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Multisensor Fusion: Advanced Methods and Applications

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interactIVe Summer School

4-6 July, 2012

Prior to its technical realization or the scientific reflection on it:

Information Fusion – an Omnipresent Phenomenon!

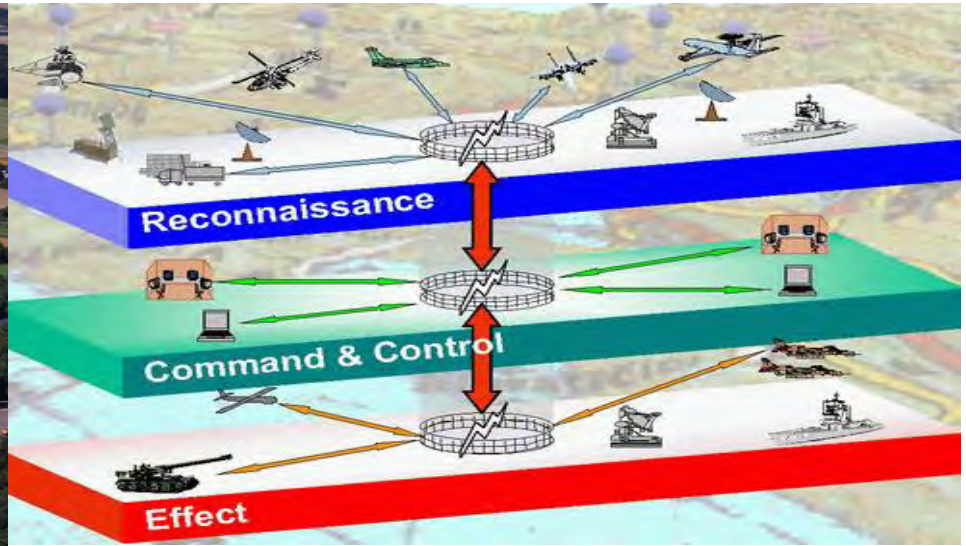
All living creatures by nature perform information fusion:

- Multiple, mutually complementary sense organs
- Knowledge learned from previous experiences
- Communications obtained from other creatures

Result: “mental model”, the basis of behaving appropriately to avoid harm or reach a goal

Branch of Applied Informatics: „Cognitive Tools“

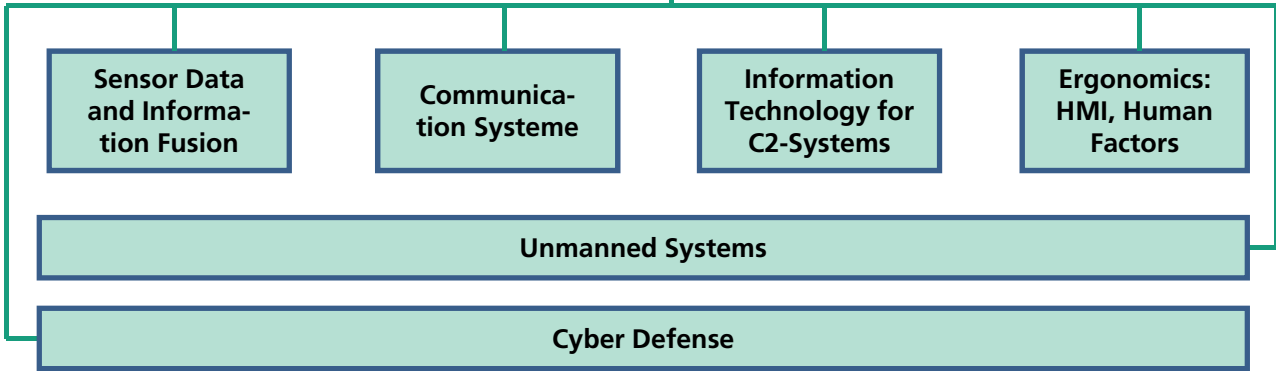
1. Understand, automate, enhance.
2. Integrate new information sources.
 - networking, mobile sensors of high sensitivity, range
 - new dimensions of apprehension otherwise hidden
 - data base systems containing vast context information
 - interaction with humans: exploit natural intelligence!



Bonn University
 Chair for Communication and Distributed Systems (CS-IV)
 Prof. Dr. Peter Martini

FKIE: Fraunhofer Institute for Communications, Information Processing, and Ergonomics
 Director: Prof. Dr. Peter Martini, Deputy: Prof. Dr.-Ing. Christopher Schlick

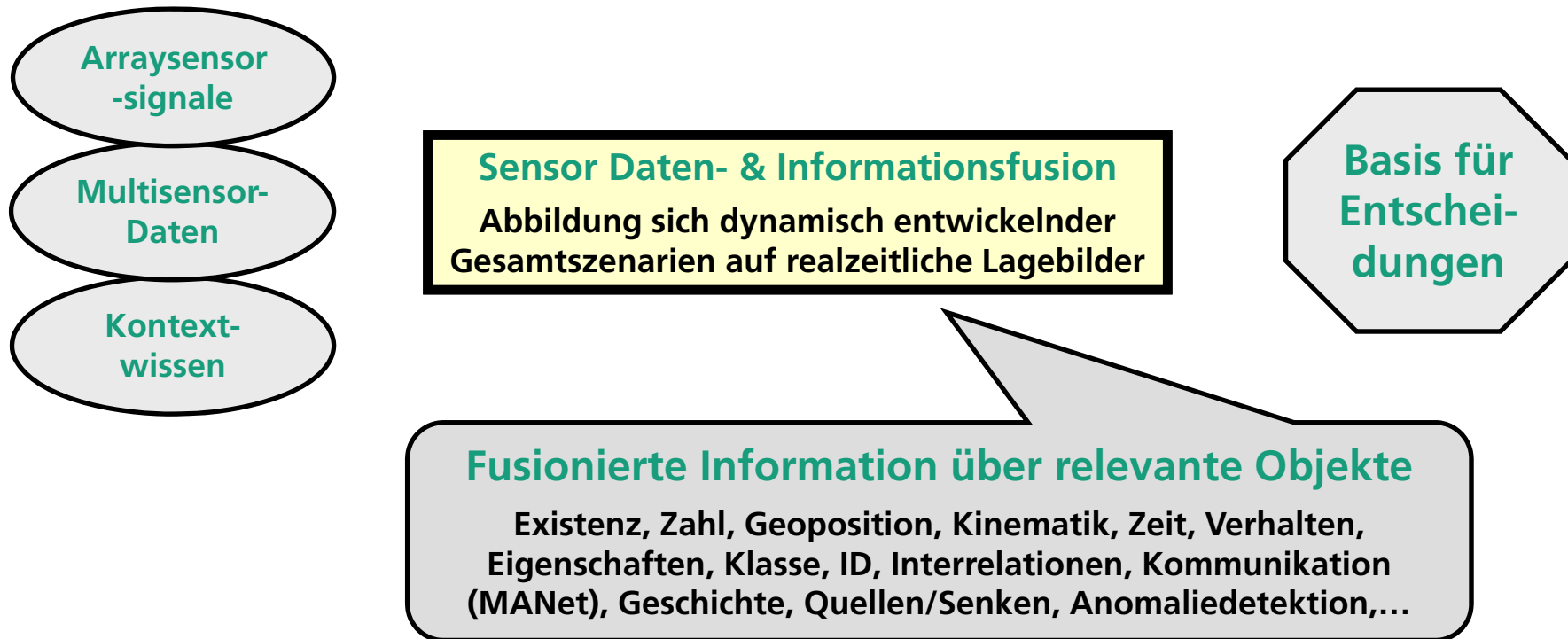
RWTH Aachen
 Institute/Chair of Industrial Engin. & Ergonomics (IAW)
 Prof. Dr.-Ing. Christopher Schlick



“Institute for Network Enabled Capabilities”

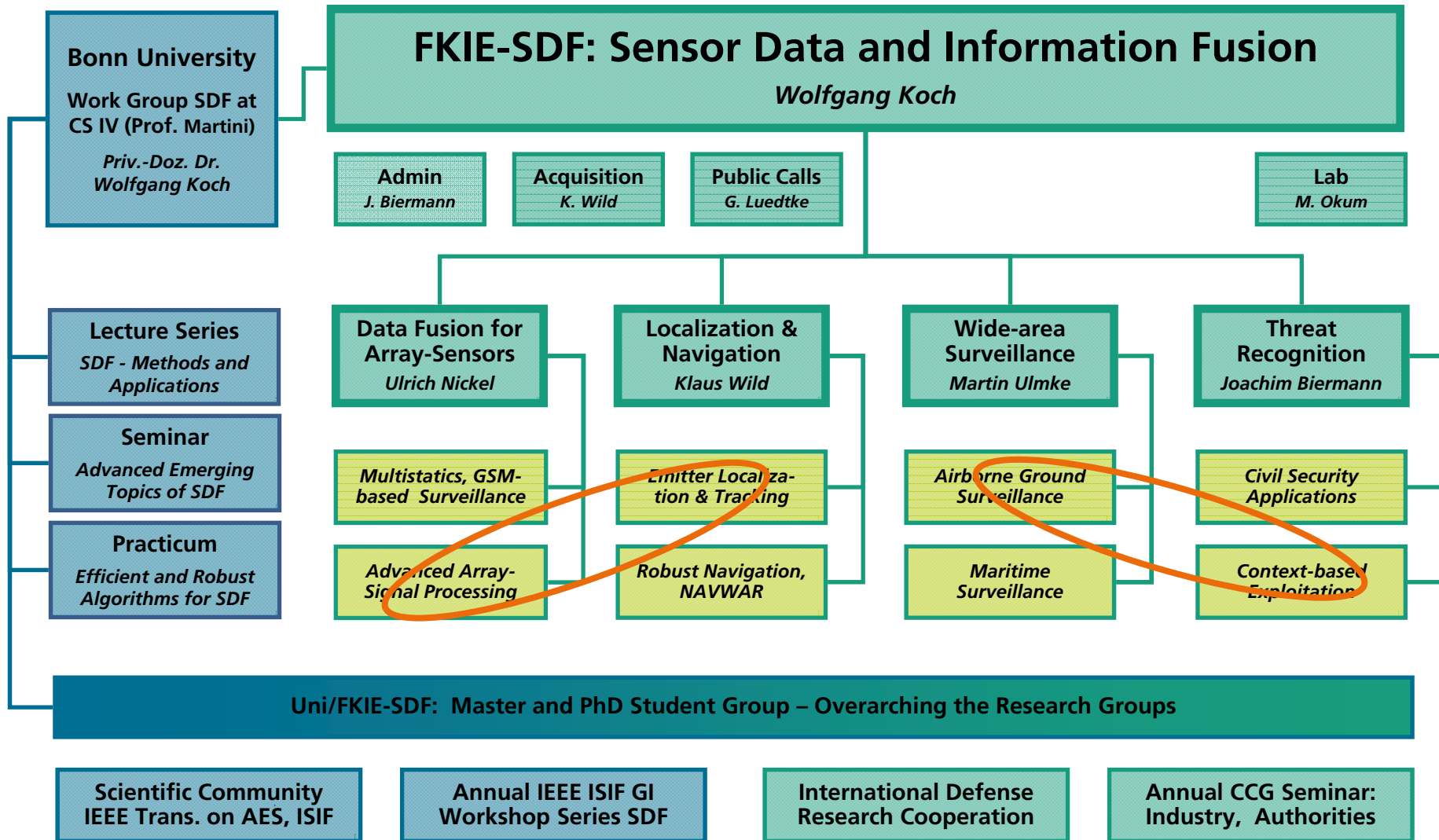


FUSION: Mission Statement



Forschungsthema: **zu fusionierende Information ist unscharf!** (ungenau, unvollständig, mehrdeutig, unaufgelöst, falsch, verfälscht, schwer formalisierbar, widersprüchlich,...)

Kritische Masse durch interdisziplinär aufgestelltes Team: > 40 Ingenieure, Physiker, Mathematiker, Informatiker (+ Techniker, Math.-Techn. Assistenten, Studenten, ...)



Typically: temporally limited cross-group research projects



7th Workshop SDF 2012

Sensor Data Fusion: Trends, Solutions, Applications

Call for Papers

Motivation

To a degree never known before, human decision makers or decision making systems have access to a vast amount of data. For making use of this information potential, real-time data streams must not overwhelm the actors involved. On the contrary, the data are to be fused to high-quality information to provide decision support on various archical levels. Being a challenging exploitation technology at the common interface between sensors, command & control systems, data and information fusion has a large potential for future security systems and Intelligence, Surveillance, Reconnaissance in defence and civilian applications.

Scope

Sensor Data Fusion techniques provide higher-level information from multiple sensor data by spatio-temporal data integration, the exploitation of redundant and complementary information, and the available context. This growing branch of applied informatics aims at the production of comprehensive, precise, and near real-time situation pictures, which are basic for further decisions or actions. Important applications exist in logistics, advanced driver assistance systems, medical care, public security, defence, aerospace, robotics, industrial production, precision agriculture, traffic monitoring.

Key Aspects

- Distributed sensor fusion in complex scenarios
- Fusion of heterogeneous sensor information
- Exploitation of non-sensor context knowledge
- Detection & analysis of large scale phenomena
- Performance: measures, evaluation, prediction
- Risk analysis / data driven sensor management
- Case studies of multiple sensor fusion systems

Participants

The workshop addresses end users, software developers, research engineers, and scientists working in the area of sensor data fusion. They gain insight into current research trends, innovative algorithms/system solutions, and new applications in a prospering evolving branch of applied informatics.

Contributions

Prospective authors are encouraged to submit high-quality full draft papers (4-6 pages, IEEE format) via www.fkie.fraunhofer.de/sdf2012. All submissions are subject to a peer-review process by the technical program committee. Industry participation is much encouraged. Accepted papers will appear on a DVD and be made searchable via the IEEE Xplore data base. At least one of the authors of each accepted contribution is expected to register for Future Security 2012 to be held in Bonn in the former West-German Parliament and to present the paper orally. For details follow www.future-security.eu or contact w.koch@ieee.org.

Important Dates

01.06.2012	Submission of full draft papers
29.06.2012	Notification of acceptance
03.08.2012	Submission of the final version

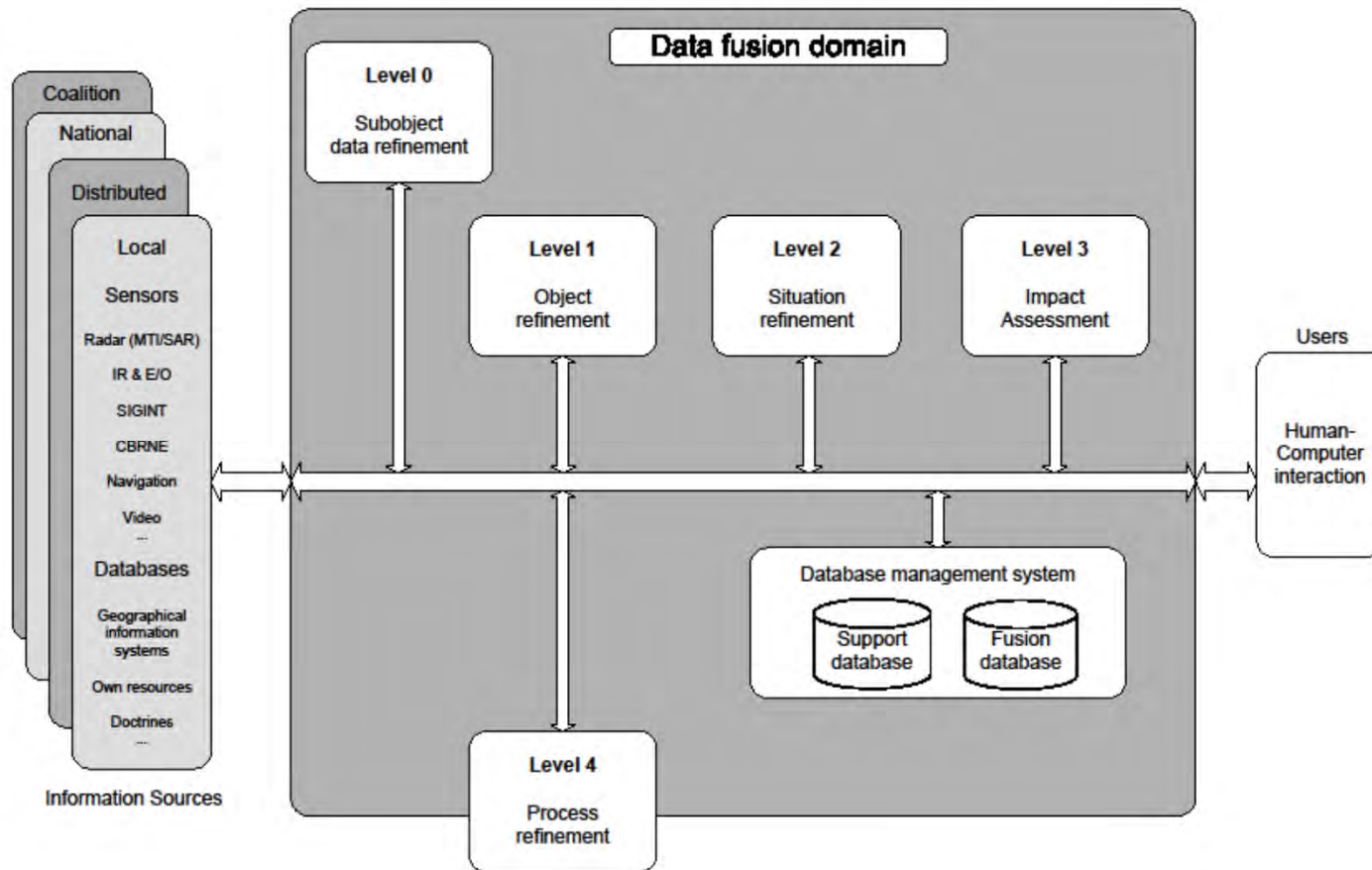
Organisation

Wolfgang Koch, Fraunhofer FKIE and University of Bonn, w.koch@ieee.org; Peter Willett, University of Connecticut, USA, p.willett@ieee.org; Felix Govaarders, Fraunhofer FKIE. SDF 2012 is technically co-sponsored by the IEEE AESS and the International Society of Information Fusion ISIF.

