k$ :  $\mathbf{x}_k = (\text{position, velocity, } \dots)$
- **object extension** at time  $t_k$ : approximately by an ellipse
- **size**: volume, **shape**: ratio of semi-axes, spatial **orientation**
- extension: **SPD matrix**  $\mathbf{X}_k$  (Symmetric, Positively Definite)

augmented state: kinematical state *vector*  $\mathbf{x}_k$ , extension *matrix*  $\mathbf{X}_k$

# Generalize BAYESian tracking to extended objects.

$n_k$  plots  $Z_k = \{z_k^j\}_{j=1}^{n_k}$  at time  $t_k$ , accumulated data  $\mathcal{Z}^k = \{Z_k, n_k, \mathcal{Z}^{k-1}\}$

The conditional pdf  $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k)$  describes what is known about the extended object state  $\mathbf{x}_k, \mathbf{X}_k$  based on all sensor data up to time  $t_k$ .

‘extended object tracking’: *iterative calculation* of  $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k)$ .

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- $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k) = p(\mathbf{x}_k | \mathbf{X}_k, \mathcal{Z}^k) p(\mathbf{X}_k | \mathcal{Z}^k)$       **extended object ‘track’**
- $p(Z_k, n_k | \mathbf{x}_k, \mathbf{X}_k)$  **sensor output to be processed, i.e. the likelihood**
- $p(\mathbf{x}_k | \mathcal{Z}^k) = \int d\mathbf{X}_k p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k)$  **kinematics of the extended object**

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- $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k) = p(\mathbf{x}_k | \mathbf{X}_k, \mathcal{Z}^k) p(\mathbf{X}_k | \mathcal{Z}^k)$       **extended object ‘track’**

$p(\mathbf{x}_k | \mathbf{X}_k, \mathcal{Z}^k)$  :    **assume Gaussian density**

$p(\mathbf{X}_k | \mathcal{Z}^k)$  :    **assume inverse Wishart density**

# modeling: sensor data produced by extended objects

- actual measurement errors of individual scattering centers unimportant
- the ‘message’ of individual plots is dominated by the object extension
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measurement eq.: 
$$\mathbf{z}_k^j = (h_k^1 \mathbf{I}_d, h_k^2 \mathbf{I}_d, h_k^3 \mathbf{I}_d) \mathbf{x}_k + \mathbf{u}_k, \quad \mathbf{u}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_k)$$
$$= (\mathbf{H}_k \otimes \mathbf{I}_d) \mathbf{x}_k + \mathbf{u}_k$$

simple example:  $\mathbf{H}_k = (1, 0, 0)$  (position measurement)

measurement error:  $\mathbf{R}_k \propto \mathbf{X}_k$  *unknown!*

# Excursus: Properties of Kronecker products (1/3)

The Kronecker product  $\mathbf{A} \otimes \mathbf{B}$  of two matrices

$\mathbf{A} = (a_{ij})_{i=1, j=1}^{m, n}$ ,  $\mathbf{B}$  is defined by:

$$\mathbf{A} \otimes \mathbf{B} = \begin{pmatrix} a_{11}\mathbf{B} & a_{12}\mathbf{B} & \cdots & a_{1n}\mathbf{B} \\ a_{21}\mathbf{B} & a_{22}\mathbf{B} & \cdots & a_{2n}\mathbf{B} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1}\mathbf{B} & a_{m2}\mathbf{B} & \cdots & a_{mn}\mathbf{B} \end{pmatrix}.$$

# Excursus: Properties of Kronecker products (2/3)

For matrices  $A$ ,  $B$ ,  $C$  and a scalar  $\alpha$ :

$$(A \otimes B) \otimes C = A \otimes (B \otimes C)$$

$$\alpha \otimes A = \alpha A = A \alpha = A \otimes \alpha$$

$$(A \otimes B)(C \otimes D) = AC \otimes BD$$

$$(A \otimes B)^\top = A^\top \otimes B^\top$$

$$(A \otimes B)^{-1} = A^{-1} \otimes B^{-1}.$$

# Excursus: Properties of Kronecker products (3/3)

For quadratic matrices  $A, B$  we obtain:

$$\text{tr}[A \otimes B] = (\text{tr}A) (\text{tr}B).$$

The determinant of  $A \otimes B$  is given by the determinants of  $A, B$

with  $m = \dim(A)$ ,  $n = \dim(B)$ :

$$|A \otimes B| = |A|^n |B|^m.$$



# modeling: 'collective' kinematics of extended objects

**kinematics:**  $\mathbf{x}_k = \left( \mathbf{r}_k^\top, \dot{\mathbf{r}}_k^\top, \ddot{\mathbf{r}}_k^\top \right)^\top, \quad d = \dim(\mathbf{r}_k), \dim(\mathbf{X}_k) = d \times d$

**temporal evolution:**  $\mathbf{x}_k = \Phi_{k|k-1} \mathbf{x}_{k-1} + \mathbf{v}_k, \quad \mathbf{v}_k \sim \mathcal{N}(\mathbf{o}, \Delta_{k|k-1})$

**evolution matrix:**  $\Phi_{k|k-1} = \begin{pmatrix} \mathbf{I}_d & \Delta t_k \mathbf{I}_d & \frac{1}{2} \Delta t_k^2 \mathbf{I}_d \\ \mathbf{O}_d & \mathbf{I}_d & \Delta t_k \mathbf{I}_d \\ \mathbf{O}_d & \mathbf{O}_d & e^{-\Delta t_k / \theta} \mathbf{I}_d \end{pmatrix} = \mathbf{F}_{k|k-1} \otimes \mathbf{I}_d$

**plant noise:**  $\Delta_{k|k-1} = \mathbf{D}_{k|k-1} \otimes \mathbf{X}_k$

**important assumption!**

# plant noise covariance $\mathbf{D}_{k|k-1} \otimes \mathbf{X}_k$ : discussion of its structure

- **formal argument:**

- assuming this structure, there exists a mutually *conjugate pair* of pdfs  $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^{k-1})$  and  $p(Z_k, n_k | \mathbf{x}_k, \mathbf{X}_k)$ ; i.e.  $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k)$  belongs to the same family as  $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^{k-1}) \Rightarrow$  **analytical update equations!**

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- **practical arguments:**

- Trajectories of group targets are the predictable, i.e. the inertial, the smaller their extension: ‘maneuvering becomes dangerous’.
- The larger a formation/convoy, the more probable are ‘split-off’ maneuvers; ‘large’ prediction covariances take this into account.
- Large target groups/object swarms produce so many measurements that the prediction step becomes unimportant compared to filtering.

# prediction: kinematical state, object extension matrix

$$p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^{k-1}) = \underbrace{p(\mathbf{x}_k | \mathbf{X}_k, \mathcal{Z}^{k-1})}_{\text{vector variate}} \underbrace{p(\mathbf{X}_k | \mathcal{Z}^{k-1})}_{\text{matrix variate}}$$

track structure at time  $t_{k-1}$   $p(\mathbf{x}_{k-1} | \mathbf{X}_k, \mathcal{Z}^{k-1}) = \mathcal{N}(\mathbf{x}_{k-1}; \mathbf{x}_{k-1|k-1}, \mathbf{P}_{k-1|k-1} \otimes \mathbf{X}_k)$

is preserved after prediction to  $t_k$ :  $p(\mathbf{x}_k | \mathbf{X}_k, \mathcal{Z}^{k-1}) = \mathcal{N}(\mathbf{x}_k; \mathbf{x}_{k|k-1}, \mathbf{P}_{k|k-1} \otimes \mathbf{X}_k)$

with:  $\mathbf{x}_{k|k-1} = (\mathbf{F}_{k|k-1} \otimes \mathbf{I}_d) \mathbf{x}_{k-1|k-1}$ ,  $\mathbf{P}_{k|k-1} = \mathbf{F}_{k|k-1} \mathbf{P}_{k-1|k-1} \mathbf{F}_{k|k-1}^\top + \mathbf{D}_{k|k-1}$  **KALMAN type prediction**

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**Assume for  $p(\mathbf{X}_k | \mathcal{Z}^{k-1})$  and  $p(\mathbf{X}_k | \mathcal{Z}^k)$  *inverse WISHART densities*:**

$$p(\mathbf{X}_k | \mathcal{Z}^{k-1}) = \mathcal{IW}(\mathbf{X}_k; \nu_{k|k-1}, \mathbf{X}_{k|k-1}) \propto |\mathbf{X}_k|^{-\frac{\nu_{k|k-1} + d + 1}{2}} \text{etr}\left[-\frac{1}{2} \mathbf{X}_{k|k-1} \mathbf{X}_k^{-1}\right].$$

$$\mathbb{E}[\mathbf{X}_k] = \frac{\mathbf{X}_{k|k-1}}{\nu_{k|k-1} - d - 1}, \quad \text{etr}[\mathbf{A}] = \exp[\text{tr} \mathbf{A}], \quad |\mathbf{A}| = \det \mathbf{A}$$

**Calculate  $\nu_{k|k-1}$ ,  $\mathbf{X}_{k|k-1}$  from  $\nu_{k-1|k-1}$ ,  $\mathbf{X}_{k-1|k-1}$  (i.e. the filtering)!**

# structure of the measurement likelihood function

in general:  $p(Z_k, n_k | \mathbf{x}_k, \mathbf{X}_k, \mathcal{Z}^{k-1}) = p(Z_k | n_k, \mathbf{x}_k, \mathbf{X}_k) p(n_k | \mathbf{x}_k, \mathbf{X}_k)$

at present: no false returns, unresolved measurements are allowed.

$$p(Z_k | n_k, \mathbf{x}_k, \mathbf{X}_k) = \prod_{j=1}^{n_k} \mathcal{N}(\mathbf{z}_k^j; (\mathbf{H}_k \otimes \mathbf{I}_d)\mathbf{x}_k, \mathbf{X}_k) \quad (\text{independent plots})$$
$$\propto \mathcal{N}(\mathbf{z}_k; (\mathbf{H}_k \otimes \mathbf{I}_d)\mathbf{x}_k, \frac{1}{n_k}\mathbf{X}_k) \mathcal{LW}(\mathbf{Z}_k; n_k - 1, \mathbf{X}_k)$$

$$\mathbf{z}_k = \frac{1}{n_k} \sum_{j=1}^{n_k} \mathbf{z}_k^j, \quad \mathbf{Z}_k = \sum_{j=1}^{n_k} (\mathbf{z}_k^j - \mathbf{z}_k)(\mathbf{z}_k^j - \mathbf{z}_k)^\top$$

$$\mathcal{LW}(\mathbf{Z}_k; n_k - 1, \mathbf{X}_k) = |\mathbf{X}_k|^{-\frac{n_k-1}{2}} \text{etr}\left[-\frac{1}{2}\mathbf{Z}_k\mathbf{X}_k^{-1}\right]$$