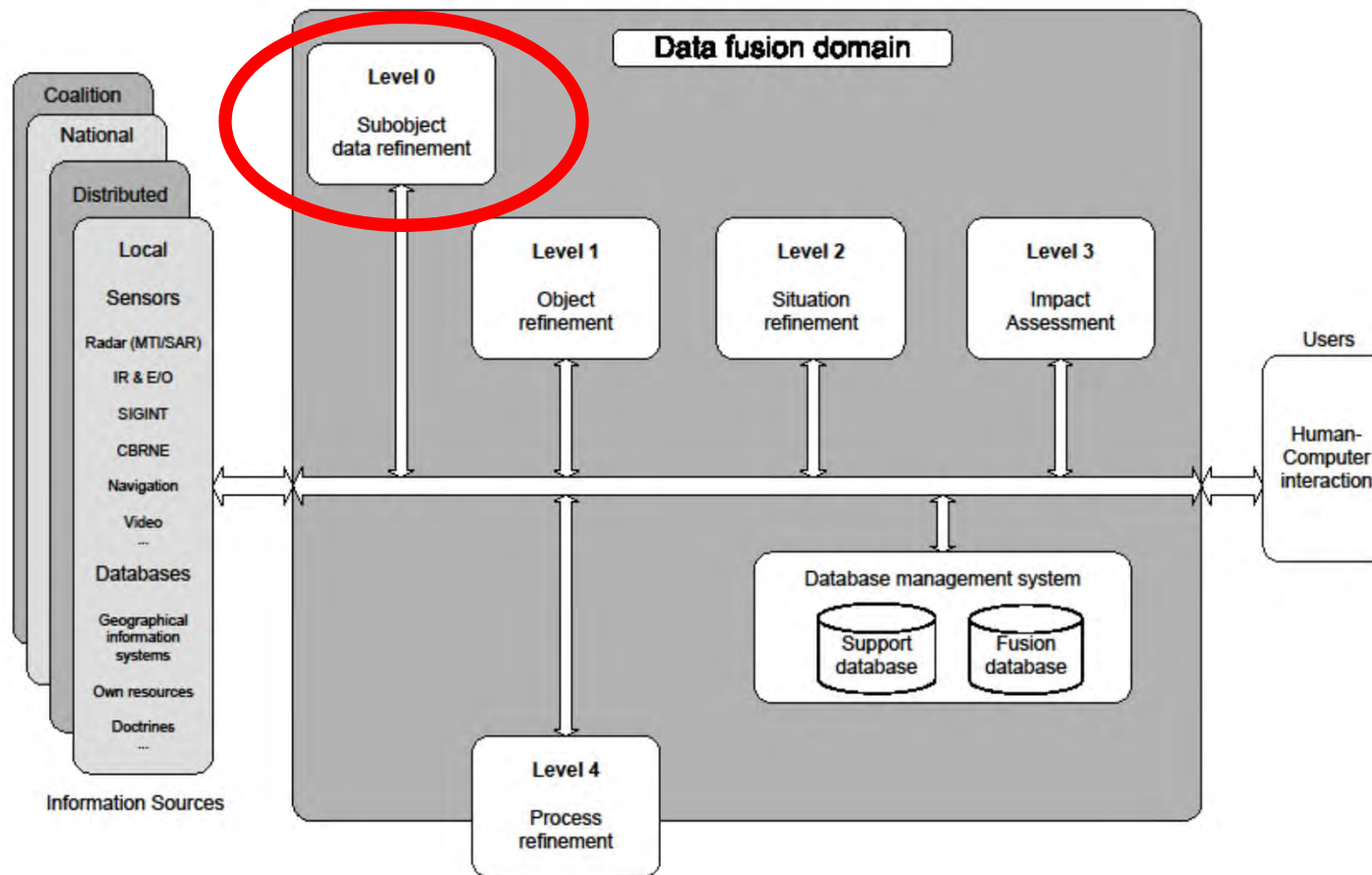
Technical Program Committee

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Scientific Systematization in "George Orwell's Year" 1984



Joint Directors of Laboratories (JDL): Data Fusion Model



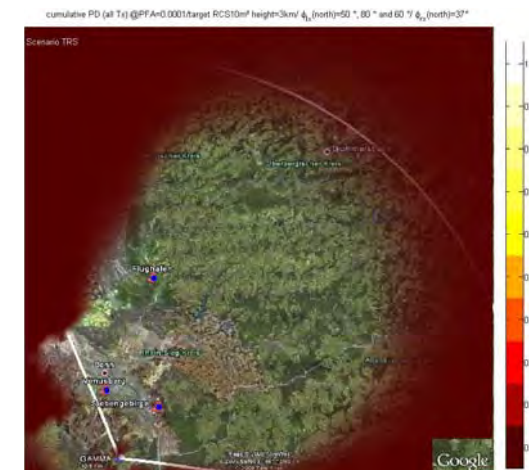
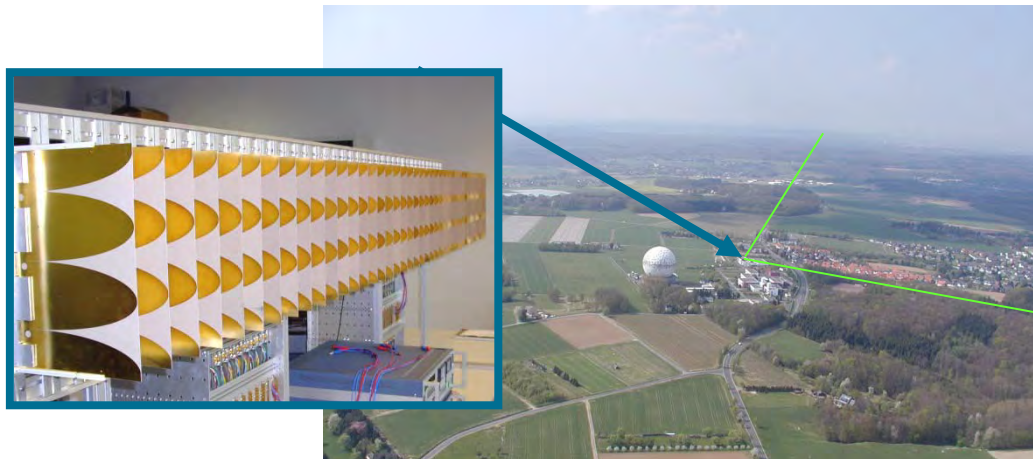
Level 0 processing (subobject data association and estimation) is aimed at combining signal level data to obtain initial information about an observed target's characteristics.

A Look at GSM Illuminators for Covert Observation

- Development of a demonstrator for GSM passive radar
- Tracking / De-ghosting also for other illuminators: DAB / DVB frontend

GSM Mobile Phone Base Stations

- ✓ Illuminators even in remote areas: OOA, littoral regions
- ✓ Frequency diversity of illuminators: less ghosts
- ✓ "Radar"-frequency 1.8 GHz → good angular resolution



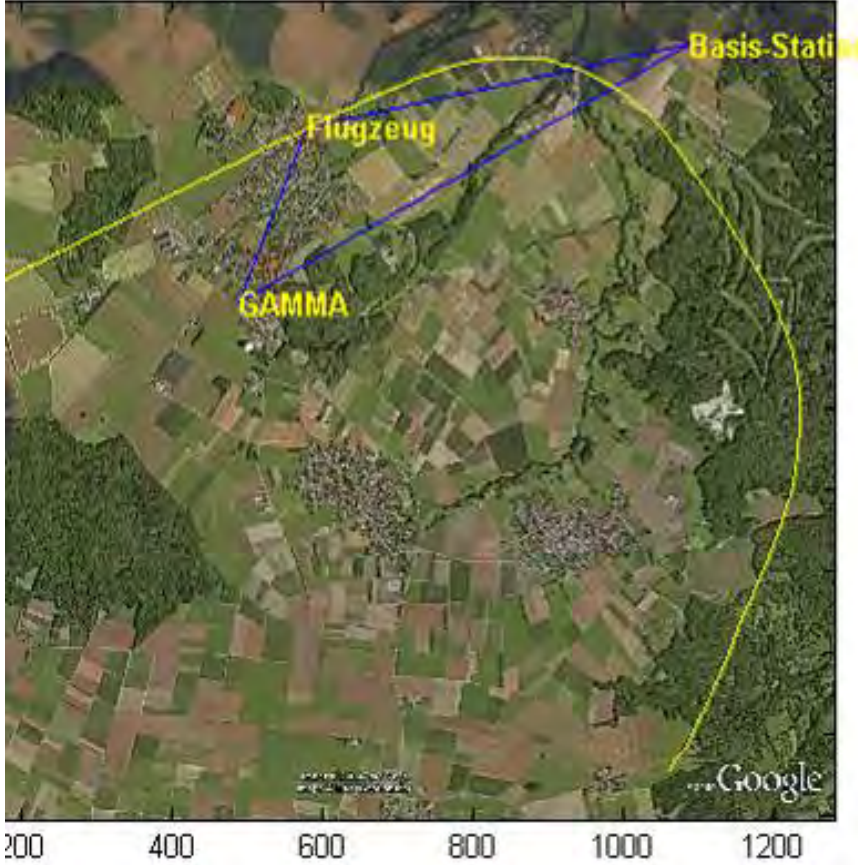
(**GAMMA**: Gruppenantenne für militärische Mobilfunkaufklärung)

Measurements with TRANSALL Aircraft

$$\Phi = 3.6292^\circ, \frac{\beta}{2} = 8.6942^\circ, f_{bD} = 702.1116\text{Hz}$$



$$\Phi = 104.7465^\circ, \frac{\beta}{2} = 60.6972^\circ, f_{bD} = -120.4001\text{Hz}$$



Measurements with TRANSALL Aircraft

R.Oberb/km=3.0289
R.Berku/km=0.54478

$\Delta r/\text{km}=0.466$

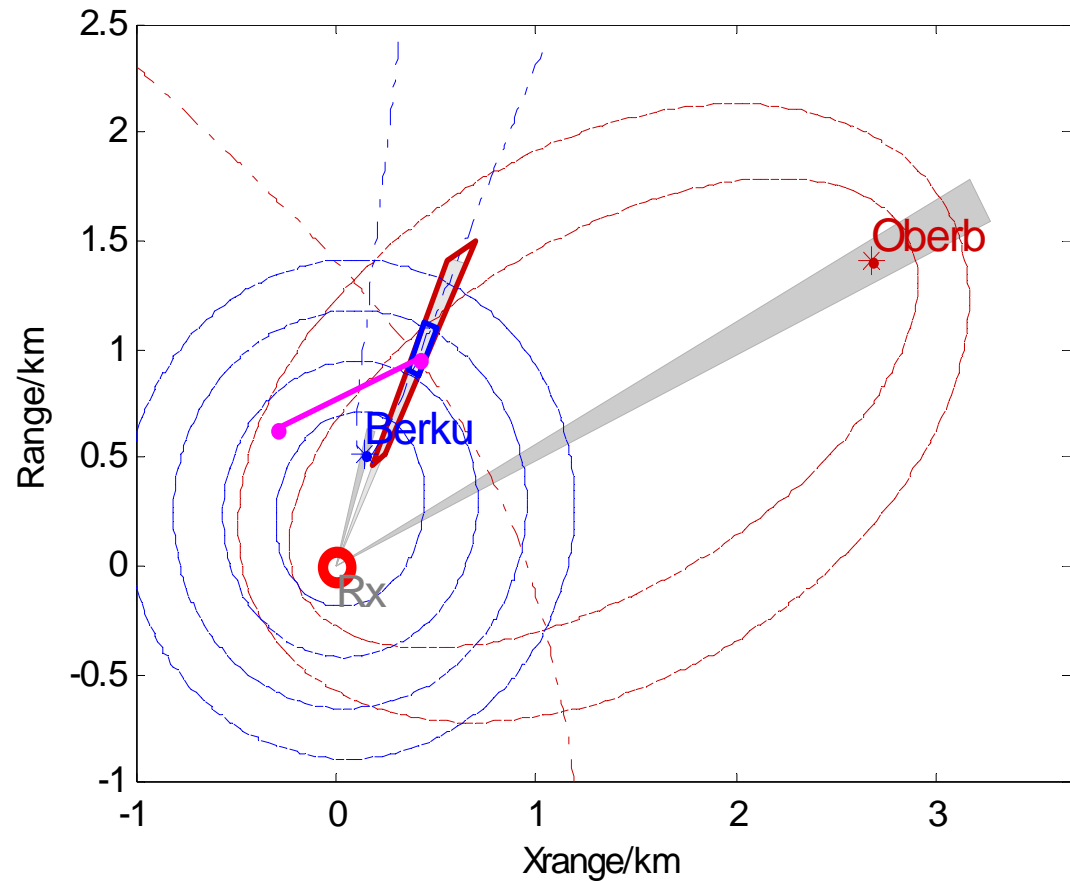
r.Trans/km=1.069

Trans@bin 1 3

Trans@Dop -121 690

Base station Oberbachem
expected Doppler frequency -121 Hz
Range difference 380 m
◇ Range bin 1

Base station Berkum
expected Doppler frequency 690 Hz
Range difference 1000 m
◇ Range bin 3



Measurements with TRANSALL Aircraft 23 June 2009

R.Oberb/km=3.0289
R.Berku/km=0.54478

$\Delta r/\text{km}=0.466$

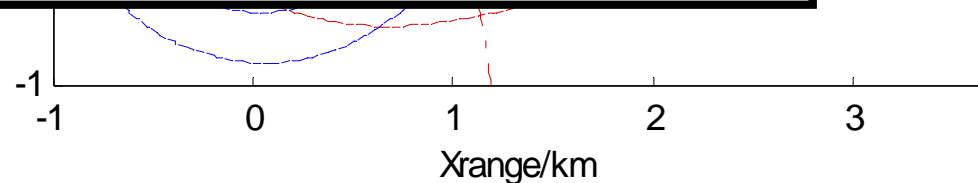
2.5

**Robust Passive Radar systems
will be hybrid systems that use
different and complementary
illuminators via data fusion!**