## structure of joint state pdf after the filtering step

$$\begin{aligned}
 \text{exploiting BAYES: } & p(Z_k | n_k, \mathbf{x}_k, \mathbf{X}_k) p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^{k-1}) \propto \underbrace{\mathcal{N}(\mathbf{x}_k; \mathbf{x}_{k|k}, \mathbf{P}_{k|k} \otimes \mathbf{X}_k)}_{\text{KALMAN type update}} \\
 & \times \underbrace{|\mathbf{X}_k|^{-\frac{1}{2}} \text{etr}\left[-\frac{1}{2} \mathbf{N}_{k|k-1} \mathbf{X}_k^{-1}\right]}_{\text{innovation factor}} \underbrace{\mathcal{LW}(\mathbf{Z}_k; n_k - 1, \mathbf{X}_k)}_{\text{from measurement likelihood}} \underbrace{\mathcal{IW}(\mathbf{X}_k; \nu_{k|k-1}, \mathbf{X}_{k|k-1})}_{\text{extension prediction}}
 \end{aligned}$$

up to a factor independent of  $\mathbf{x}_k, \mathbf{X}_k$  with *innovation matrix*  $\mathbf{N}_{k|k-1}$  and innov. cov.  $S_{k|k-1}$ :

$$\mathbf{N}_{k|k-1} = S_{k|k-1}^{-1} (\mathbf{z}_k - (\mathbf{H}_k \otimes \mathbf{I}_d) \mathbf{x}_{k|k-1}) (\mathbf{z}_k - (\mathbf{H}_k \otimes \mathbf{I}_d) \mathbf{x}_{k|k-1})^\top$$

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 \text{exploiting BAYES: } & p(Z_k | n_k, \mathbf{x}_k, \mathbf{X}_k) p(\mathbf{x}_k, \mathbf{X}_k | \mathbf{Z}^{k-1}) \propto \underbrace{\mathcal{N}(\mathbf{x}_k; \mathbf{x}_{k|k}, \mathbf{P}_{k|k} \otimes \mathbf{X}_k)}_{\text{KALMAN type update}} \\
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$$\text{finally: } p(Z_k | n_k, \mathbf{x}_k, \mathbf{X}_k) p(\mathbf{x}_k, \mathbf{X}_k | \mathbf{Z}^{k-1}) \propto \underbrace{\mathcal{N}(\mathbf{x}_k; \mathbf{x}_{k|k}, \mathbf{P}_{k|k} \otimes \mathbf{X}_k)}_{\text{KALMAN type update}} \underbrace{\mathcal{IW}(\mathbf{X}_k; \nu_{k|k}, \mathbf{X}_{k|k})}_{\text{extension update}}$$

$$\text{with simple update equations: } \mathbf{X}_{k|k} = \mathbf{X}_{k|k-1} + \mathbf{N}_{k|k-1} + \mathbf{Z}_k, \quad \nu_{k|k} = \nu_{k|k-1} + n_k.$$

*remark:* due to the innovation matrix  $\mathbf{N}_{k|k-1}$  also in case of point targets the estimation of an unknown measurement error is possible or the ‘extension’ of an unresolved target group.



## marginalization of the joint density $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k)$

sometimes: interest in estimates of the kinematical state  $\mathbf{x}_k$  only

$$\begin{aligned} p(\mathbf{x}_k | \mathcal{Z}_k) &= \int d\mathbf{X}_k p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k) \\ &= \int d\mathbf{X}_k \mathcal{N}(\mathbf{x}_k; \mathbf{x}_{k|k}, \mathbf{P}_{k|k} \otimes \mathbf{X}_k) \mathcal{IW}(\mathbf{X}_k; \nu_{k|k}, \mathbf{X}_{k|k}) \end{aligned}$$

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**multivariate Student-*t*-density** with  $\nu_{k|k}$  degrees of freedom

basis for kinematical state estimates with related error covariance matrices,  
calculation of expectation gates, extended object track-to-track correlation/fusion, ...

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# Hard & Soft Fusion in Defence and Security – Discussion of Examples

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1. Tracking-derived Anomaly Detection
2. Extended Objects and Object Clusters
3. Fusion for Security Assistance Systems

**NATO LECTURE SERIES STO IST-155**

**ADVANCED ALGORITHMS FOR EFFECTIVELY  
FUSING HARD AND SOFT INFORMATION**

**Wolfgang Koch**

Priv.-Doz. Dr. rer. nat., FIEEE  
Fraunhofer FKIE, Wachtberg

# How can “security” be provided?

A parallel: insurance industry ↔ security “industry”

“Security” by mitigating financial risks of individuals by *contributions by many*:

→ statistics, informatics

Insurance industry is a highly important economic factor.

Insurance **law**: highly developed field of law with significant societal and economic impact.

“Security”: mitigating **risks** by threat recognition from *uncertain information*:

→ statistics, informatics

Public security: growth market  
BMW study: 15 B€ in 2016

Emerging security **law**: supervise Security technology on behalf of liberality and individual rights

# On the Notion of “Public Security”

**Public Security.** The notion of P. S. comprises the integrity of the ... fundamental institutions ... of the state as well as the integrity of health, honor, freedom, property, and related objects of legal protection of its citizens. Defense against endangerments of P. S. is the task of public security authorities.

*Rechtswörterbuch.* Hrsg.: C. Creifelds, K. Weber, C.-H. Beck, 2007

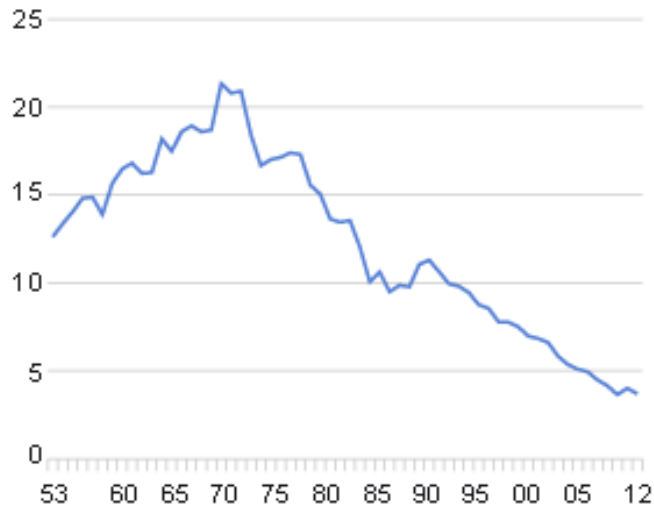
## Danger defense for P. S.: profound transformations

- Omnipresence of networks of surveillance sensors
- Algorithms of sensor data fusion: „Cognitive Tools“

**High-quality information from streams of uncertain data!**

# Excursus: “Physical Integrity” of the Citizens

Traffic Deaths: Germany [thousand]



traffic deaths 2012: 28,000 (EU), 1,2 Mio. (global)

Actually, the state should forbid cars.

But: mobility is a desirable good.

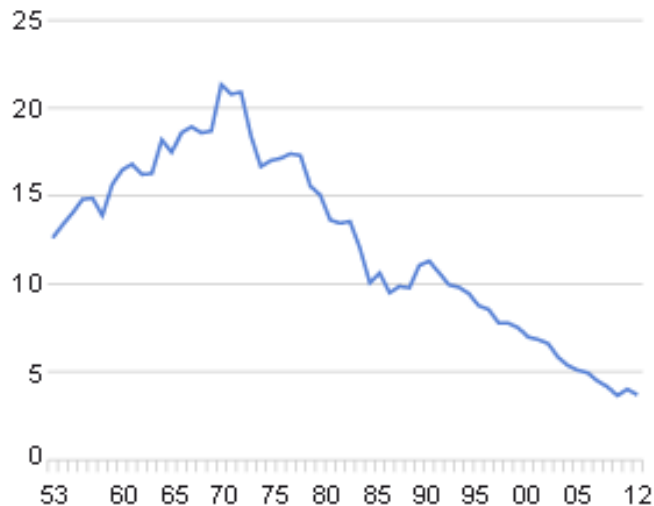
- **Technology:** inspection, robust car body, belts, airbags, ...
- **Law:** traffic regulations, obligatory belts, no phones, ...
- **Insurance:** damages may exceed individual fortunes

Analogously for risk technologies (nuclear plants)

**Obviously effective!**

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Analogously for risk technologies (nuclear plants)

Obviously effective!



11. 09. 2001, USA: 2,976 †

11. 03. 2004, Madrid: 191 †

07. 07. 2005, London: 56 †

**Governmental duty:**

**Prevent terror attacks!**

Liberality, privacy, ... are (highly!) desired goods.

Why not similarly unexcited actions  
(**technology, laws, insurance, ...**)?



## Example: Hazardous Material in Public Infrastructures

- rare events, large damage
- many persons involved
- complex surveillance task

Responsibility with human beings  
New profession: **security personnel**

## Security Assistance Systems: **Focus attention!**

- Mitigate operator fatigue
- Constant quality standards
- Exploit new information sources
- Space for human expertise



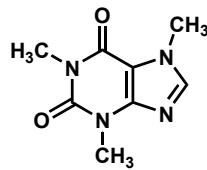
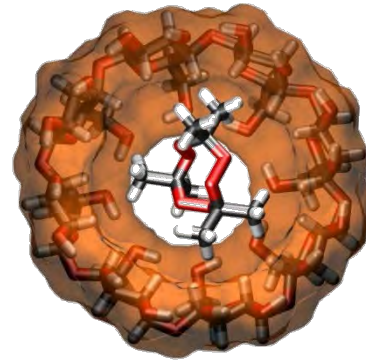
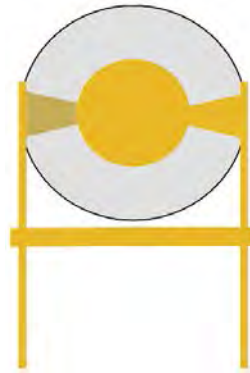
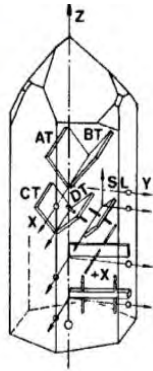


# Security Assistance Systems: Basic Elements

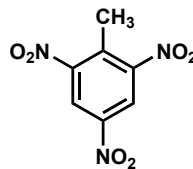
- Disburden from routine and mass tasks → room for human expertise
- Assistance: focus attention to potential threats, hazards.
  