**Omnipresent GSM illuminators: application
potential for camp protection, border control!**

Base station
expected Do
Range differ
◇ Range bin 1

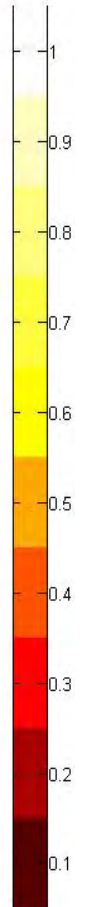
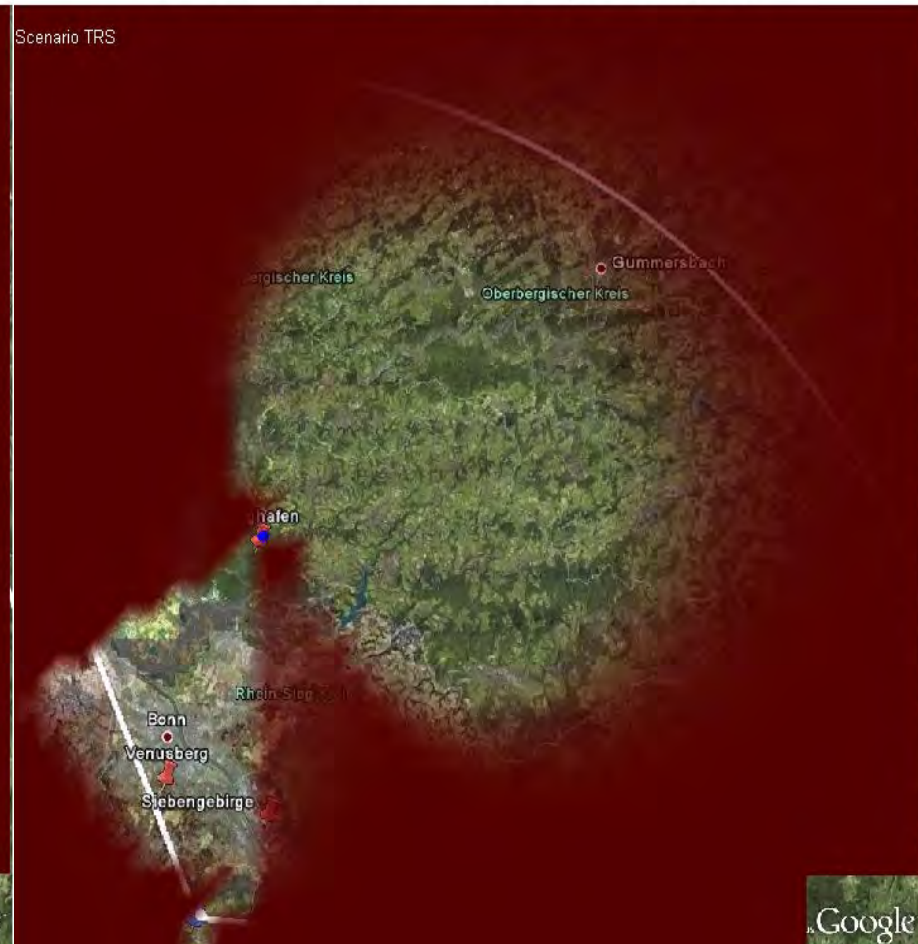
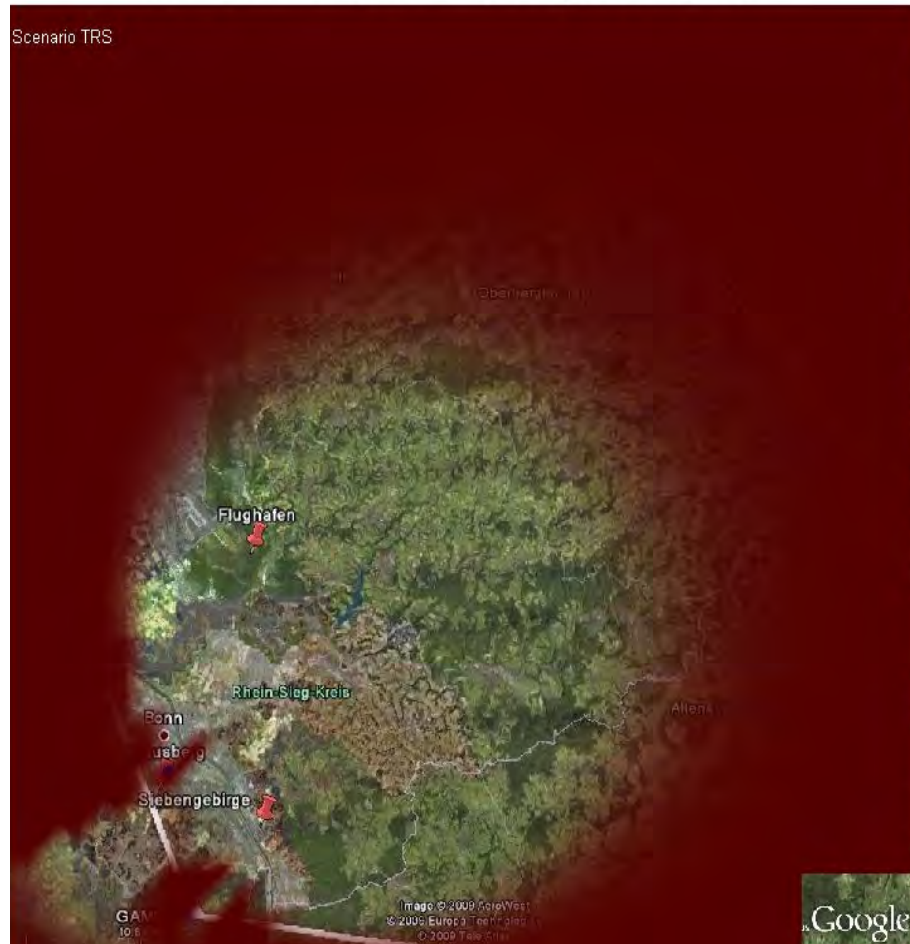
Base station Berkum
expected Doppler frequency 690 Hz
Range difference 1000 m
◇ Range bin 3



Coverage with GSM Radar with RX/Tx-Diagramm (Az&El)

PD for Tx1 @PFA=0.0001/target RCS10m² height=3km/ $\phi_{tx}(\text{north})=50^\circ$ / $\phi_{rx}(\text{north})=37^\circ$

PD for Tx3 @PFA=0.0001/target RCS10m² height=3km/ $\phi_{tx}(\text{north})=60^\circ$ / $\phi_{rx}(\text{north})=37^\circ$



Basisstation Venusberg
 Bündelung 70° Elevation 120°
 Azimut
 Zielhöhe 3 km

Basisstation Flughafen
 Bündelung 70° Elevation 120°
 Azimut
 Zielhöhe 3 km

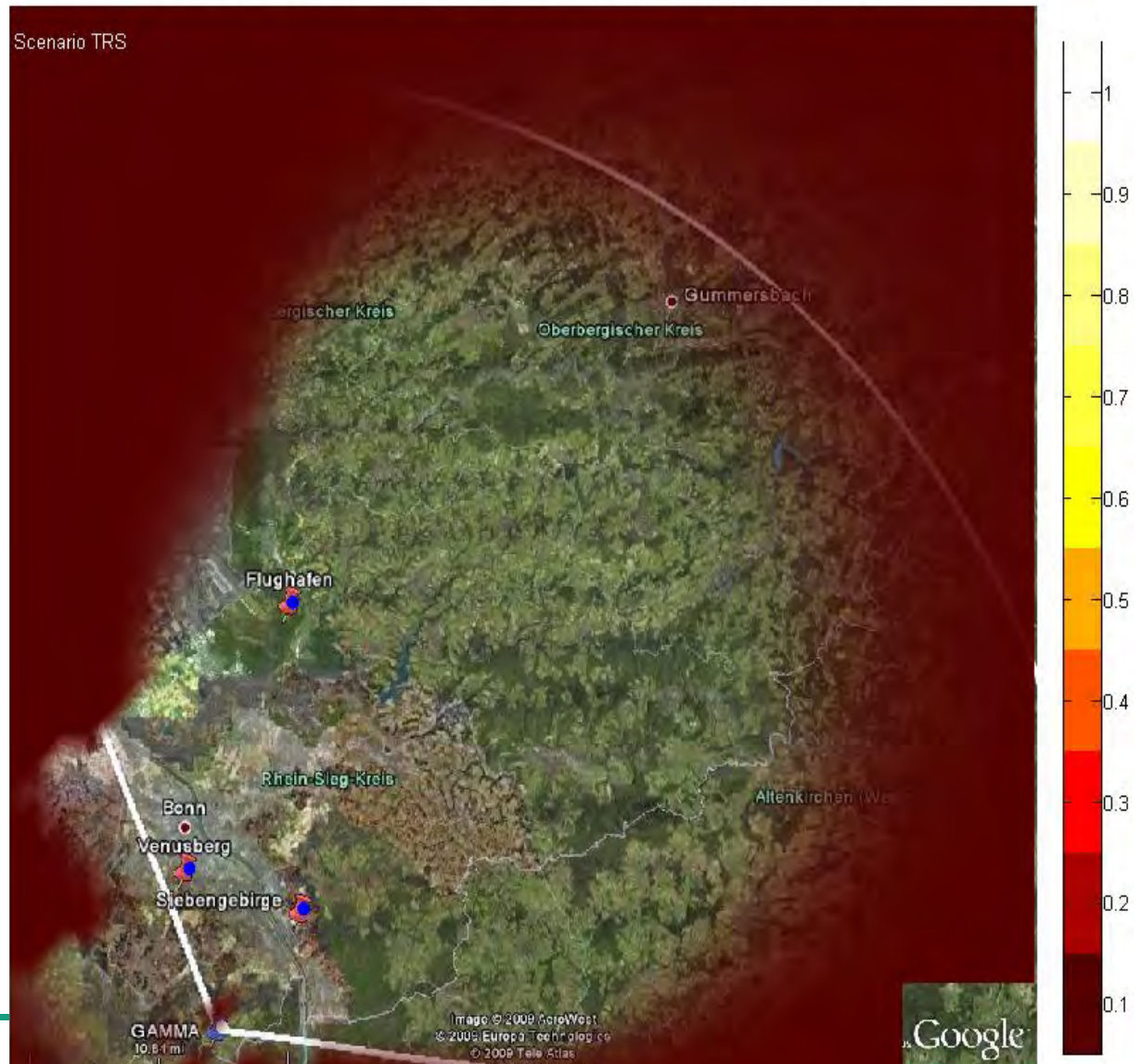
Coverage with GSM Radar by Fusing 3 Illuminators

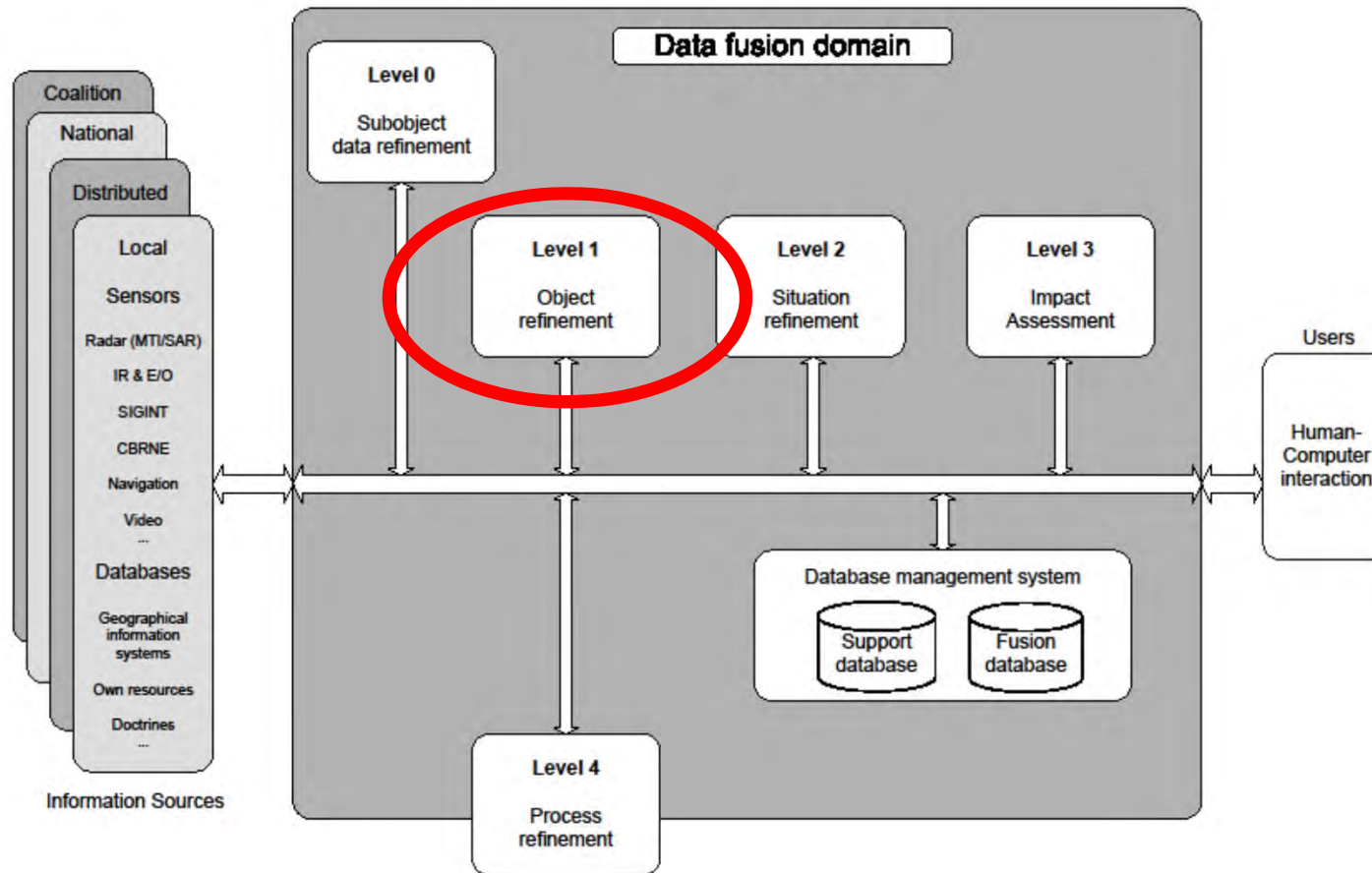
cumulative PD (all Tx) @PFA=0.0001/target RCS10m² height=3km/ $\phi_{tx}(\text{north})=50^\circ, 80^\circ$ and 60° / $\phi_{rx}(\text{north})=37^\circ$

Cumulative PD, PFA=10⁻⁴,
10m² target at 3km height

Dislocation of illuminators is
decisive for illumination of
the observation area!

→ GIS based base station
selection manager is
necessary.





Level 1 processing (object refinement) is aimed at combining sensor data to obtain estimates of an entity's position, velocity, attributes, and identity.

Why is Tracking so important? *Example: Passive Radar*

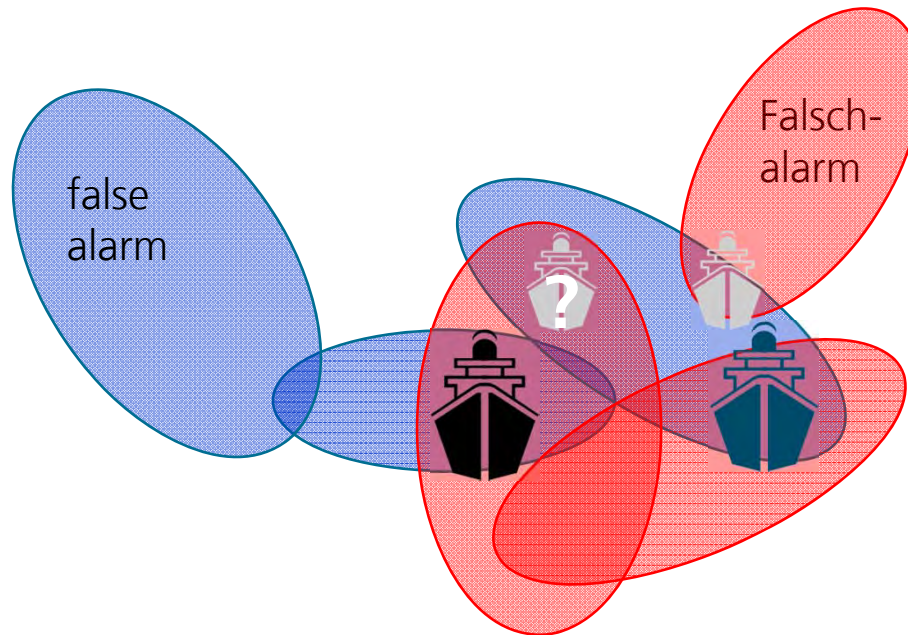
Target positions and motion can only be extracted by **observing** a longer time series of imprecise, ambiguous measurements.