- Permanent operation without disturbing or annoying public life.
- Informational self-determination, privacy: threat-relevant data only.
  
- Exploit “artificial sense organs” (sensors) for detecting anomalies.
- An **informatics topic**: “fuse” sensor data and context information.
  - Sensor technology, communications, data bases, processing power
  - intelligent exploitation algorithms, interface to human decision makers
  
- Combine the strengths of automated and human data exploitation.
  - real-time analysis of vast sensor data streams with constant quality
  - high decision competence in individual situations, expert knowledge

# Which Classes of Sensors may be Considered?

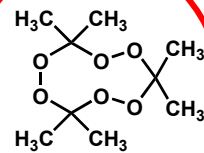
ONE Example: Quartz Micro-Balances (QMB) as “artificial noses”



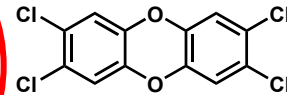
caffeine



TNT



TATP



TCDD

Prof. Dr. S. Waldvogel  
Kekulé Institute for  
Organic Chemistry  
and Biochemistry

„Home-made explosive“: triacetone triperoxide: **measure frequency differences.**



Interdisziplinäres Projekt: Fraunhofer FKIE, Bonn University (Chemistry, Informatics IV):  
Low-cost Hazardous Material Sensors based on Quartz Micro-Balances

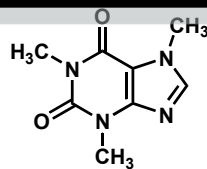
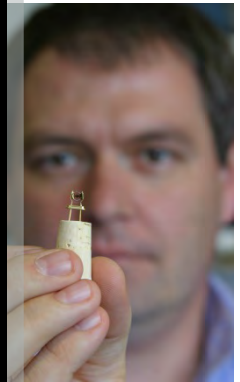
# Which Classes of Sensors may be Considered?

ONE Example: Quartz Micro-Balances (QMB) as “artificial noses”

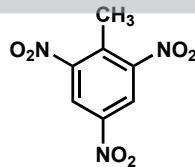
A fundamental problem: **space-time resolution!**

How to associate hazardous material signatures to an individual, a good?

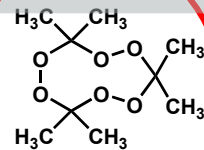
*relevant also for bio / radioactivity sensors (CBRNE)*



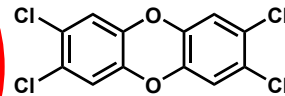
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Prof. Dr. S. Waldvogel  
Kekulé Institute for  
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„Home-made explosive“: triacetone triperoxide: **measure frequency differences.**



**Interdisziplinäres Projekt:** Fraunhofer FKIE, Bonn University (Chemistry, Informatics IV):  
*Low-cost Hazardous Material Sensors based on Quartz Micro-Balances*



**Reduction of complexity:  
Well-defined access areas.**



**A space-time approach:**

- Spanning a temporal basis
- Spatially distributed sensors



# Security Applications: **Well-defined** Access Regions.

**Task:** Detect persons carrying hazardous materials in a person flow.

Escalators / Stairways



Tunnels / Underground



**Problem:** limited **spatio-temporal resolution** of chemical sensors

**Solution:** compensate poor resolution by space-time data fusion

**Track Extraction / Maintenance**

Laser-Range-Scanner Sensors

**Video Data**

Supporting Information

**Attributes**

Chemical Sensors



**EU Project HAMLeT: Hazardous Material Localization and Person Tracking**

# What is the methodological essence of *Multiple Source Object Tracking*?

Learn classified tracks of time-varying objects from uncertain data!

Which object properties are of interest?

Define an *object state* at varying time instants.

Which information is to be fused?

Time series of report data, context information

How to describe imprecise information?

E.g. functions of the state: pdfs, PHDs, intensities

What does “learning” from reports mean?

Iteratively calculate these functions (Bayes!)

What is required for the learning process?

Source and evolution models, data association

How to initiate/terminate object tracks?

Sequential decision making (implicitly, explicitly)

# Data Augmentation Methods: Basic Idea

**wanted:** statements about a quantity  $\mathcal{X}$  provided measurements  $\mathcal{Z}$  are given.

**known:** all available knowledge about  $\mathcal{X}$  is represented by the pdf  $p(\mathcal{X}|\mathcal{Z})$ .

**problem:** the calculation of the probability density  $p(\mathcal{X}|\mathcal{Z})$  can be rather difficult.

**observation:**  $p(\mathcal{X}|\mathcal{A}, \mathcal{Z})$  assuming additional information  $\mathcal{A}$  may be available.

**trick:** use the augmented pdf  $p(\mathcal{X}|\mathcal{A}, \mathcal{Z})$  to calculate characteristics of  $p(\mathcal{X}|\mathcal{Z})$ .

**EM algorithm :** a practical realization of the concept.

iterative localization of a *posterior mode*

**Expectation**

$\mathcal{X}^l, \mathcal{P}^l$  current estimate related to  $p(\mathcal{X}|\mathcal{Z})$ ; initialization!

$$Q(\mathcal{X}; \mathcal{X}^l, \mathcal{P}^l) = \int_{\text{dom}_{\mathcal{A}}} d\mathcal{A} \log[p(\mathcal{X}|\mathcal{A}, \mathcal{Z})]p(\mathcal{A}|\mathcal{X}^l, \mathcal{P}^l, \mathcal{Z})$$

**Maximization**

$$\mathcal{X}^{l+1} = \operatorname{argmax}_{\mathcal{X}} Q(\mathcal{X}; \mathcal{X}^l, \mathcal{P}^l), \quad p(\mathcal{X}^{l+1}|\mathcal{Z}) > p(\mathcal{X}^l|\mathcal{Z})$$

iterate until  $|Q(\mathcal{X}^{l+1}; \mathcal{X}^l, \mathcal{P}^l) - Q(\mathcal{X}^l; \mathcal{X}^l, \mathcal{P}^l)| < \epsilon$

# Extended Target Tracking Filter

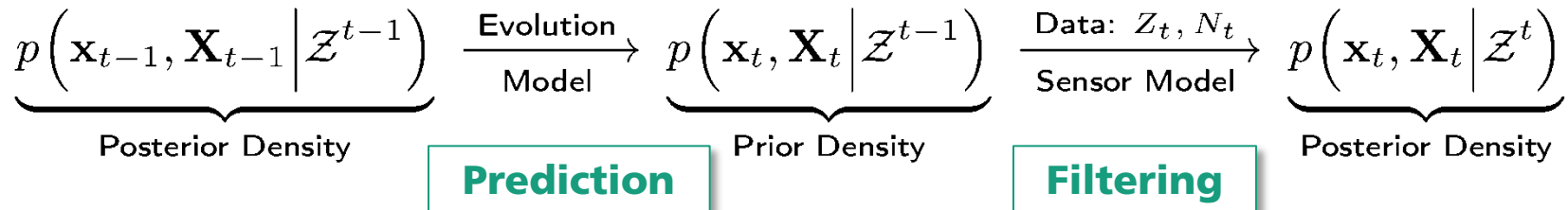
## Bayesian Extended Target Filter using Random Matrices [Koch 2008]

Application of the Bayesian Formalism yields:

$$\begin{aligned}
 p(\mathbf{x}_t, \mathbf{X}_t | \mathcal{Z}^t) &= p(\mathbf{x}_t | \mathbf{X}_t, \mathcal{Z}^t) p(\mathbf{X}_t | \mathcal{Z}^t) \\
 &= \mathcal{N}(\mathbf{x}_t; \mathbf{x}_{t|t}, \mathbf{P}_{t|t} \otimes \mathbf{X}_t) \mathcal{IW}(\mathbf{X}_t; \zeta_{t|t}, \mathbf{X}_{t|t})
 \end{aligned}$$



### Iterative Update Scheme for the Joint State of a **Single Target**



**Closure Property** of Wishart + Inverted Wishart Densities under Multiplication  $\Rightarrow$  Principle of Conjugate Priors



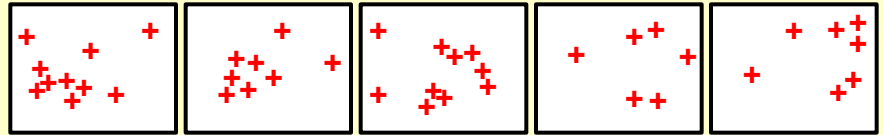
# PMHT for Extended Objects: EM Modeling [Wieneke, Koch 2012]