More precise:

- Estimate the target kinematical state by statistical methods = **Tracking**,
Parameter : position, velocity, acceleration

- Partial problems
 - Associate measurements (plots) to existing tracks
 - Track extraction (birth of new tracks)
 - Track deletion (death of tracks)
 - Evolution model or ships (estimate velocity, acceleration)
 - Definition of feasible motion space (at sea, illumination by transmitters)

Challenge: Resolution

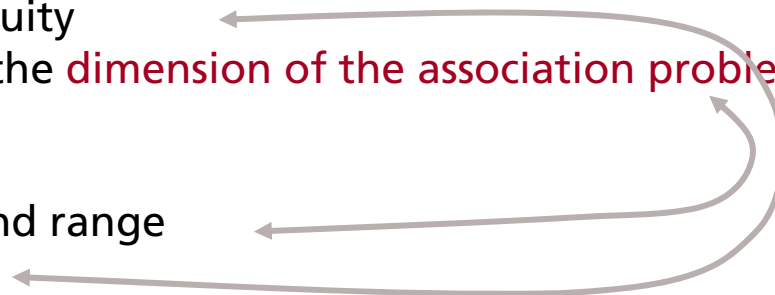


- How many targets are in the Field of View?
- Which measurements belong to which target? (data association)
- State estimation from measurements of *multiple transmitters* at *multiple instants of time*

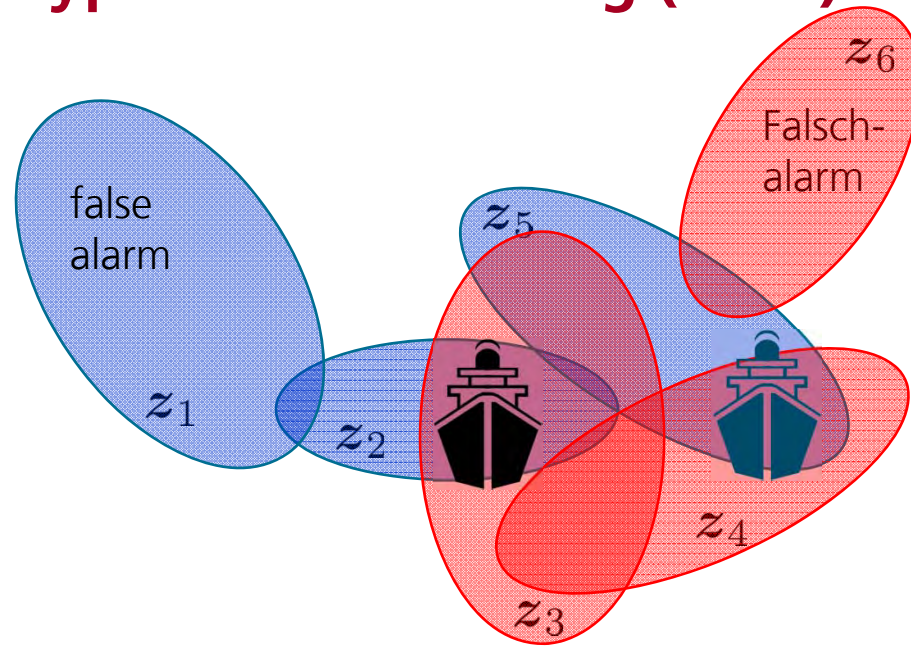
- *multi-target conflicts*, if measurements of different targets intersect
- *False measurements* increase ambiguity
- Size of measurement error defines the **dimension of the association problem**

Challenges of GSM-PCL

- Relatively large errors in azimuth and range
- Strong clutter by direct signal



Solution of the tracking and association problem: Multi-Hypothesen Tracking (MHT)



Interpretation by
different hypotheses:

Hypothesis 1: z_2 & z_3

Hypothesis 2: z_3 & z_5

Hypothesis 3: z_4 & z_5

Hypothesis 4: z_5 & z_6

- Estimated probabilities of hypotheses over time t
- Use informationen of *target evolution* (model & Doppler measurement!) and *a-priori knowledge* (sea abd clutter maps, ...)

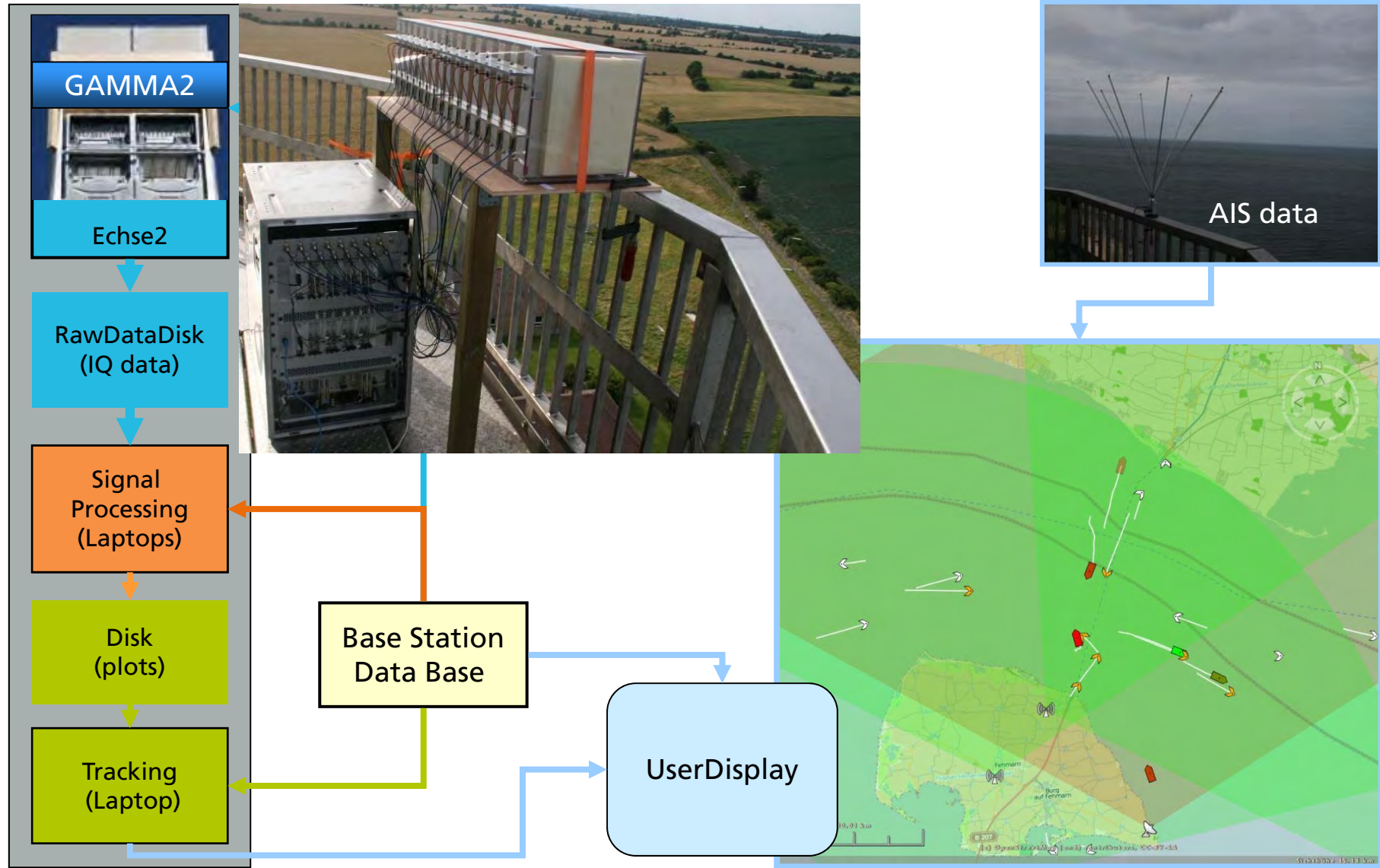
Exploration of GSM Base Stations at the Baltic Sea Shore



Generation of a data base of GSM stations (broadcast signal)