## Multiple Extended Target Tracking as Maximization Problem

**Given:** Sequence of Measurements comprising Noise and Target Data

$$\mathcal{Z} = [Z_t]_{t=1}^T$$

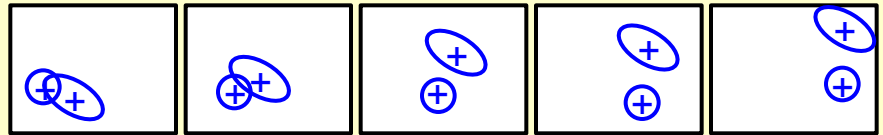
$Z_t \equiv$  Data at scan  $t$



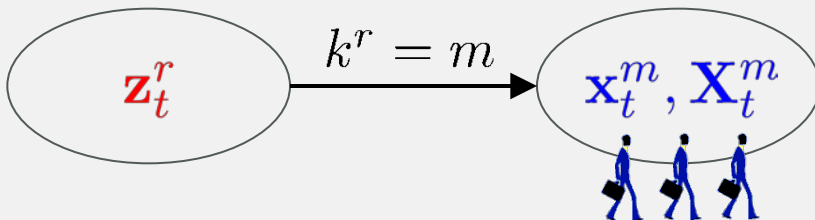
**Wanted:** Sequences of **Joint Target States** (kinematics, extents)

$$\mathcal{X} = [X_t]_{t=1}^T$$

$$X_t = [\mathbf{x}_t^m, \mathbf{X}_t^m]_{m=1}^M$$



**Unknown:** Assignments



**Problem to solve:**

$$\arg \max_{\mathcal{X}} p(\mathcal{X} | \mathcal{Z})$$

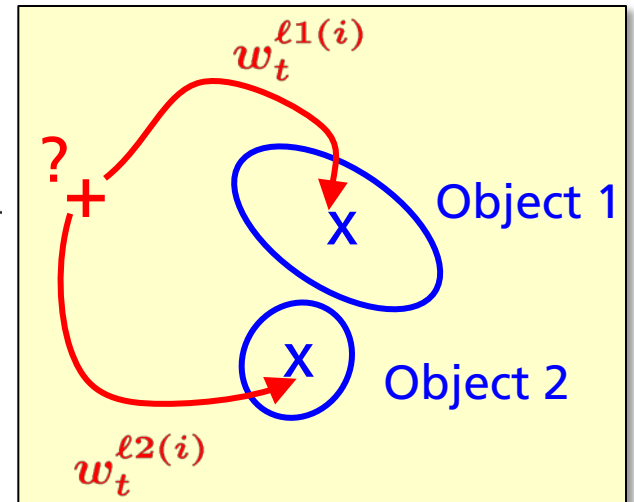
**Apply:** Expectation-Maximization (EM)

# PMHT for Extended Targets: Assignments

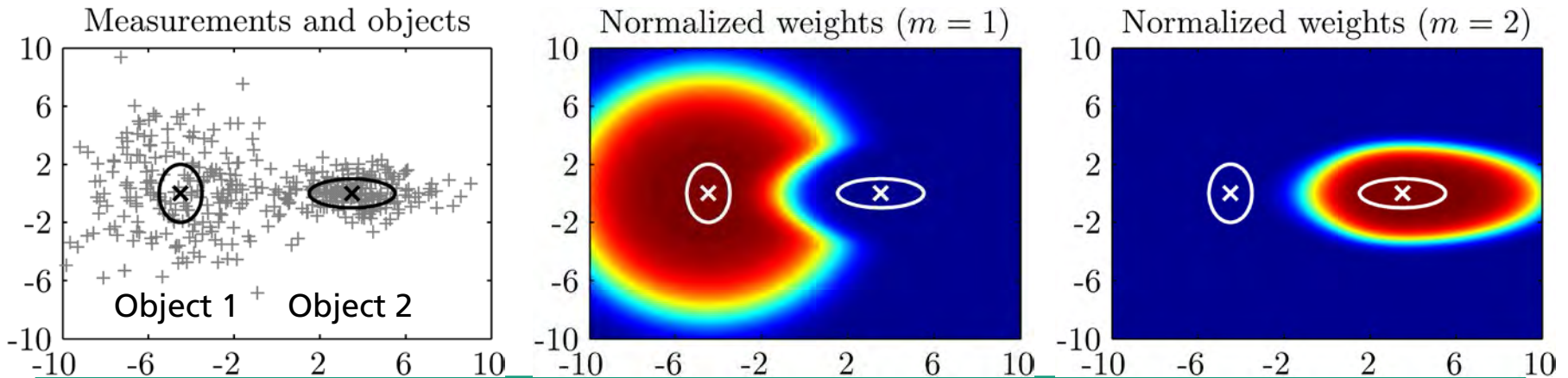
**E-Step:** Compute Assignment Probabilities

$$w_t^{rm(i)} = \frac{\pi_t^{m(i)} \mathcal{N}(\mathbf{z}_t^r; \mathbf{H}\mathbf{x}_t^{m(i)}, \mathbf{X}_t^{m(i)} + \mathbf{R})}{\sum_{m'=0}^M \pi_t^{m'(i)} \mathcal{N}(\mathbf{z}_t^r; \mathbf{H}\mathbf{x}_t^{m'(i)}, \mathbf{X}_t^{m'(i)} + \mathbf{R})}$$

Dependent on Extent Estimate



Example with two Gaussian-Shaped Objects

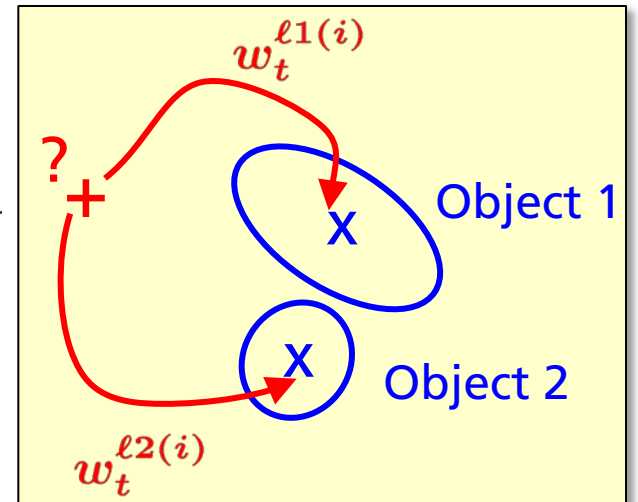


# Complete PMHT-E Iteration

**E-Step:** Compute Assignment Probabilities

$$w_t^{rm(i)} = \frac{\pi_t^{m(i)} \mathcal{N}\left(\mathbf{z}_t^r; \mathbf{H}\mathbf{x}_t^{m(i)}, \mathbf{X}_t^{m(i)} + \mathbf{R}\right)}{\sum_{m'=0}^M \pi_t^{m'(i)} \mathcal{N}\left(\mathbf{z}_t^r; \mathbf{H}\mathbf{x}_t^{m'(i)}, \mathbf{X}_t^{m'(i)} + \mathbf{R}\right)}$$

Dependent on Extent Estimate



## M-Step: Optimize State Estimates

1. Run a **Bank of M Bayesian Extended Target Filters** (one per Target) using Synthetic Measurements and Spread Matrices

Result:  $\left[ \mathbf{x}_1^{m(i+1)}, \dots, \mathbf{x}_T^{m(i+1)} \right], \left[ \mathbf{X}_1^{m(i+1)}, \dots, \mathbf{X}_T^{m(i+1)} \right] \forall m$

2. Update **Mixing Proportions** for each Target

Result:  $\left[ \pi_1^{m(i+1)}, \dots, \pi_T^{m(i+1)} \right] \forall m$



## Given

Kinematic States of the observed Persons






$$\mathcal{X} = \mathcal{X}_{1:T} = \left\{ \left\{ \mathbf{x}_t^1, \dots, \mathbf{x}_t^S \right\}_{t=1}^T \right.$$


Attribute-Output  $\mathbf{o}_t^{\text{ch}}$  of the Chemo-Sensors,  $\text{ch} \in [1 : 5]$

$$\mathbf{o}_t^{\text{ch}} \in \left\{ \text{green}, \text{yellow}, \text{orange}, \text{red}, \text{dark red} \right\} \quad t \in [1 : T]$$

## Wanted

Classification Matrix  $C \in [0, 1]^{5 \times S}$

		1	2	3	← Persons
Alert Levels	No Alert 				
	Alert I 				
	Alert II 				
	Alert III 				
	Alert IV 				

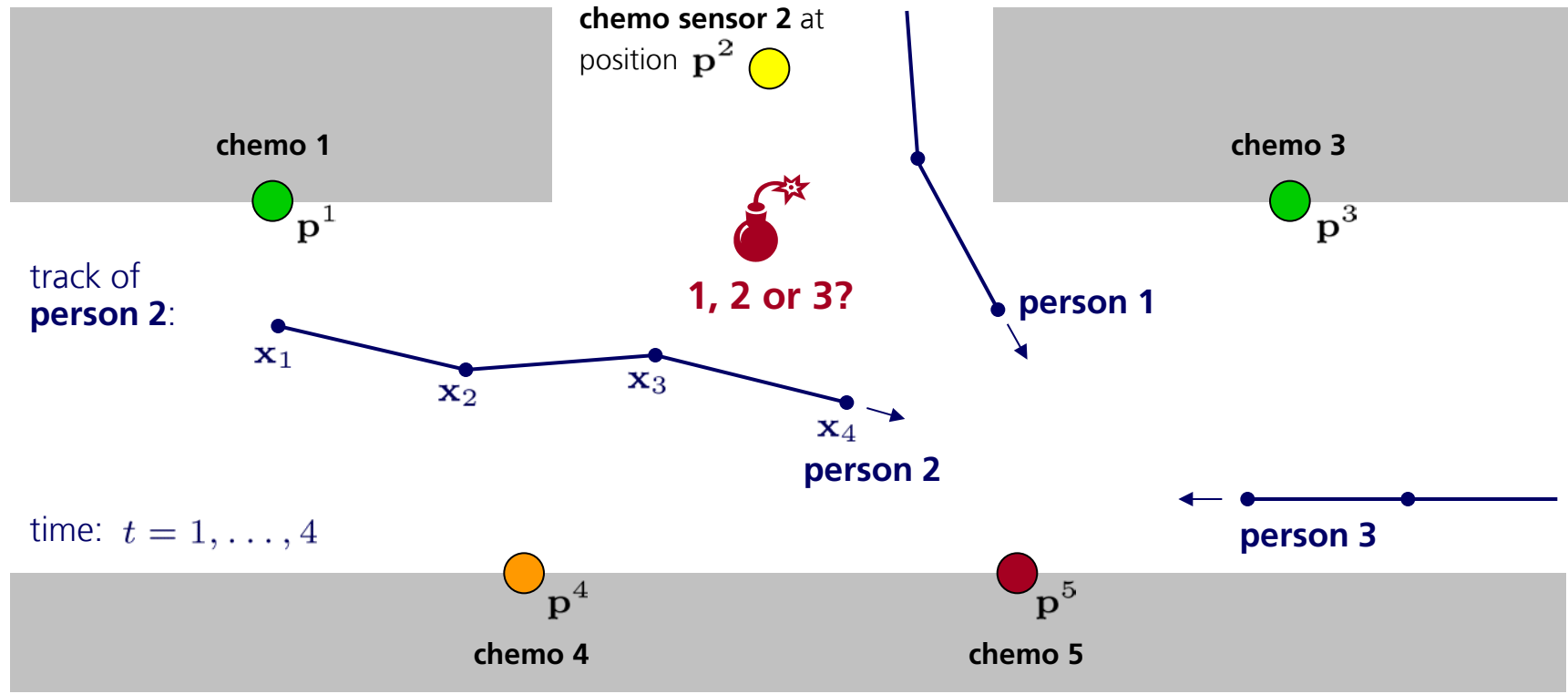
Probability that Person 3 has Attribute 

# Classification problem: Who is carrying the bomb?

Fuse all position & signature measurements over space & time!