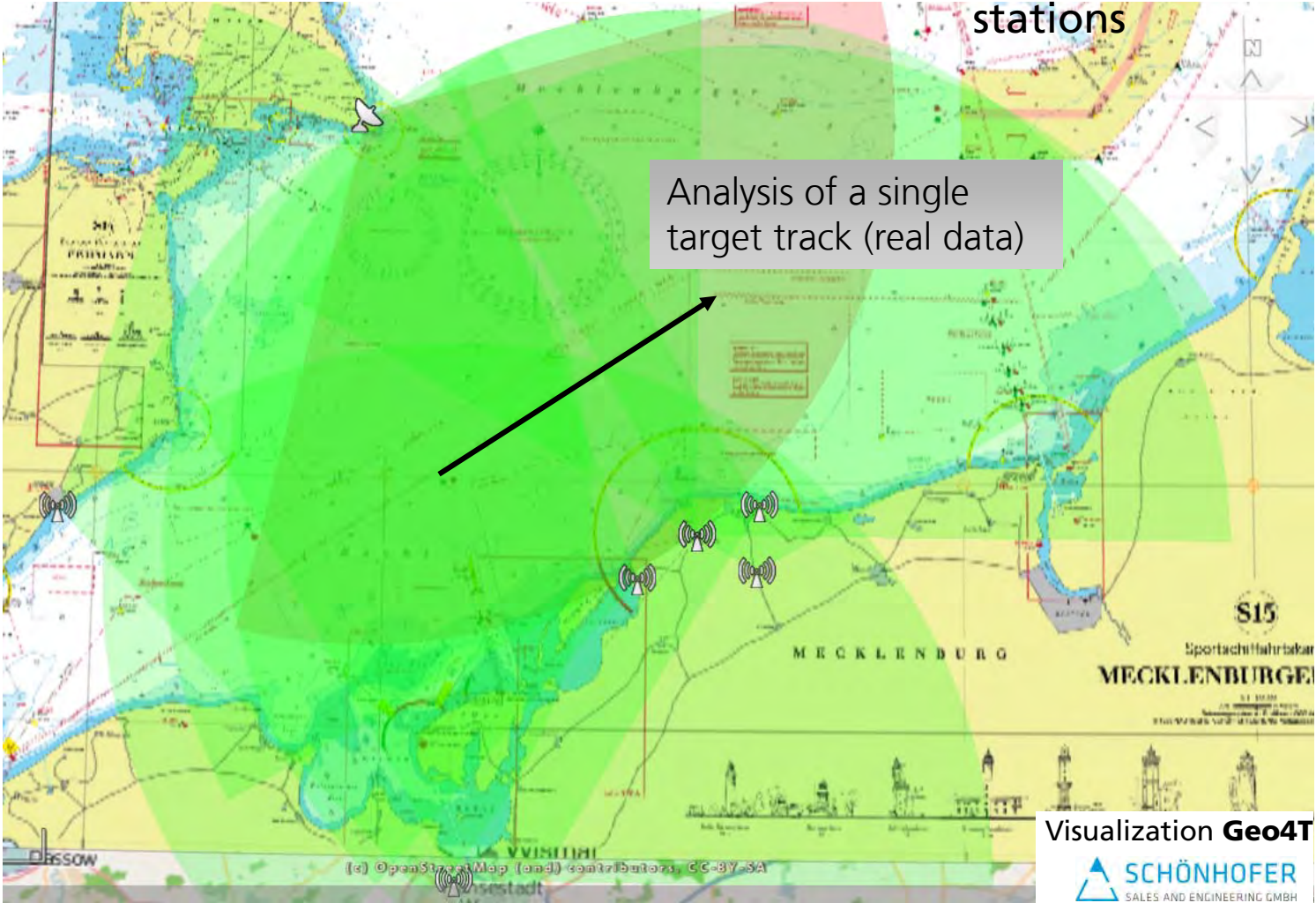


Hardware, Data Flow, and Software

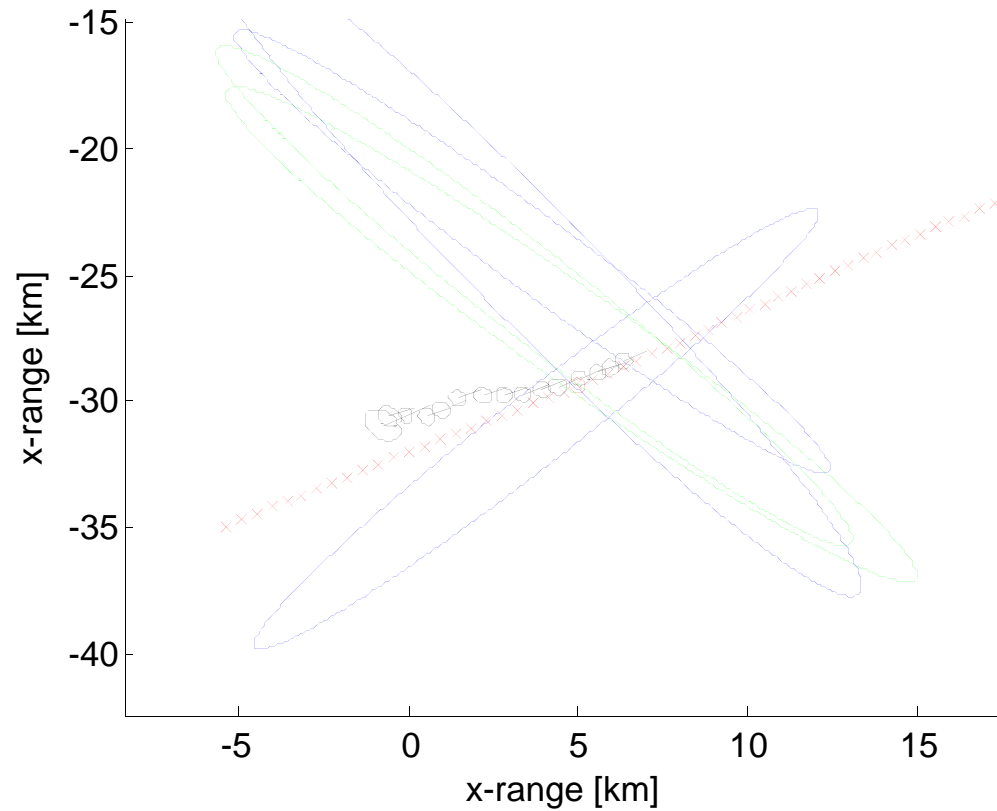


Szenario 1: Lübecker Bucht

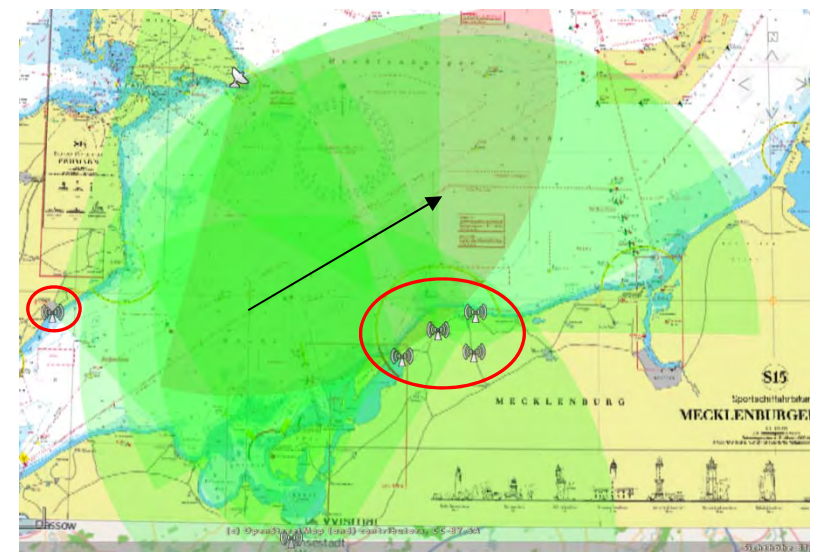
7 GSM base stations



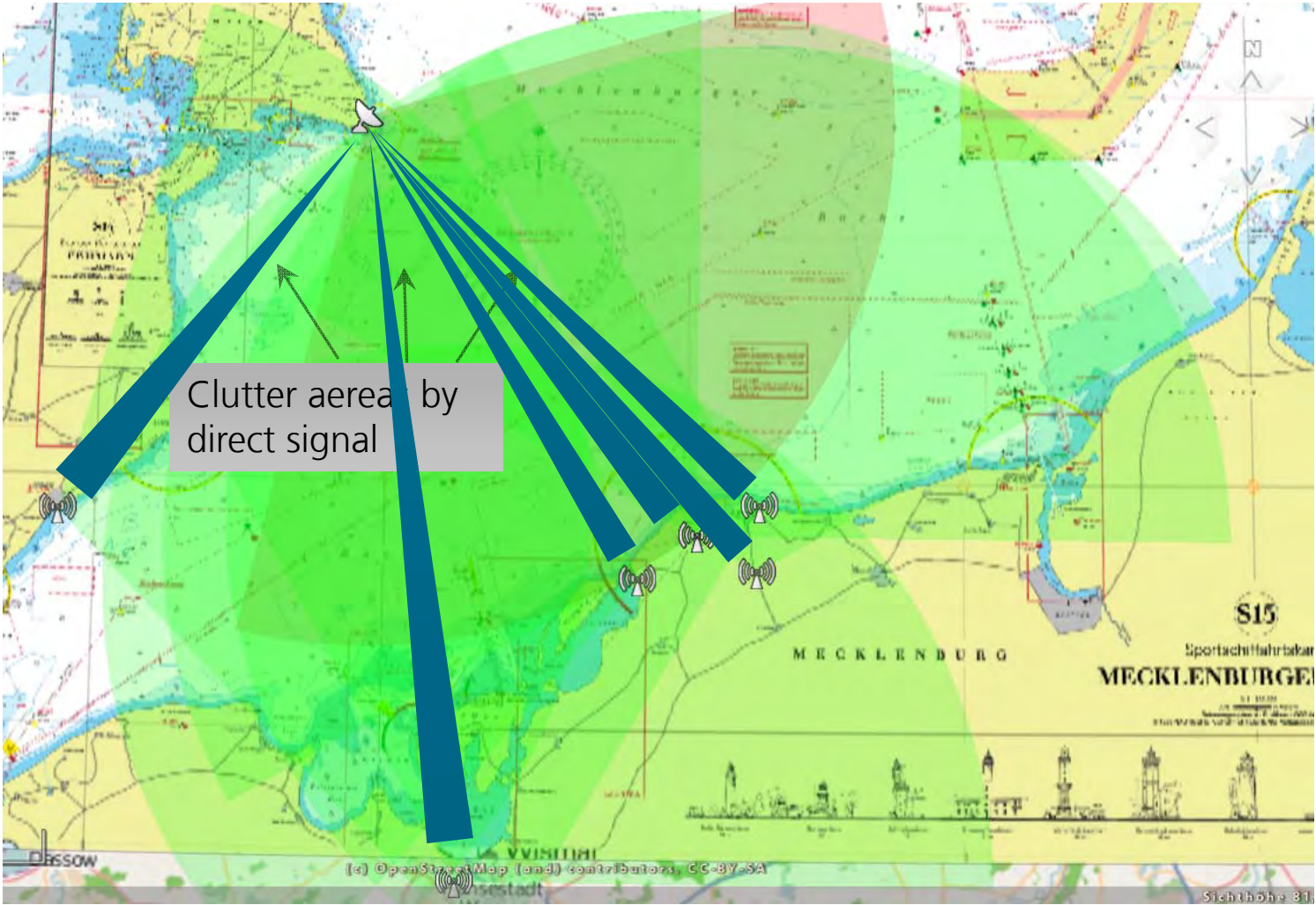
Precision and sensor-to-target geometry (real data)



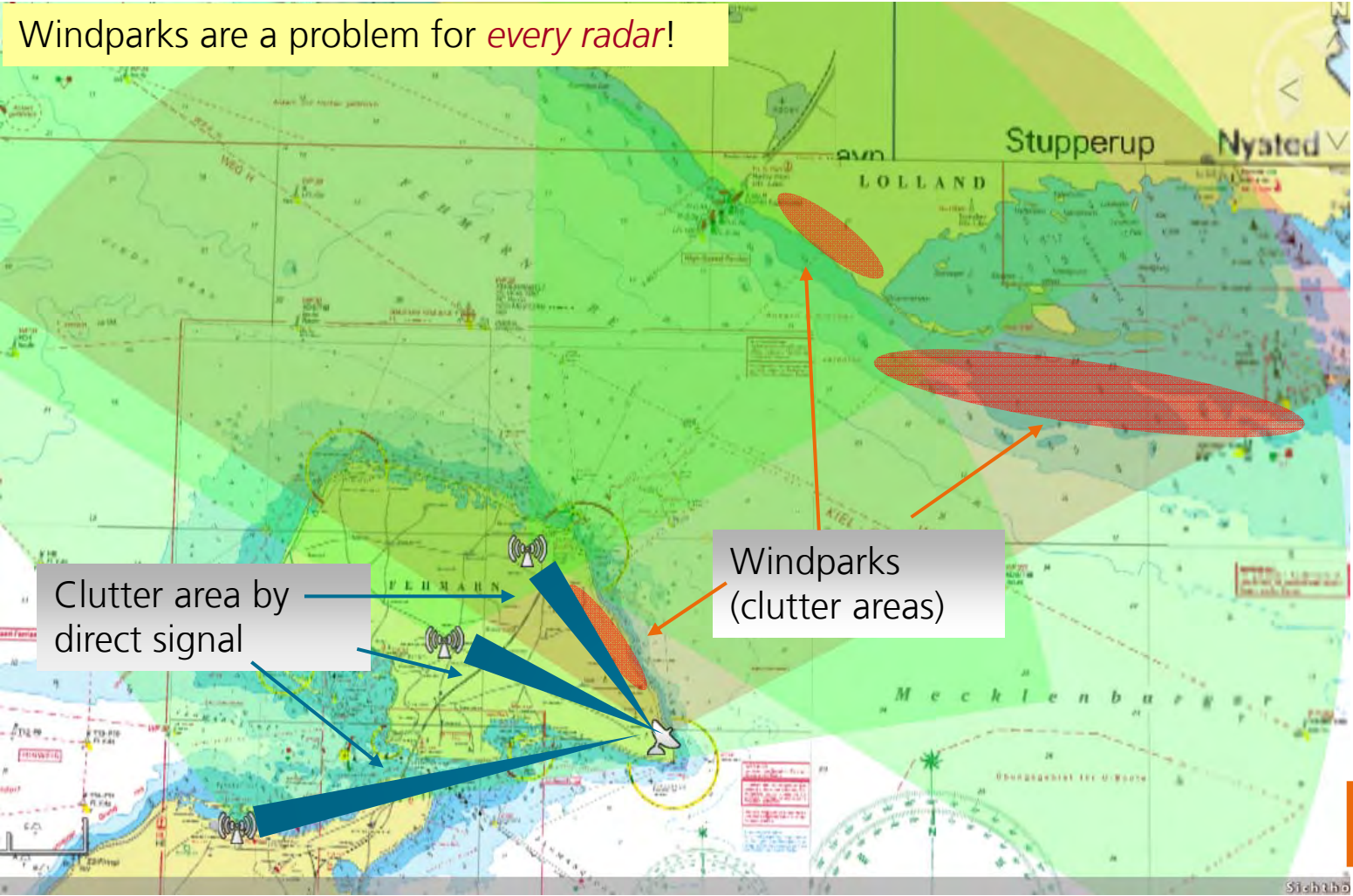
Precision of a position estimate:
ca. 200 m



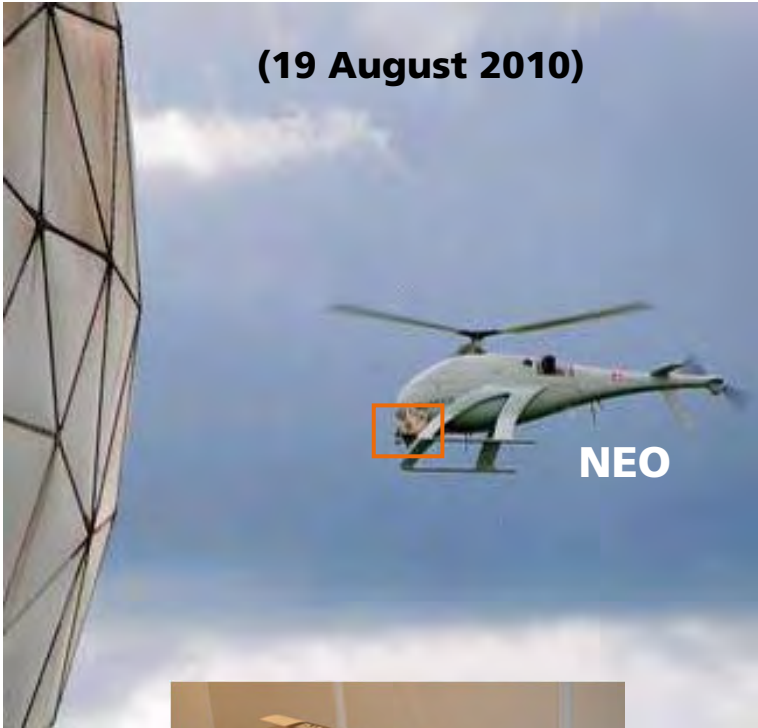
Szenario 1: Lübecker Bucht – Clutter Areas



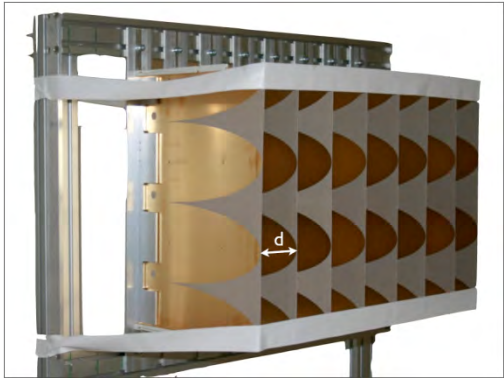
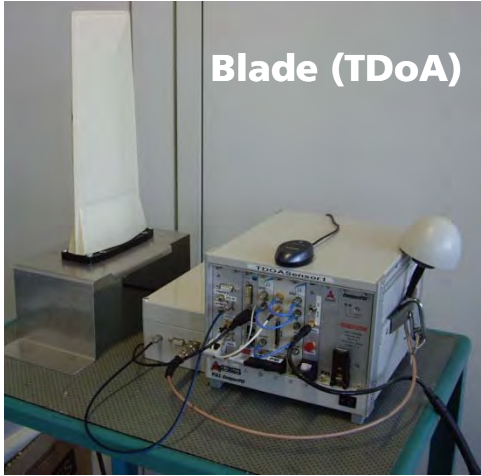
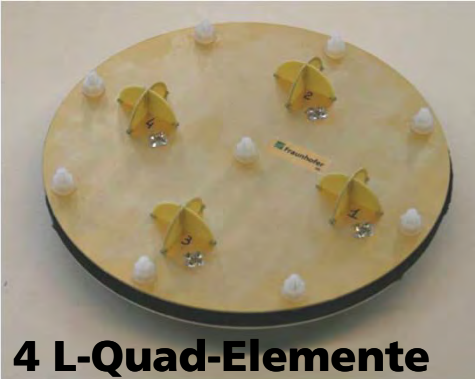
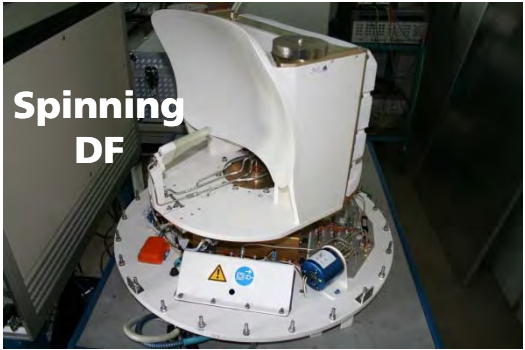
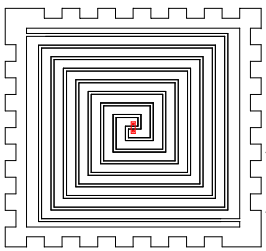
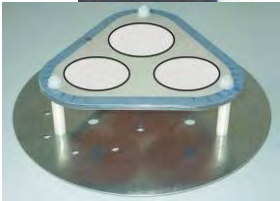
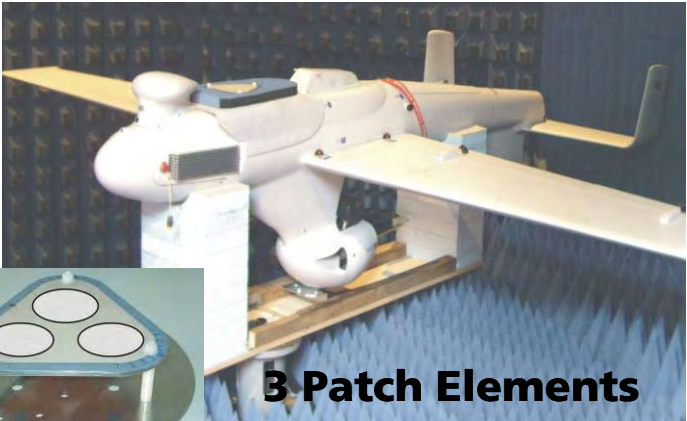
Szenario 2: Fehmarn Belt – Clutter Areas



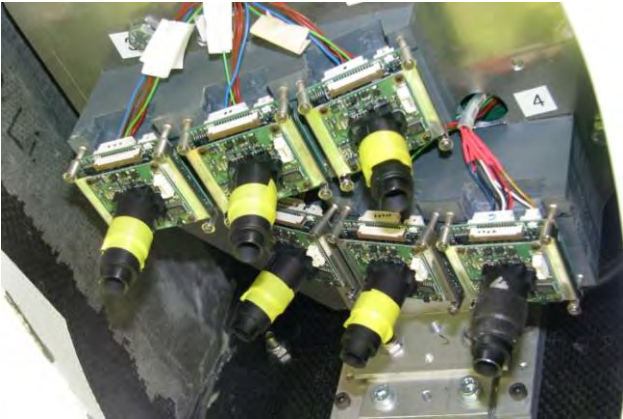
UAS sensor platforms with FKIE involvement



RF sensors used in FKIE experiments



Fusion of ESM and ImINT



Simulation: Fusion SIGINT+IMINT (\rightarrow MiSAR)

DOA sensor

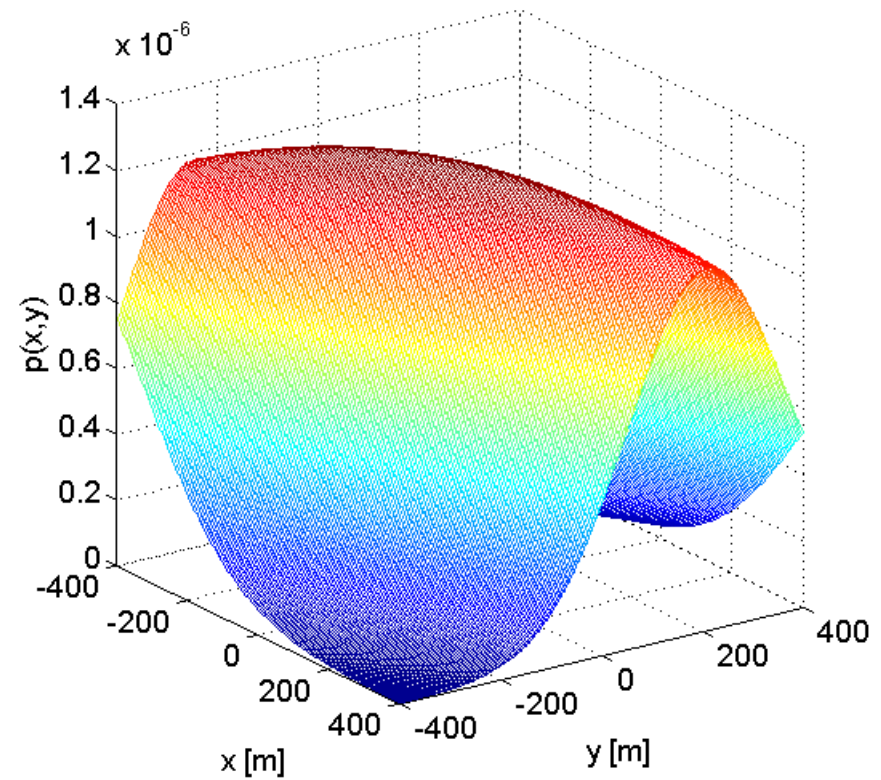
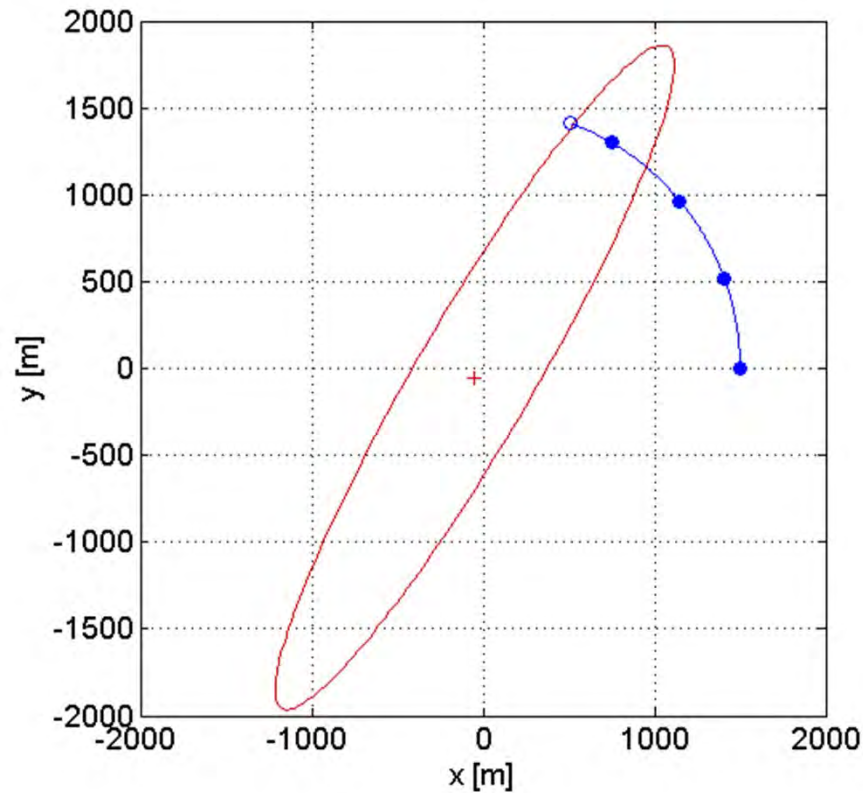
- observation point

Image sensor

- observation point

- field of view

} localization



Simulation: Fusion SIGINT+IMINT (→ MiSAR)

DOA sensor

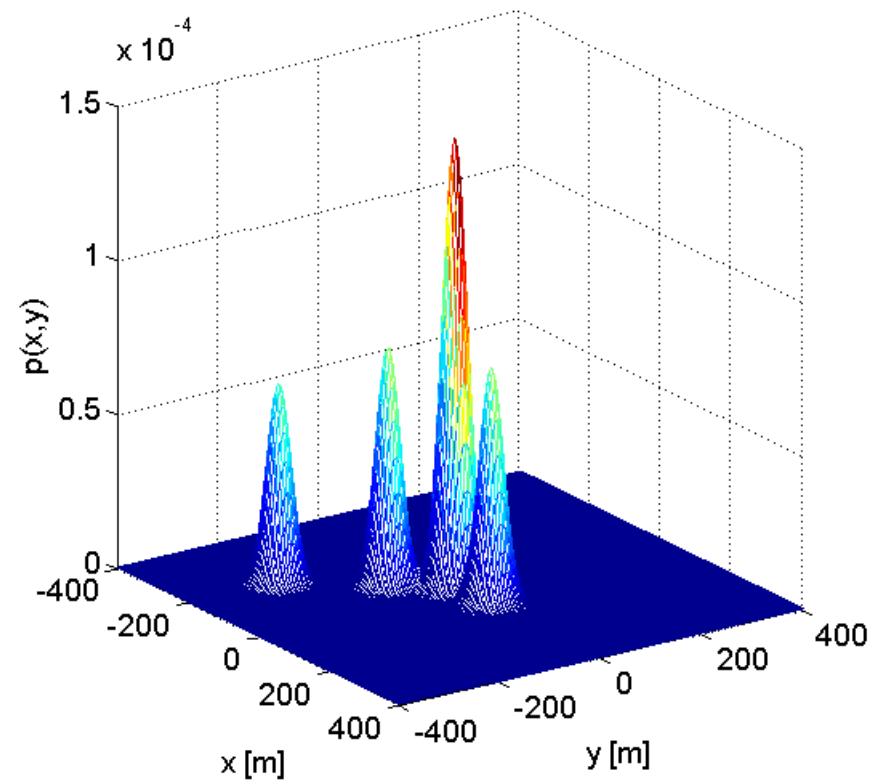
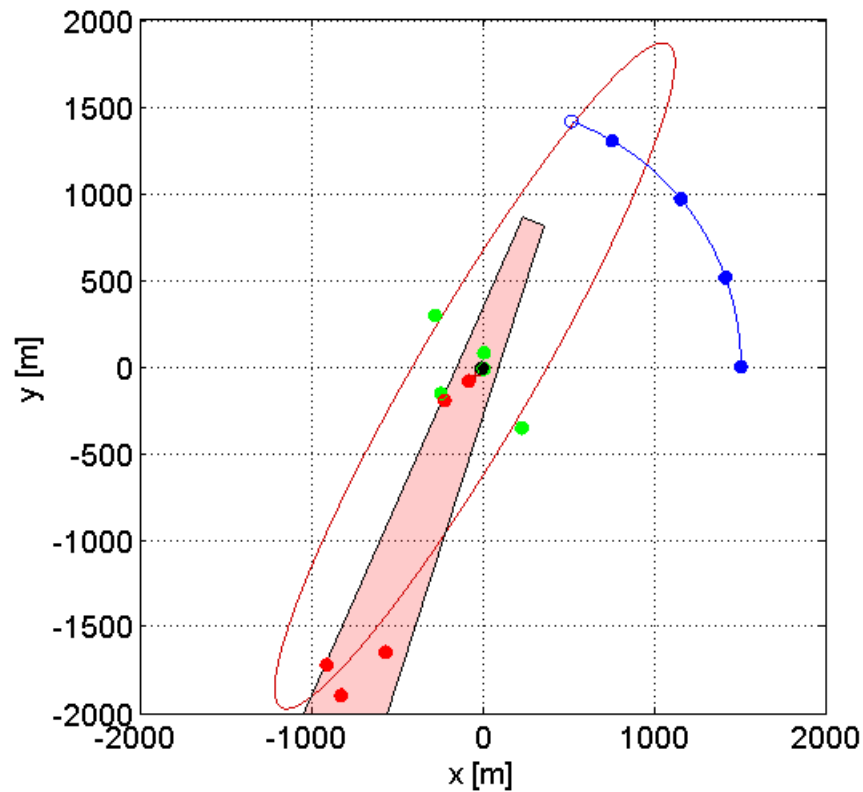
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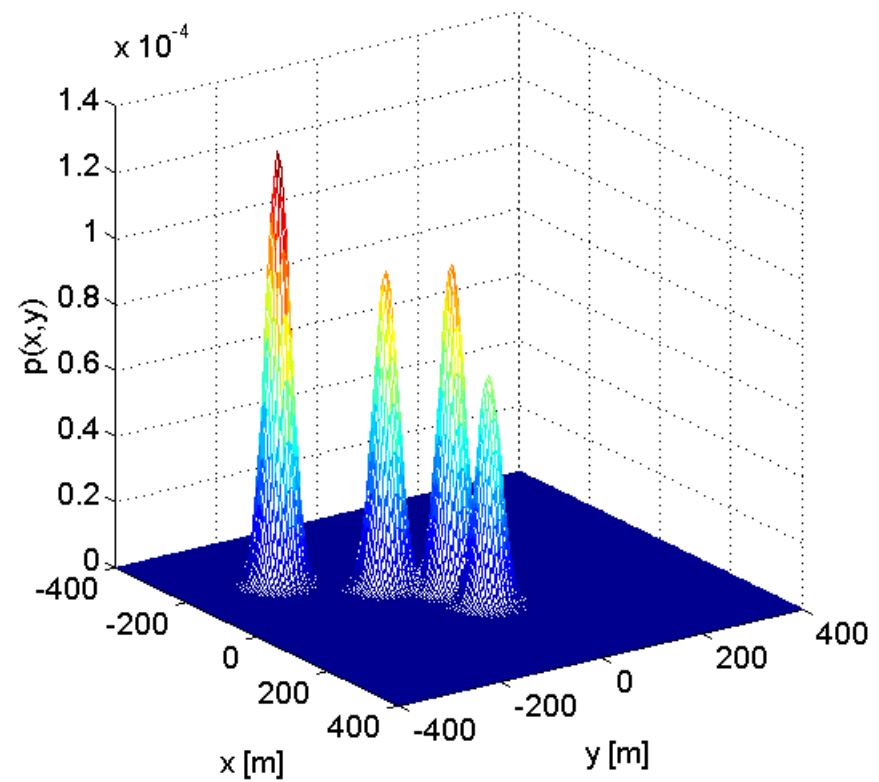
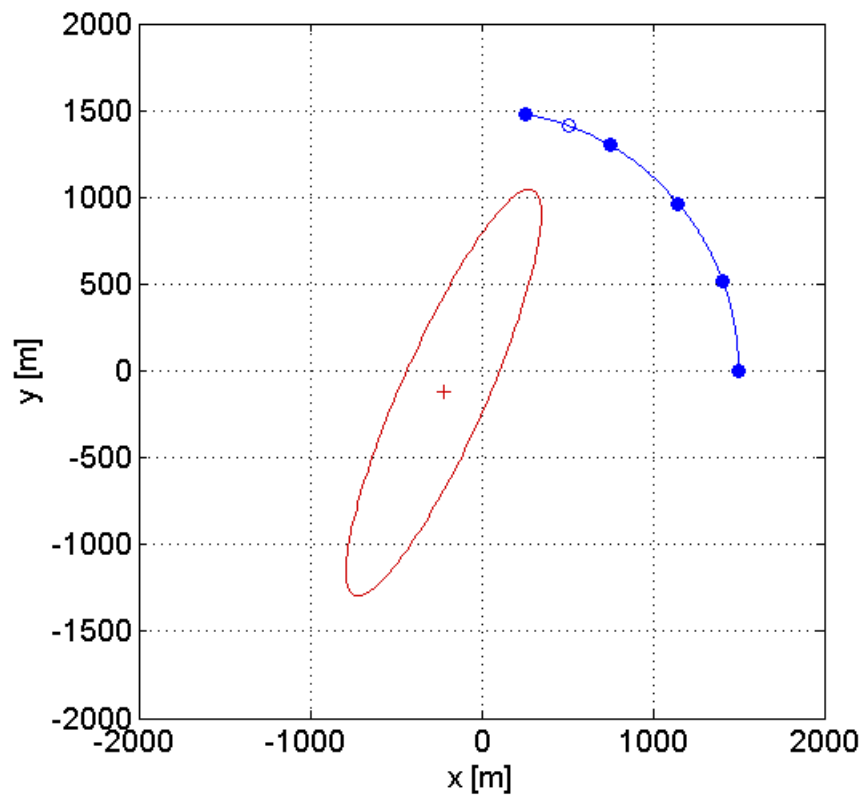
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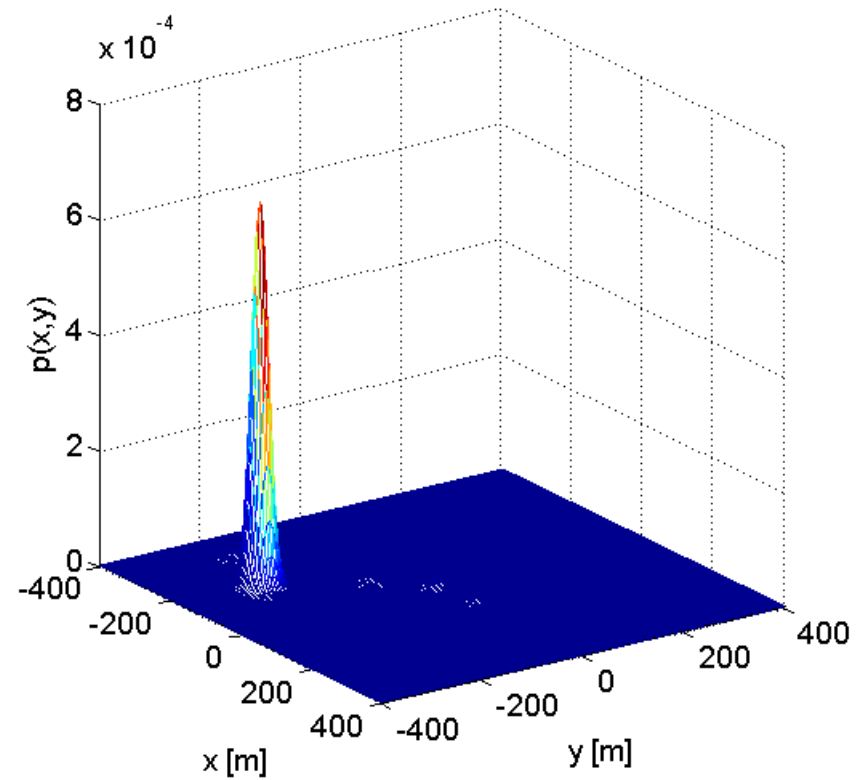
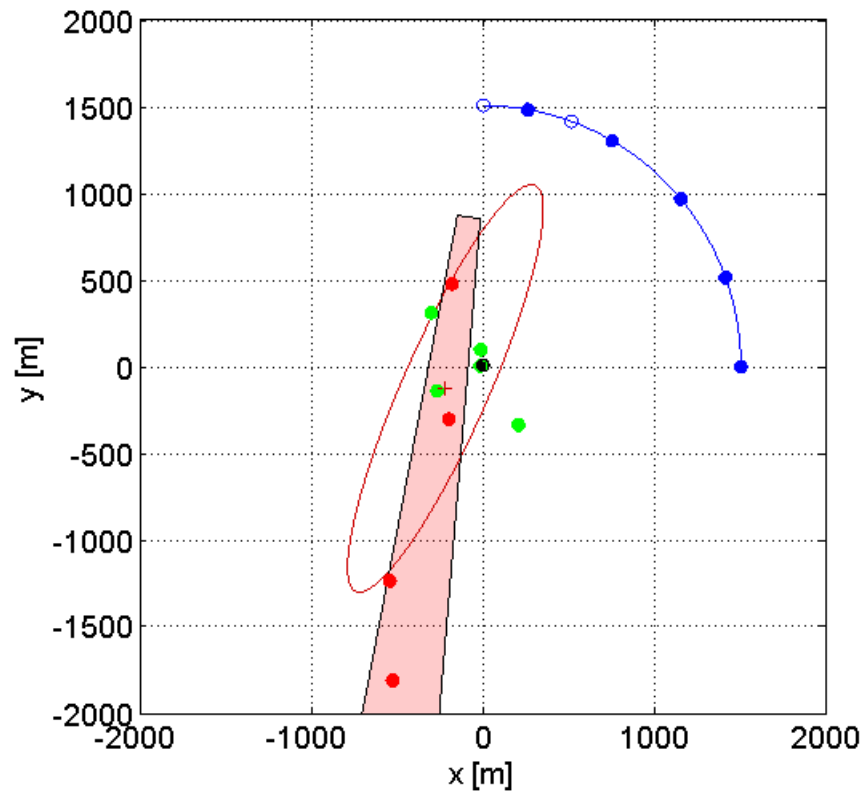
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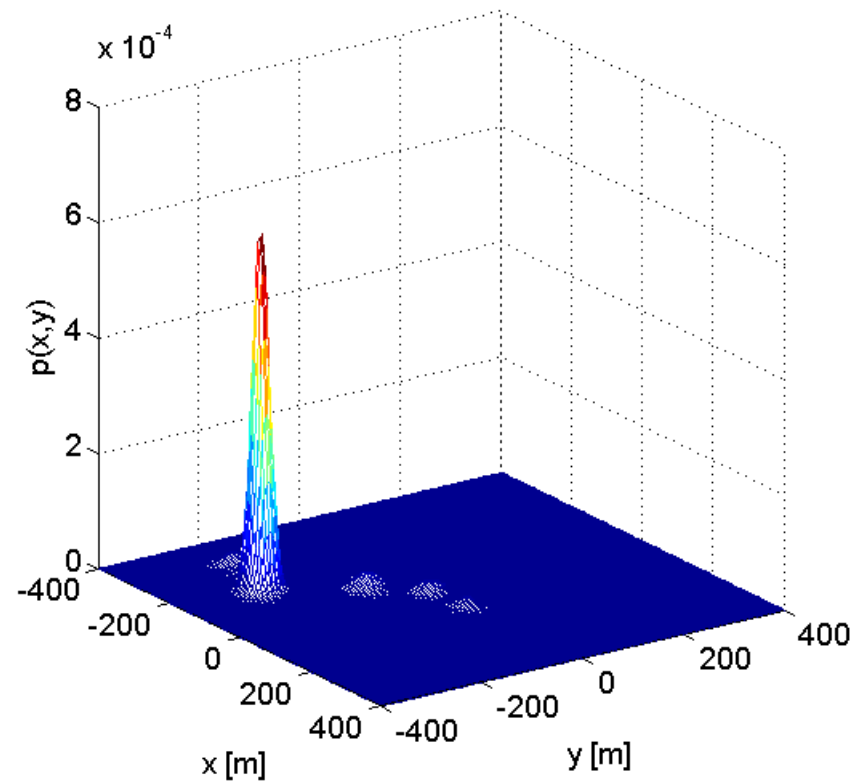
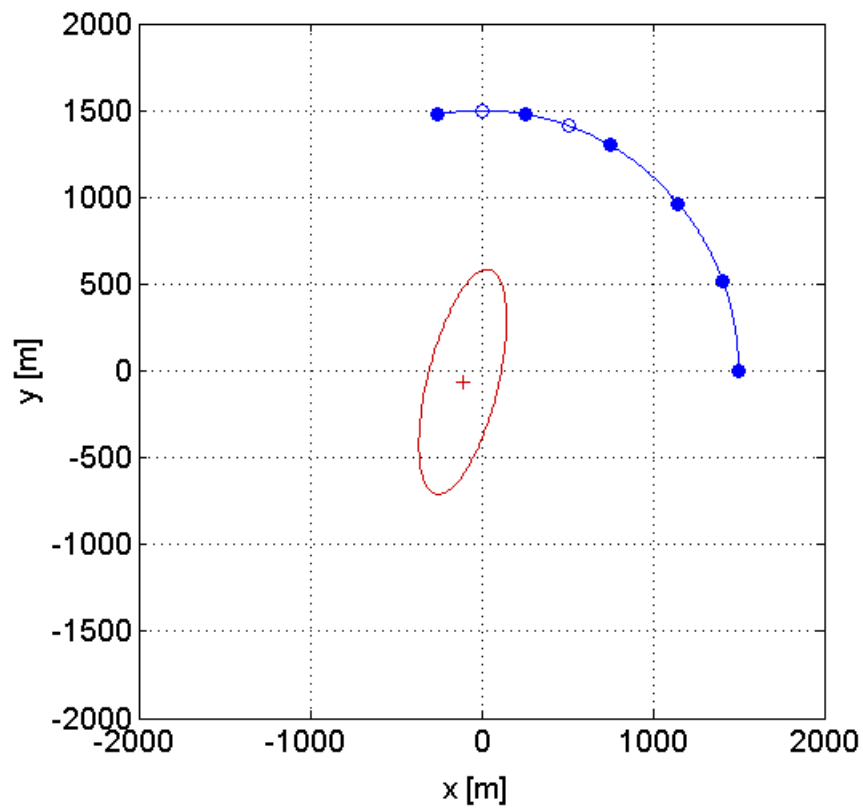
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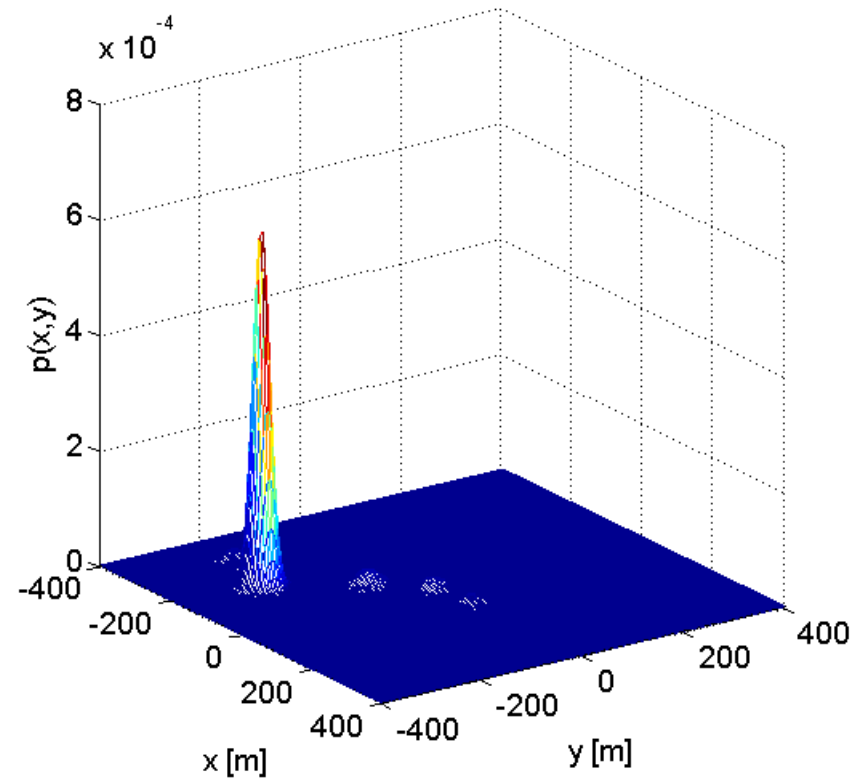