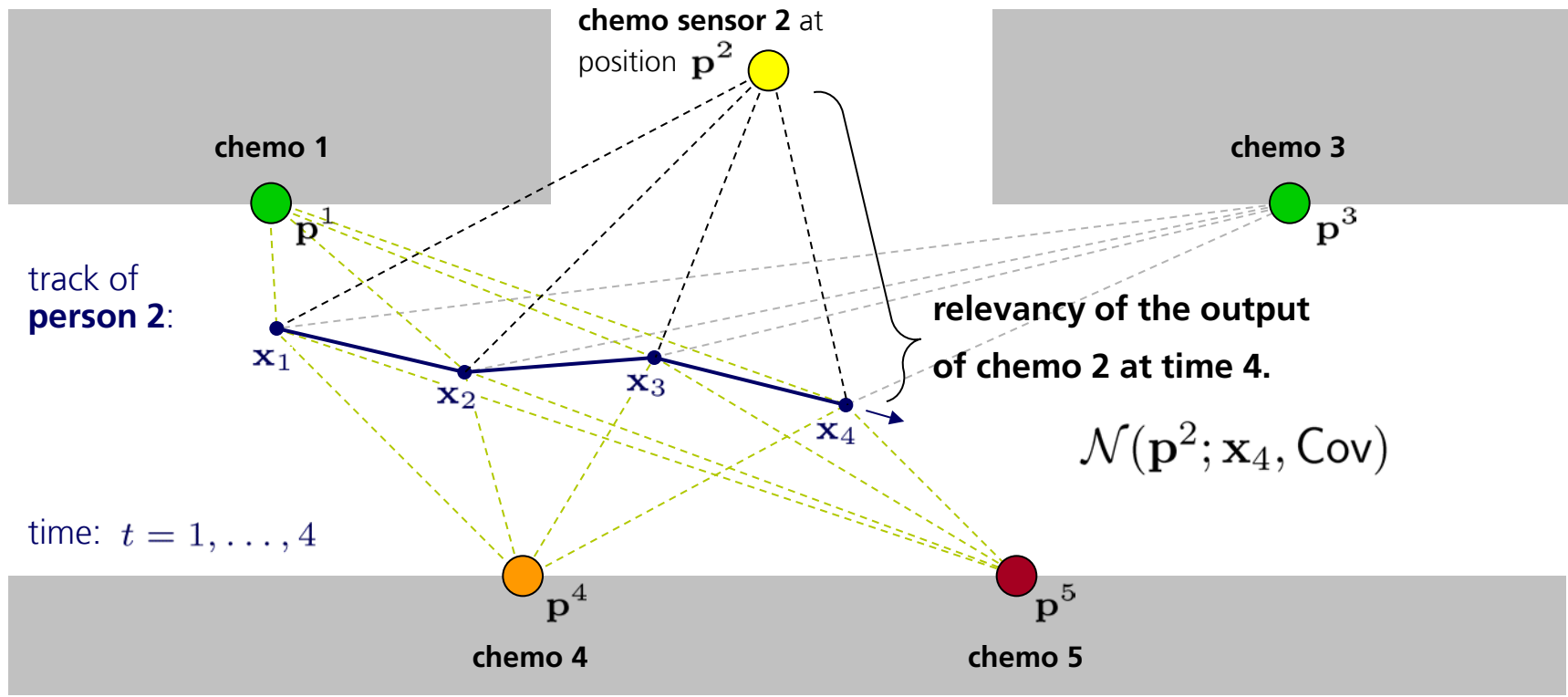
**Position measurements:** reconstruction of the kinematic behaviour

**CBRNE signatures:** low space-time resolution → non-trivial association



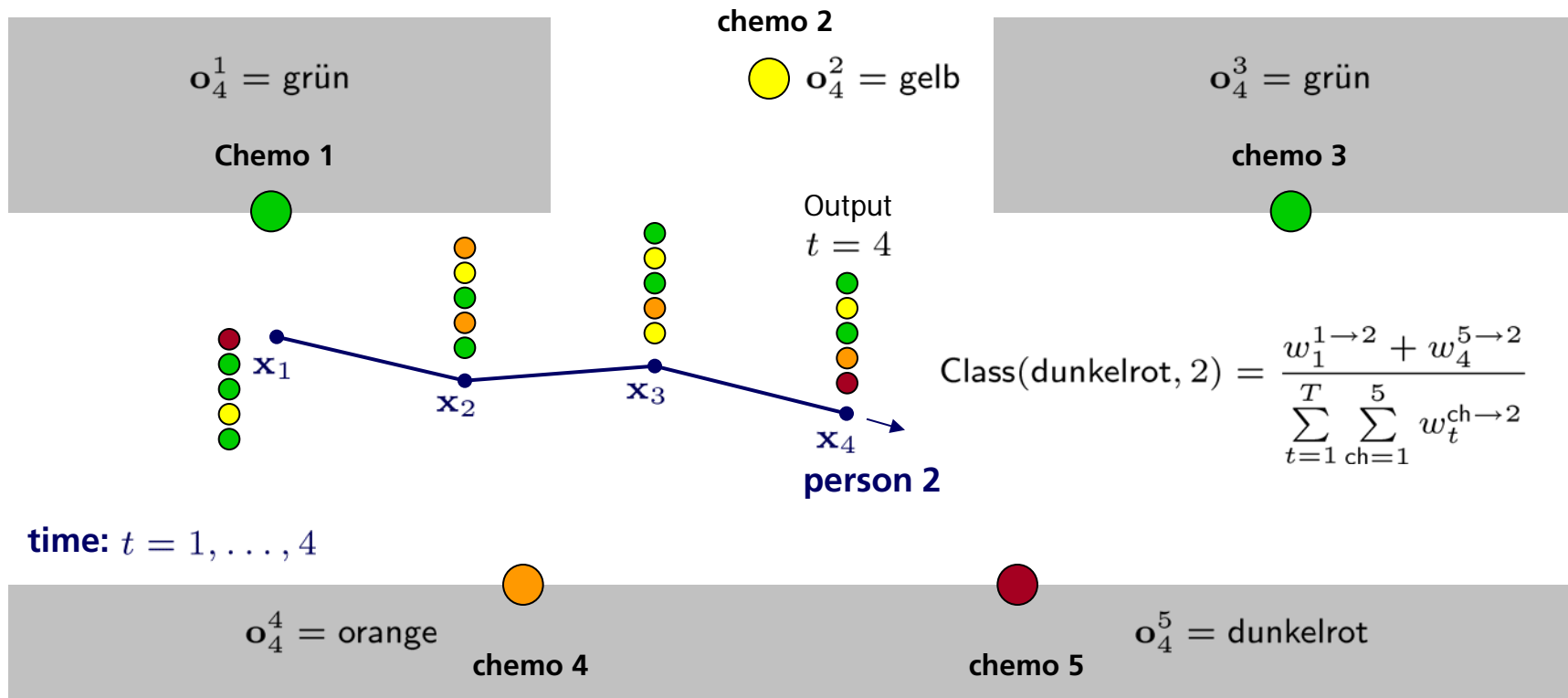
# Solve the association problem via *Expectation-Maximization!*

**Basis:** Calculate relevancy of the signatures of each chemo sensor at all instants of time for each individual person.



# Fusion of position attribut measurements

Iteratively calculate the classification matrix for each person while tracking in a unified approach (EM).





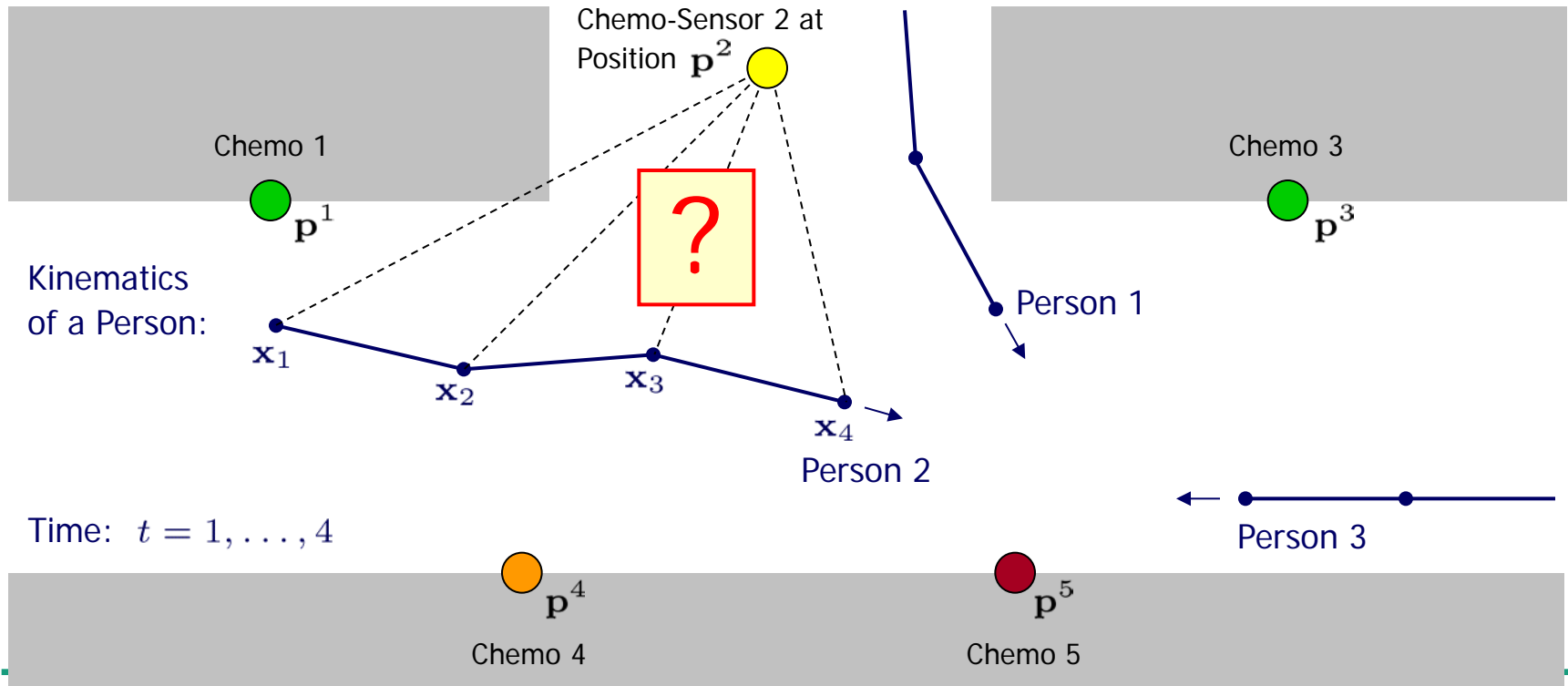
# Fusion with chemo sensors: Problems when going to reality