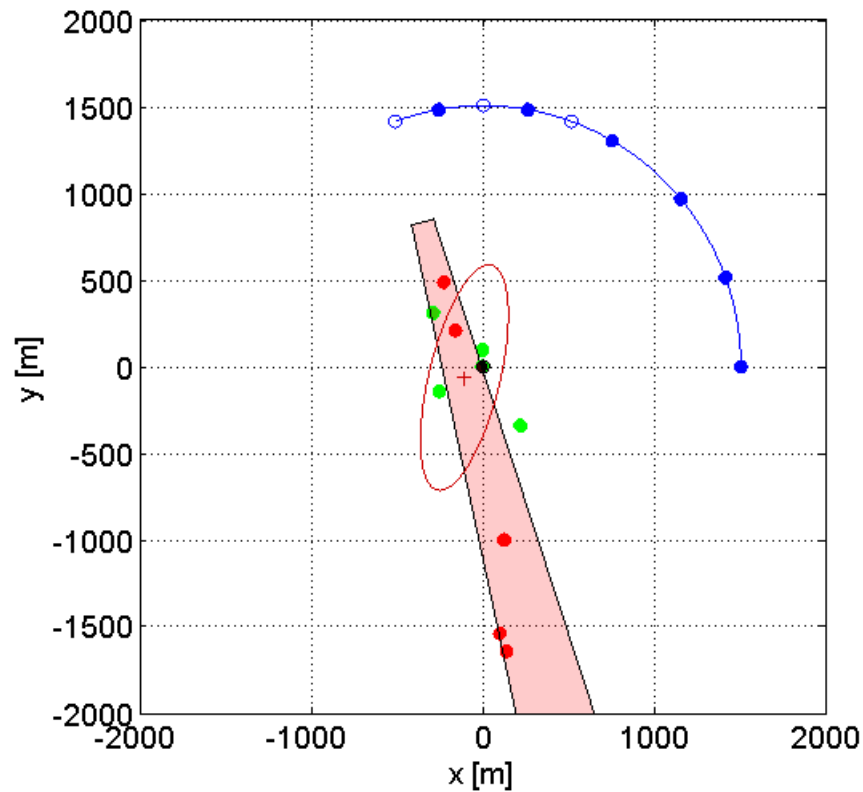
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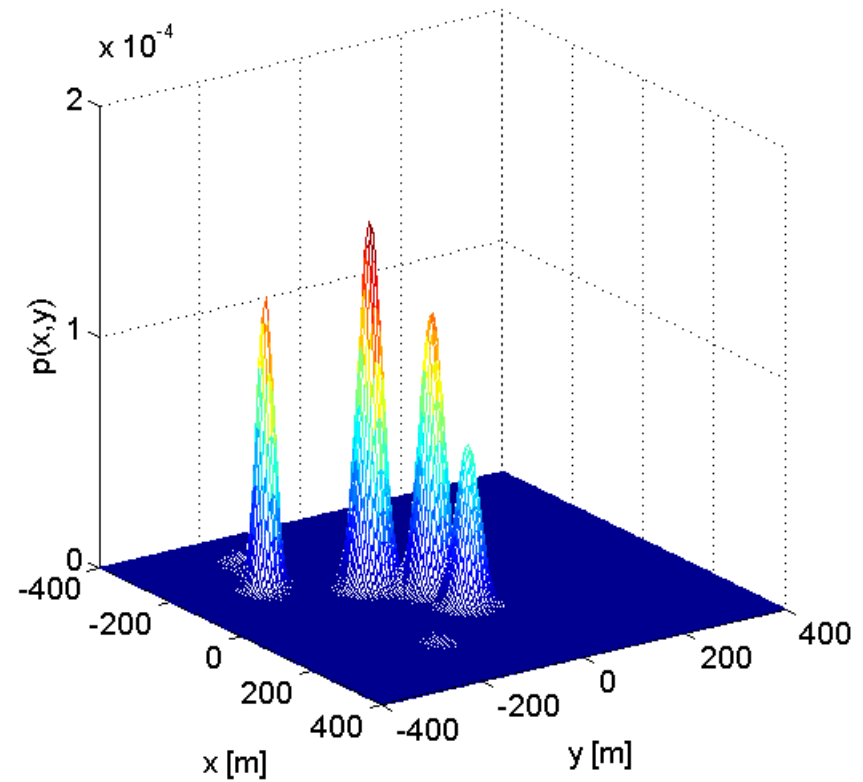
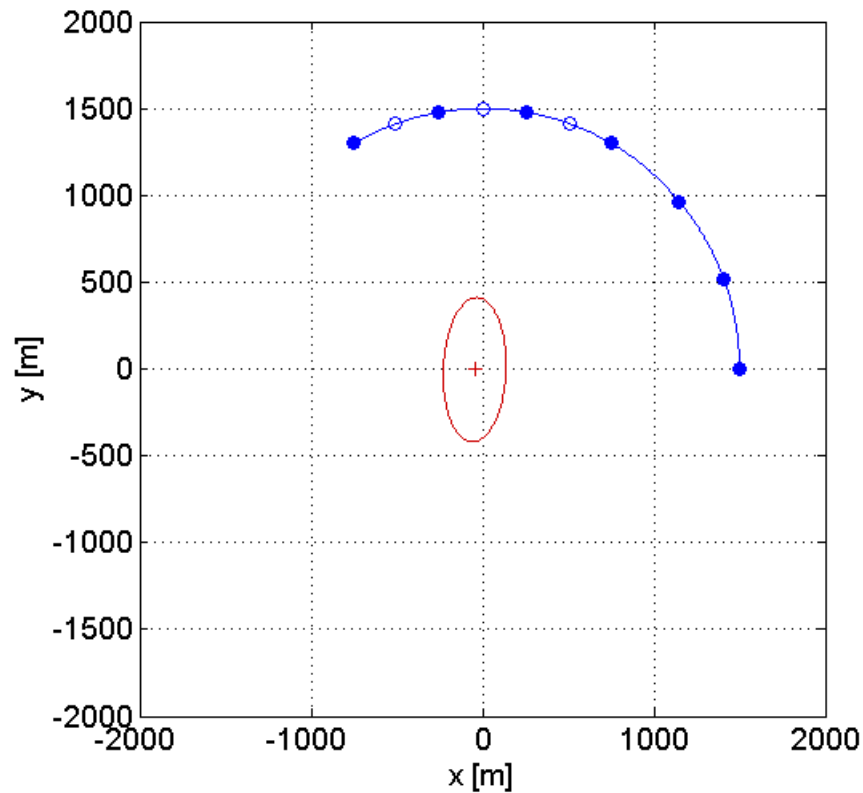
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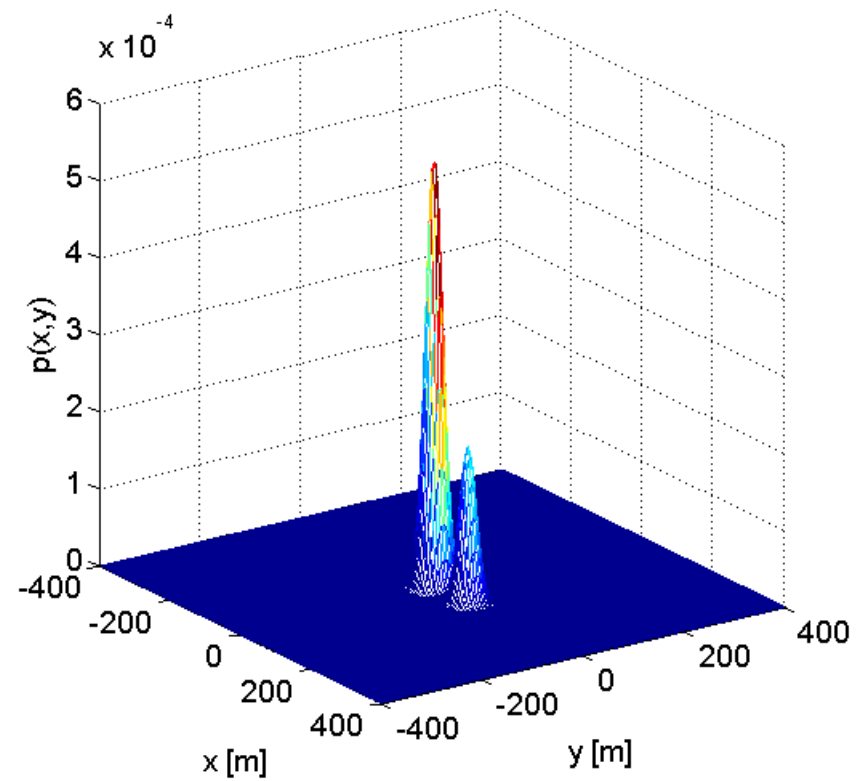
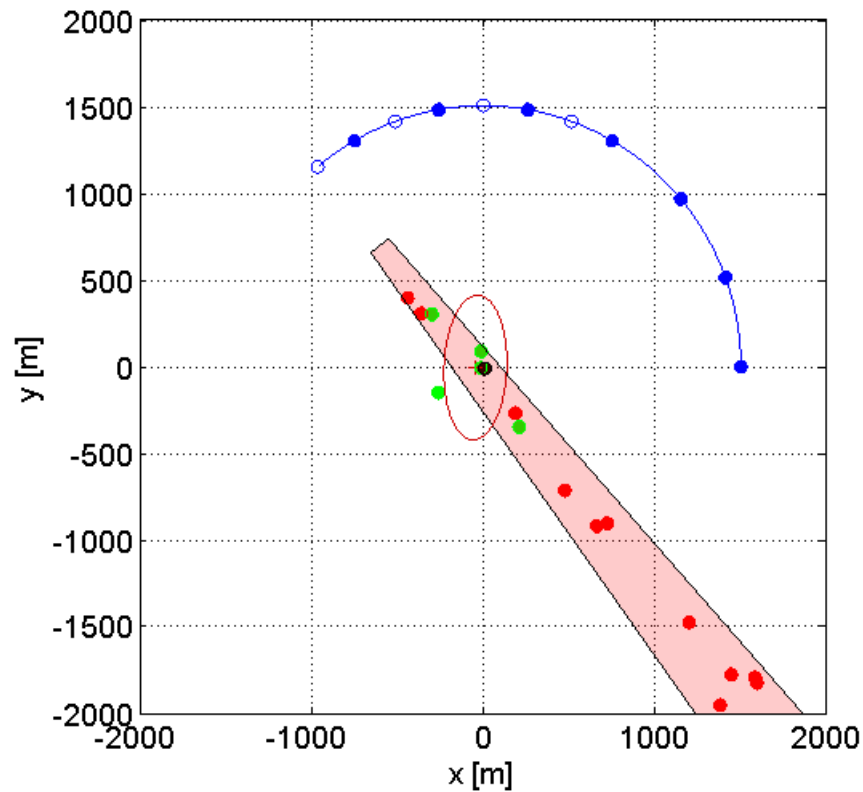
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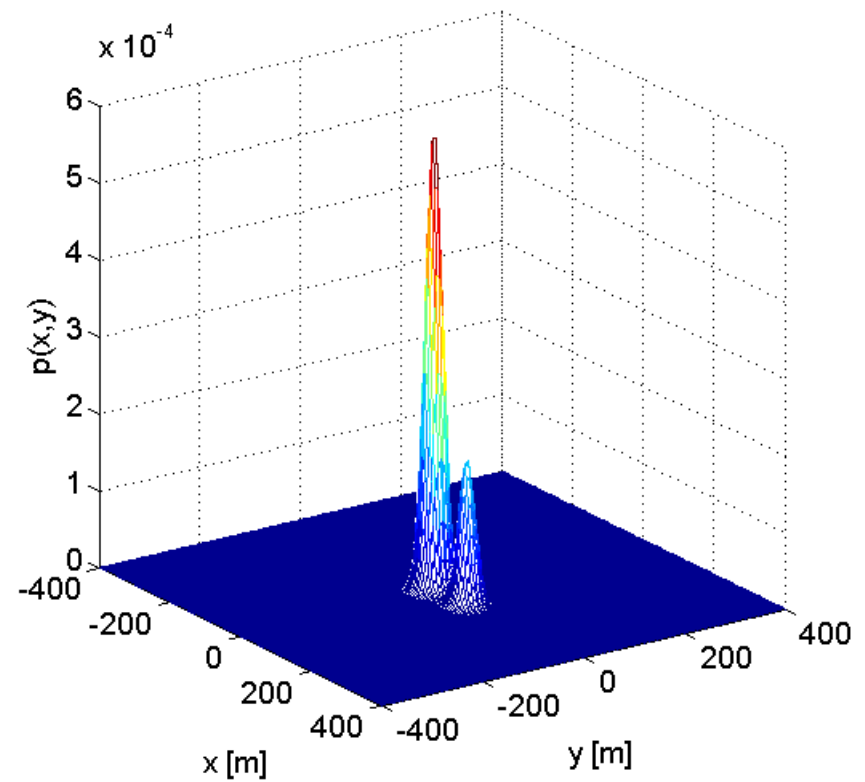
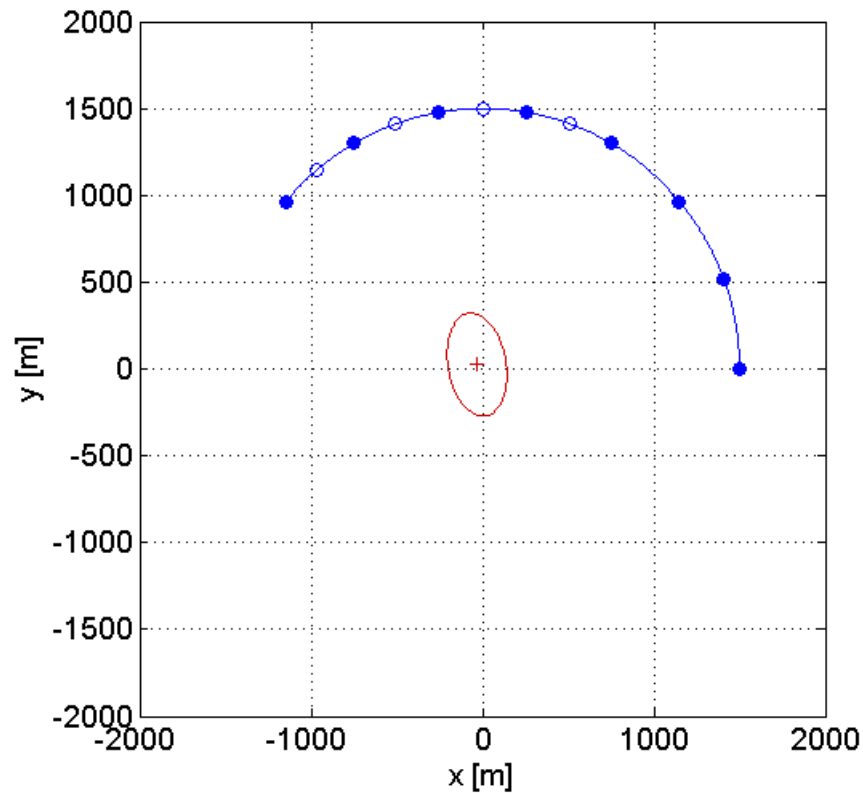
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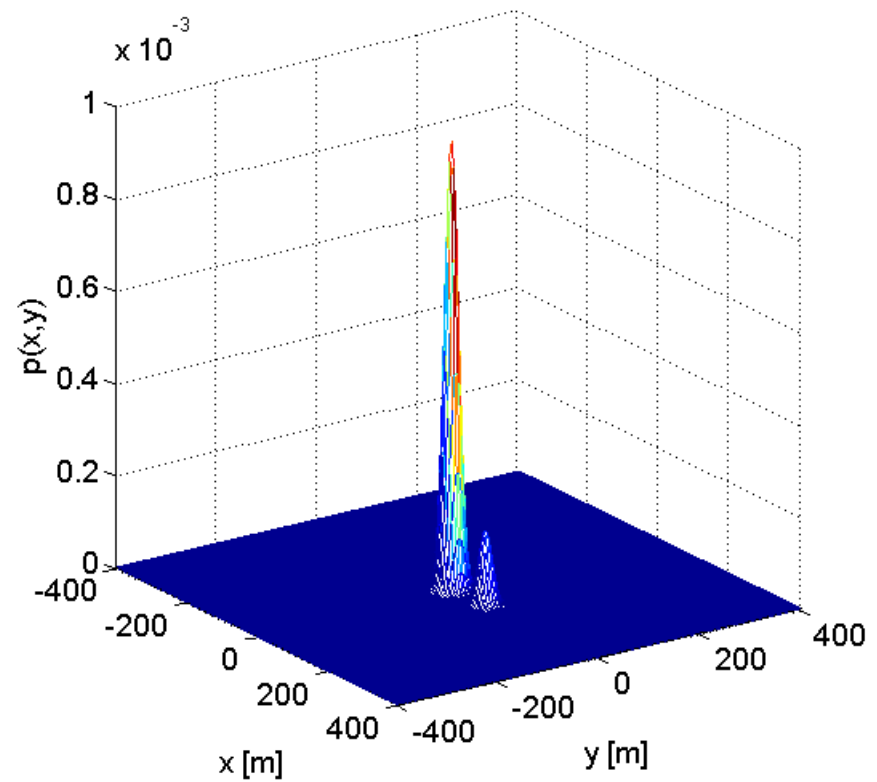
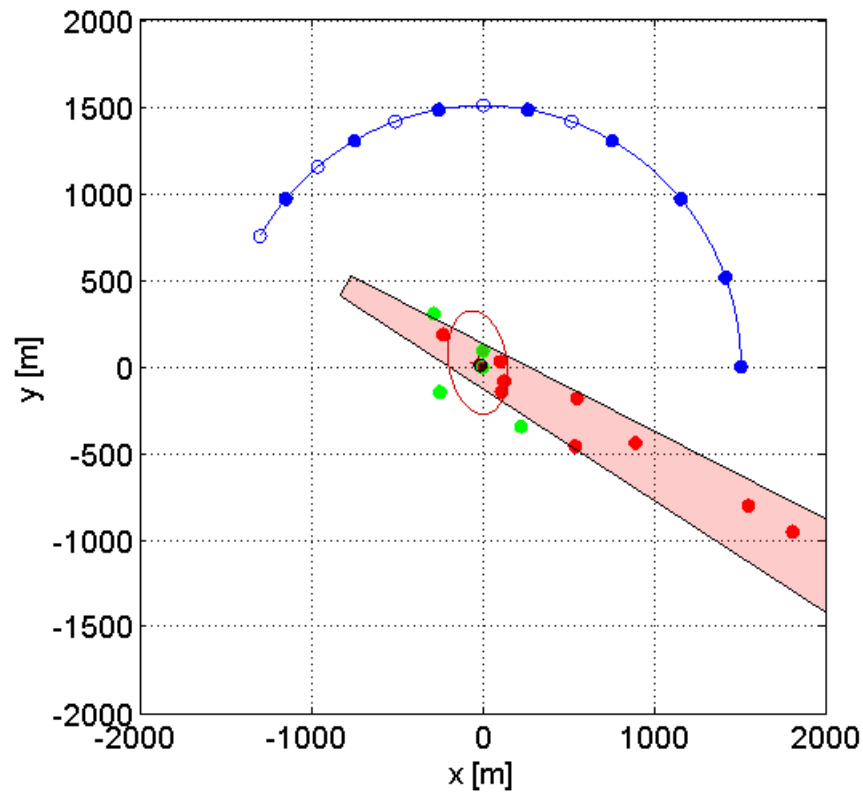
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Simulation: Fusion SIGINT+IMINT (→ MiSAR)