## Remark

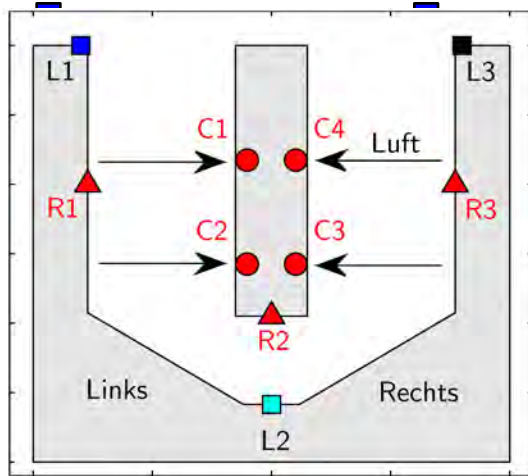
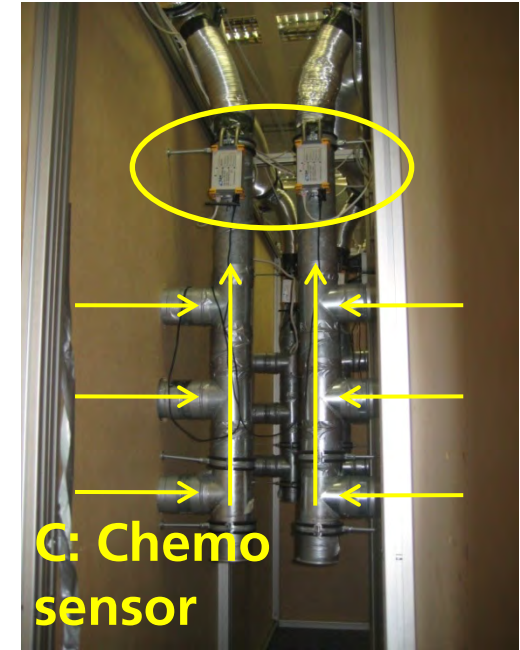
Assignment weight calculation is a difficult task that requires knowledge and models of the behavior of chemo sensors.

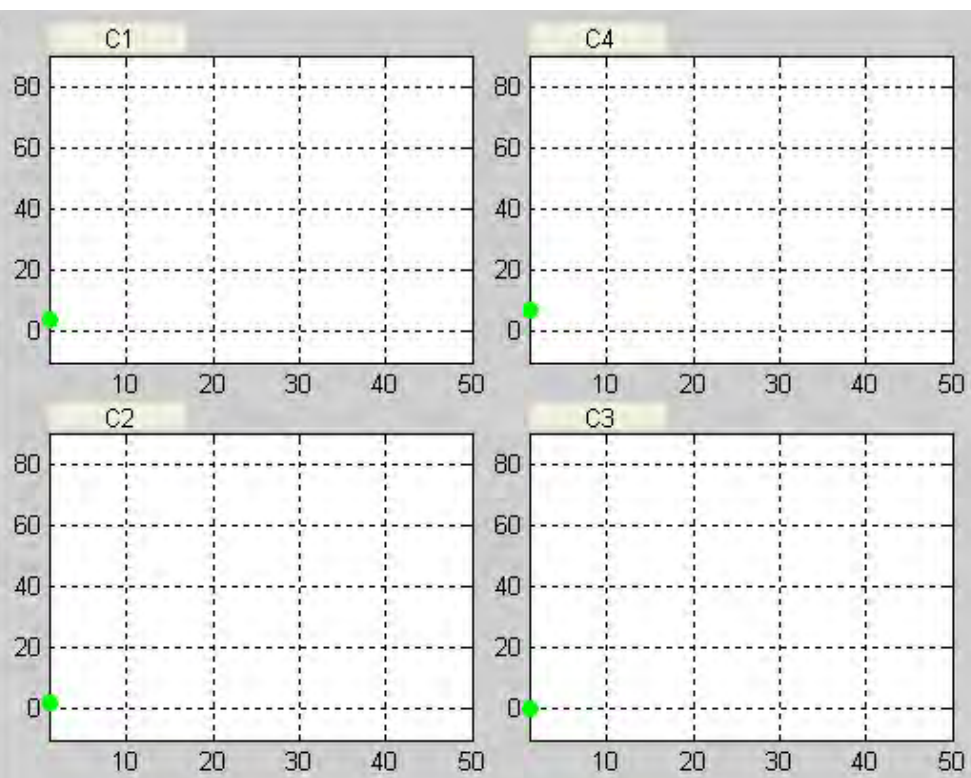
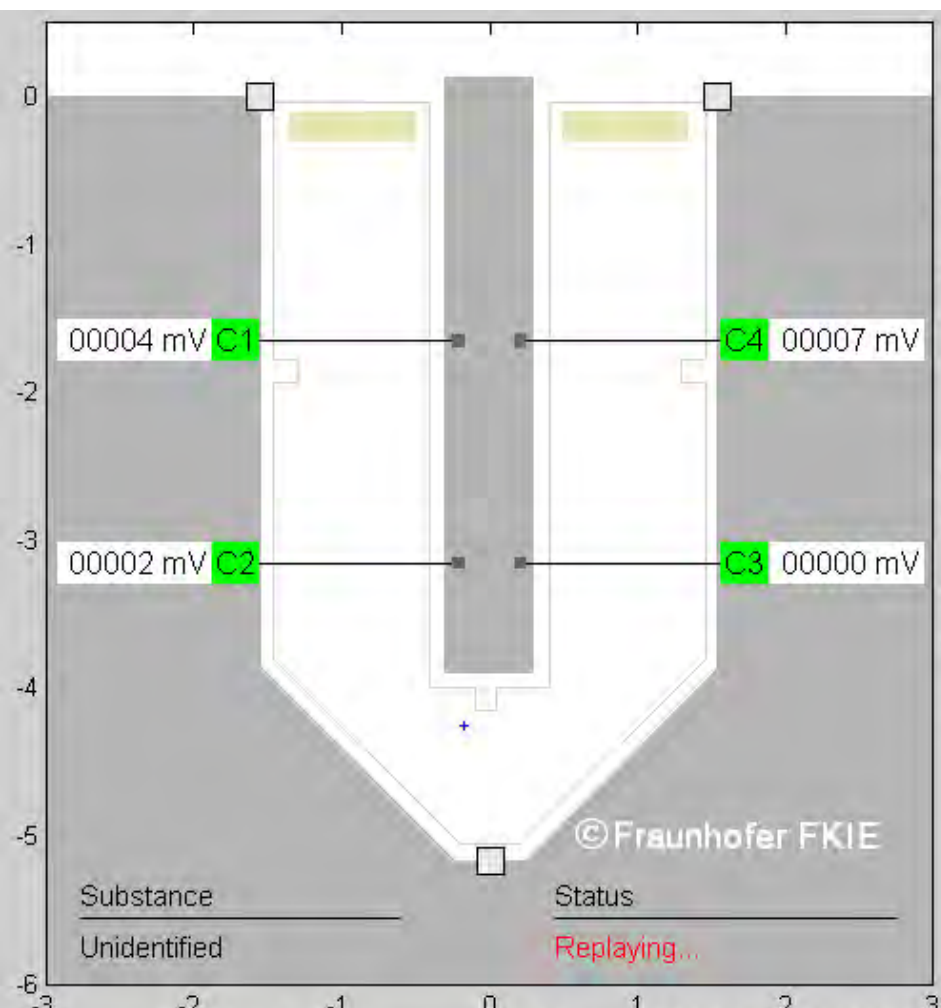
## Influences

Not only distance, but also velocity, temperature, humidity, turbulence, number of persons, ...: strong impact on **delay**.



# First Experimental Set-Up





Recorded Data Files:

- Log\_20101129\_140801562
- Log\_20101129\_141205171
- Log\_20101129\_141533718
- Log\_20101129\_142010000
- Log\_20101129\_142429562
- Log\_20101129\_142927656
- Log\_20101129\_143655328

LSR: 00000001 51549203

CHM: 00000001 51549203

- Load Measurements
- Record AVI-File
- Record PNG-Sequence
- Recompute Tracks
- Replay with Offline-Tracks

Docu: (21): 5 P, beliebige Bewegung, Quelle zügig von rechts nach links

Start Stop Close

# HAMLeT – Example for “Law-Compliance by Design”?

**Persons: NO collection of biometric parameters**

**Tracking: only kinematic quantities in the corridor**

**Goal: association of a hazardous material signature**

**No sensors (yet?) for individual person “smells”**

**HAMLeT system is “blind” for “normal people”**

**Reconquer the possibility of “normal” public life**

**False alarms: manual control of a few persons**

# HAMLeT – Example for “Law-Compliance by Design”?

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Problem: How to act when a threat is recognized?

(semi-) automated action procedures “Robo-Ethics”?

Who is allowed to live under the “security umbrella”?

How to standardize “Law-Compliance by Design”?

How to manage permission, approval, control?

Socio-cultural Awareness: societal acceptance

# Application to Ferry Traffic

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## Collaboration Projects VeSPer and VeSPer Plus

Verbesserung der Sicherheit von Personen in der Fährschifffahrt



PROJEKTRÄGER FÜR DAS

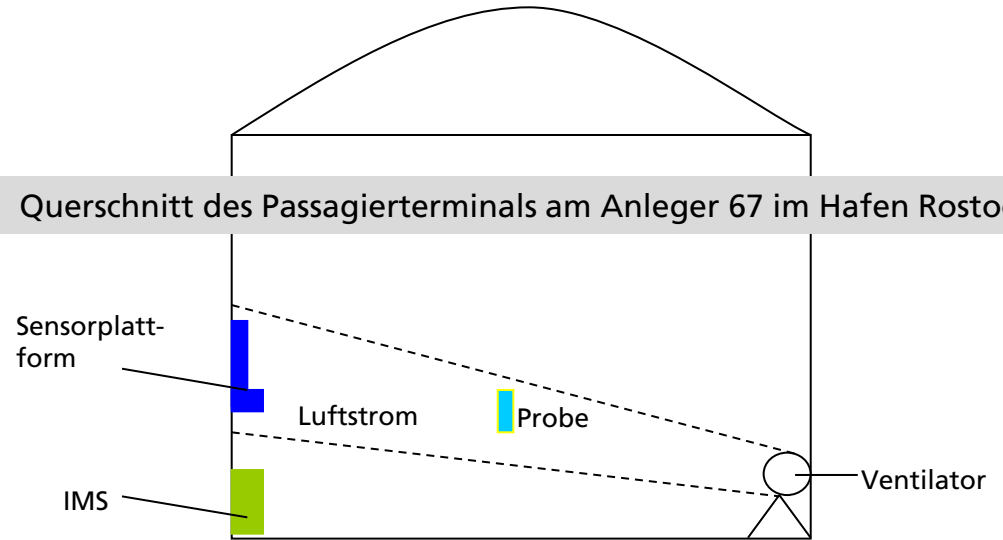


Bundesministerium  
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und Forschung

# Projekt VeSPer



Querschnitt des Passagierterminals am Anleger 67 im Hafen Rostock



# Radioactive Material as Potential Terrorist Threat



Dirty Bomb



Localization?



- **Radioactive dispersion devices (RDD / “Dirty Bomb”)**
  - ⇒ Combination of conventional explosives with radioactive material
  - ⇒ High damage potential: contaminated areas, health damage, psychology
- **RDDs have not yet been used but growing concerns (EU Project CATO)**
  - ⇒ Radioactive material readily available for medical / commercial use
  - ⇒ Numerous incidents involving loss or theft of radioactive sources
- **Localization of radioactive material in public spaces, good streams**



# Panikmache oder Bedrohung?

Terroristen bereiten Anschläge mit "schmutzigen Bomben" vor

**(BS/Uwe Kranz) Schon der Gedanke daran lässt einen frösteln: Immer wieder wird davor gewarnt, dass islamistische Terroristen den Bau einer "schmutzigen Bombe" planen oder gar vorbereiteten: Ein konventioneller Sprengsatz, der mit radioaktivem Material vermischt ist. Was ist daran wahr?**

Serie

TERRORZIELE (TEIL 2)

vierten Anschlagsvorhaben in Deutschland vorlägen.

## Leicht zu erwerben

Zahlreiche verdeckte Ermittlungen zeigten jedoch, dass die Anbieter keine Skrupel hatten, einem angeblichen Daesh-Terroristen für 2,5 Millionen US-Dollar radioaktives Material und Blaupausen für den Bombenbau zu verkaufen. Auch aus anderen Teilen der ehemaligen Sowjetunion soll bis 2011 solches Material zum Kauf angeboten worden sein, sogar hoch angereichertes Uran-235. Nach Erkenntnissen internationaler Ermittler war die Rede von bis zu zehn Kilogramm Uran. Das entspricht einem Fünftel der Bombe von Hiroshima! Im Nahen Osten

sorgte ein anderer Bericht für Schlagzeilen: Unbekannte hatten bereits 2015 einer US-Firma im irakischen Basra geringe Mengen radioaktives Iridium-192 gestohlen. Die Internationale Atomenergie-Agentur IAEA fahndet bis heute erfolglos nach Material und Täter.

Der aktuelle Bericht der Nuclear Threat Initiative (NTI) wiederum warnt vor den "signifikanten Lücken" bei der Sicherheit radiologischer Materialien, die in "zehntausenden Anlagen in mehr als 100 Ländern" lagerte.

## Erhebliche psychologische Folgen

Anschläge mit "schmutzigen Bomben" würden nach Expertenmeinung nicht allzu viele Todesopfer fordern, aber Milliardenschäden und eine verheerende psychologische Wirkung verursachen. Der Daesh hat sich daher seit Jahren einen technischen, logistischen und



Uwe Kranz ist der Terrorexperte des Behörden Spiegel. Zuvor war der Leitende Ministerialrat a. D. Präsident des Landeskriminalamtes Thüringen und nationaler Experte bei Europol.

Foto: BS/Dombrowsky

personellen Unterbau geschaffen, um einen solchen Anschlag vorzubereiten.

In Europa zeigt sich das besonders deutlich in Belgien: Im Kernkraftwerk Doel arbeitete jahrelang der Belgier marokkanischer Abstammung und radikale Islamist *Ilyass Boughalab*, bevor er sich 2012 zum Daesh absetzte, wo er 2014 getötet wurde. Im Atomkraftwerk war er sogar in der Hochsicherheitszone tätig. Ein weiterer Mitarbeiter wurde wegen terroristischer Aktivitäten zu einer kurzen Frei-

heitsstrafe verurteilt. Im August 2014 sabotierten Unbekannte einen Reaktorblock: Manuell wurden 65.000 Liter Öl abgelassen, um die Turbinen zu überhitzen. Das Computersystem der belgischen Nuklearbehörde wurde gehackt. Im Dezember 2014 wurden Drohnenflüge über dem Kraftwerk gemeldet.

## Entführung

Im November 2015 wurde bekannt, dass der Leiter des Nuklearforschungszentrums SCK-CEN in Mol mit einer Videokamera ausgespäht worden war. Vermutlich bereiteten die tatverdächtigen Brüder *Khalid* und *Ibrahim El Bakrooui* eine Entführung des Wissenschaftlers vor, um in dem Zentrum hergestellte Radionuklide zu erpressen. Ihre Wohnung war von dem Belgier *Mohamed Bakkali* angemietet worden, der gemeinsam mit dem Franzosen *Salah Abdestam* und anderen auch am Attentat in Paris im November 2015 beteiligt war. In *Bakkalis* Wohnung wurde zudem ein Sprengstoffgürtel ge-

funden, an dem DNA-Spuren von *Abdeslam* gesichert werden konnten.

## Nuklearterrorismus nicht mehr weit weg

In seiner Wohnung sollen auch Unterlagen zum deutschen Atomforschungszentrum Jülich gefunden worden sein, was das Bundesamt für Verfassungsschutz (BfV) jedoch dementierte. Dramatisch daran ist, dass sich nunmehr die operative Ebene des Daesh mit Nuklearanschlägen befasst. Der atomare Terrorismus ist, nach dem mysteriösen Terrorangriff im Jahr 2007 auf das nukleare Forschungszentrum Pelindaba in Südafrika, nun auch in Europa in greifbare Nähe gerückt. Das ist auch im Lichte der Ankündigung des Kalifen *Ibrahim* zu sehen, dass das Jahr 2016 noch chaotischer werde als 2015.

Die deutschen Vorbereitungen zur Verbesserung der nuklearen Sicherheit laufen auf Hochtouren. Die Bundesregierung überarbeitete das Konzept "Zivile Verteidigung", 2014 wurden auf Bundesebene eine Plattform zum Schutz von atomaren, biologischen oder chemischen Gefahren (CBRN) eingerichtet, sichere Warnmeldesysteme installiert sowie Krisenstrukturen und -pläne aktualisiert.

Eines steht also zweifelsfrei fest: Die Gefahr wächst. Je mehr der Daesh in seinem Herrschaftsgebiet unter Druck gerät, desto größer ist die Wahrscheinlichkeit, dass er mit einem Befreiungsschlag in Europa versucht, seine "Handlungsfähigkeit" zu beweisen.

# Praxisworkshop

Praxisworkshop

## Illegaler Zigarettenhandel und -schmuggel

Eine Veranstaltung des Behörden Spiegel

GEFÖRDERT VOM



Bundesministerium  
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# Resilience of the Franco-German High Speed Train Network

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# FKIE Contribution to RE(H)STRAIN: Detection of dirty bombs

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## WP 8.3 + 8.4 'Development of a security concept based on multiple sensor data fusion' and 'Detection of dirty bombs'

Exploitation of heterogeneous sensors:

fusion algorithms for situation picture production

→ Threat assessment

*Sensor to be used:*

### **1. Kinect cameras (kinematic data)**

*Installation above the observed area (looking-down)*

→ *Localization and tracking of single persons (no collection of personal data, e.g. face recognition algorithms not applicable)*

### **2. Gamma spectrometers (attribute data)**

*Detection of radioactive nuclides:  $^{60}\text{Co}$ ,  $^{137}\text{Cs}$*

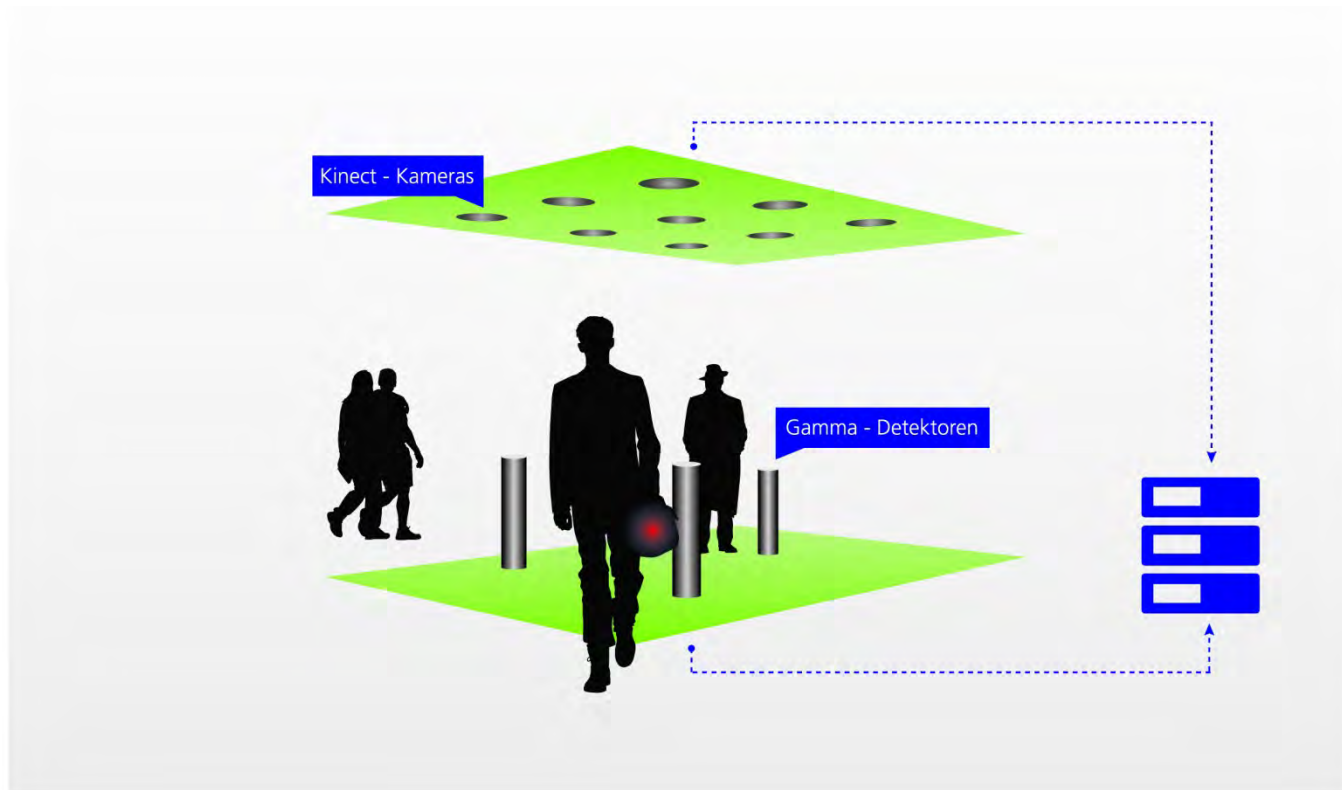
*Data fusion: measurements of gamma spectrometers + Kinect-cameras*

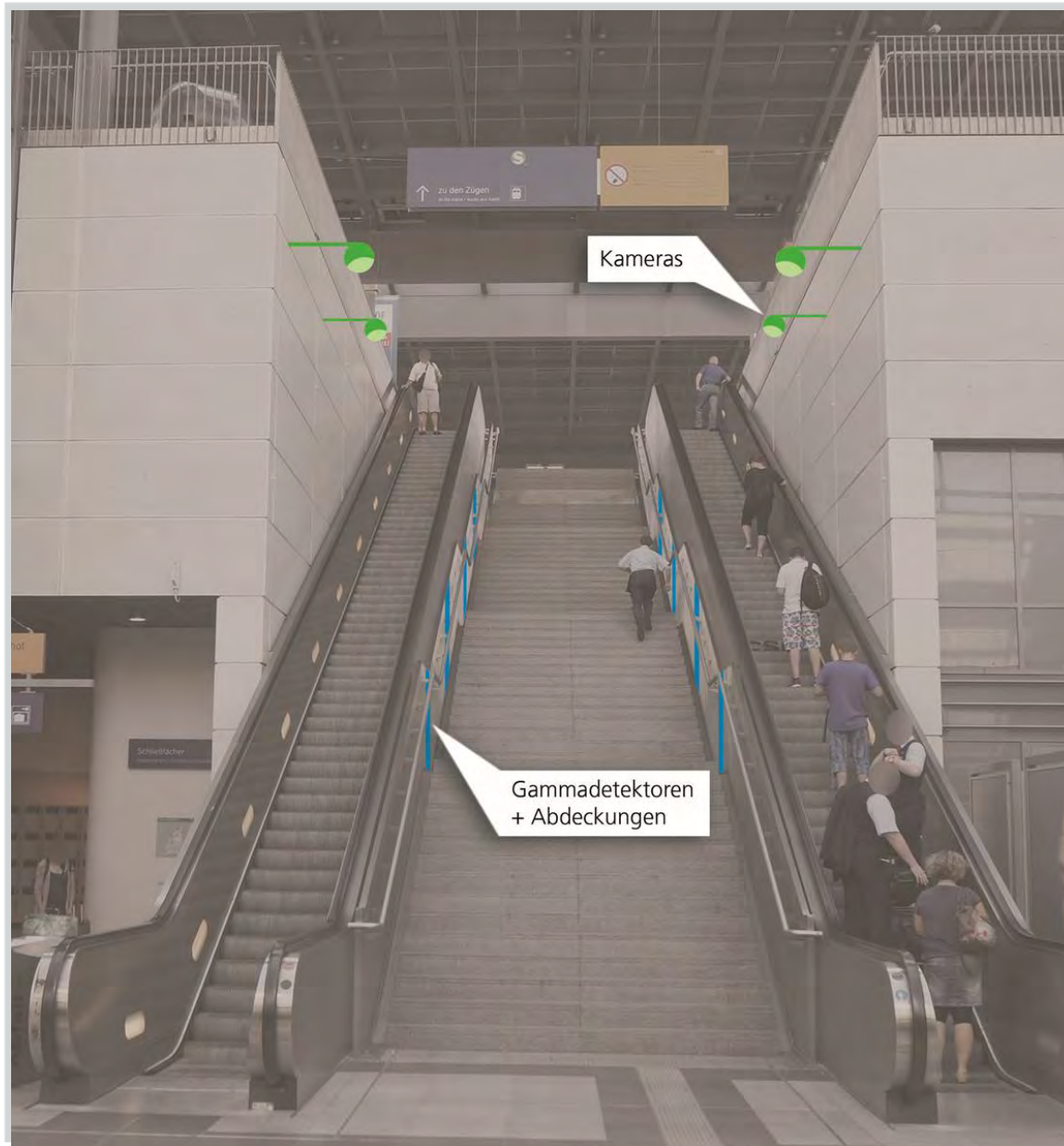
→ *"dirty bomb" can unambiguously be associated to a person.*

# RE(H)STRAIN: Detection of "dirty bombs"

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## Concept of a surveillance system for "dirty bombs"





A fundamental ethical notion: **responsibility**

Literal meaning: Being requested to **respond** to questions on the effects of own actions at court.

First associations:

What is the duty, who is judging and accusing according to which law?

What about resulting praise or punishment?

p  
e  
r  
c  
e  
i  
v  
e  
  
a  
c  
h  
i  
e  
v  
e

Elements of thought:

Only **free** beings can take over any responsibility:

Readiness of **interior** acceptance of rules / laws.

Behaving **well** also when external rules are missing or mutually conflicting.

**Good**: Overarching notion?

“In the end, everybody is alone with his freedom ...”

**individual, groups, society**

**Who?  
Freedom**

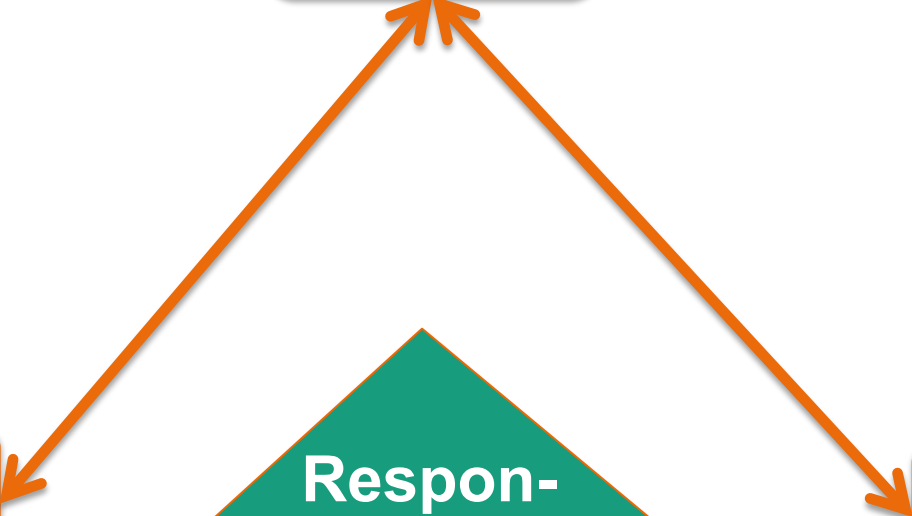
**oneself  
individuals  
groups, society  
extrahuman nature  
technology design**

**God  
conscience  
society  
nature  
...**

**For whom?  
Care**

**Respon-  
sibility**

**To whom?  
Authority**



individual, groups, society

**Who?  
Freedom**

prospectively

retrospectively

act

react

justify

judge

**Respon-  
sibility**

**For whom?  
Care**

**To whom?  
Authority**

oneself  
individuals  
groups, society  
extrahuman nature  
technology design

God  
conscience  
society  
nature  
...



individual, groups, society

Who?  
Freedom

prospectively

retrospectively

act

react

justify

judge

Respon-  
sibility

oneself  
individuals  
groups, society  
extrahuman nature  
technology design

God  
conscience  
society  
Nature  
...

For whom?  
Care

To whom?  
Authority

Notions of keeping a society balanced: **Responsibility** versus **Liability**:  
elements of insight, personal commitment, comprehensive care

Insight, freedom, self-reflectivity, dialog, merit / guilt, carelessness:  
“Assist” humans to act responsibly, e.g. hard & soft fusion!

Mathematical Engineering

Wolfgang Koch

# Tracking and Sensor Data Fusion

Methodological Framework and  
Selected Applications

 Springer

**Many topics of previous  
work at Fraunhofer FKIE,  
Dept. *Sensor Data and  
Information Fusion*.**

***Appeared in 2014.***

---

 **Fraunhofer**  
FKIE

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