DOA sensor

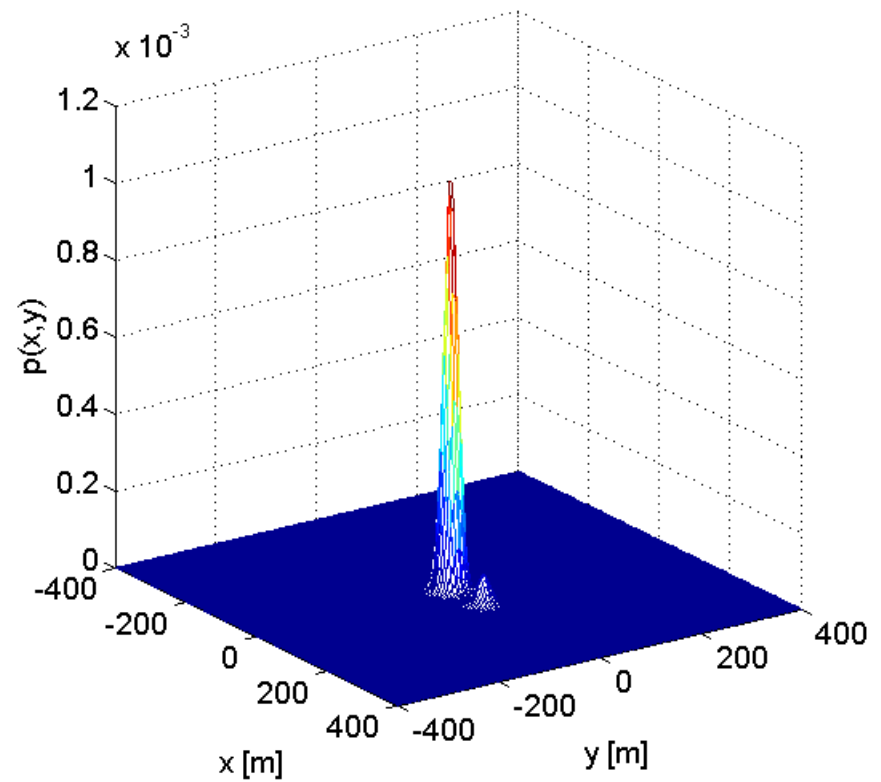
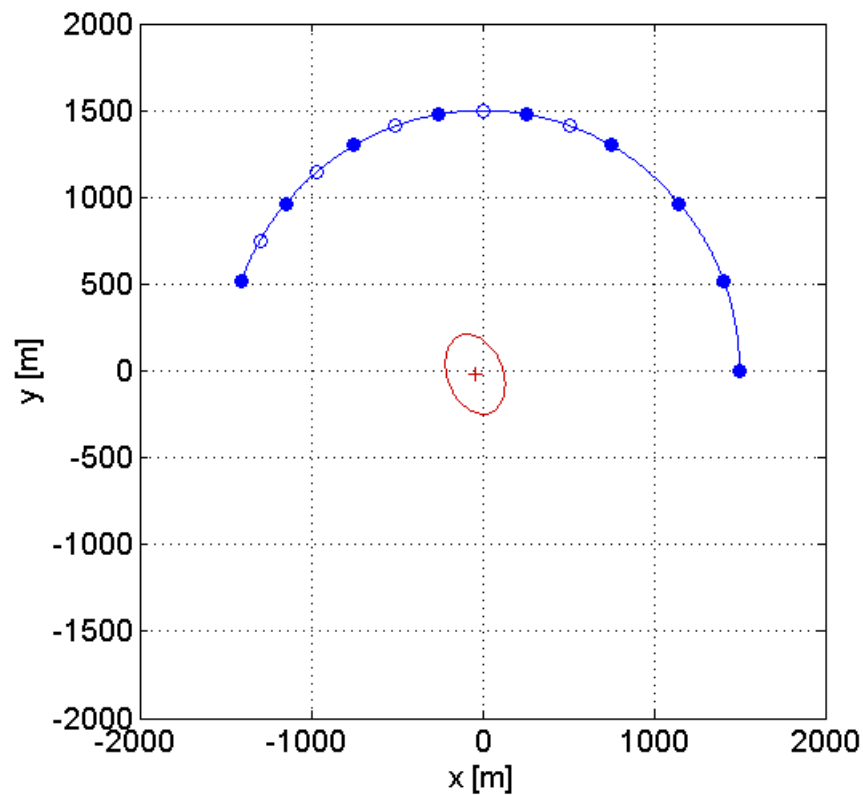
- observation point

Image sensor

- observation point

- field of view

} localization



Simulation: Fusion SIGINT+IMINT (→ MiSAR)

DOA sensor

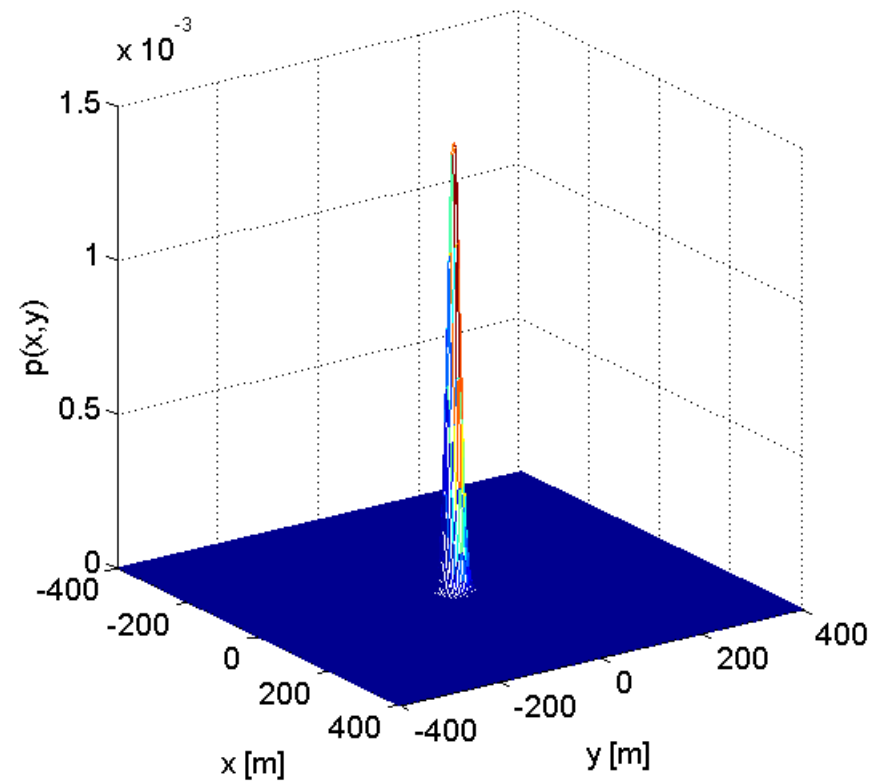
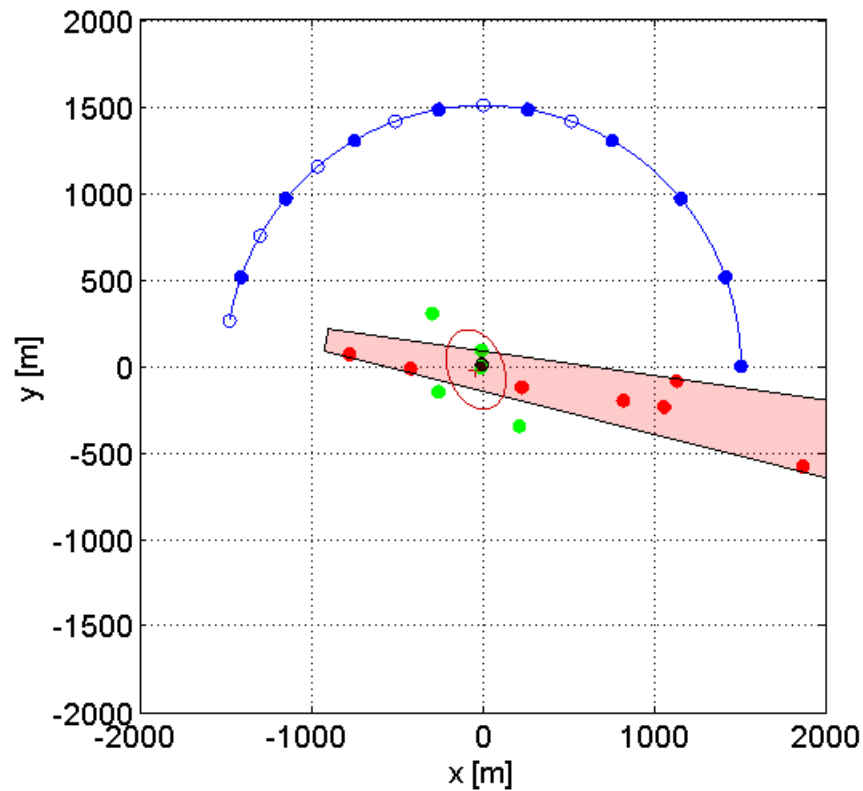
- observation point

Image sensor

- observation point

- field of view

} localization



Simulation: Fusion SIGINT+IMINT (→ MiSAR)

DOA sensor

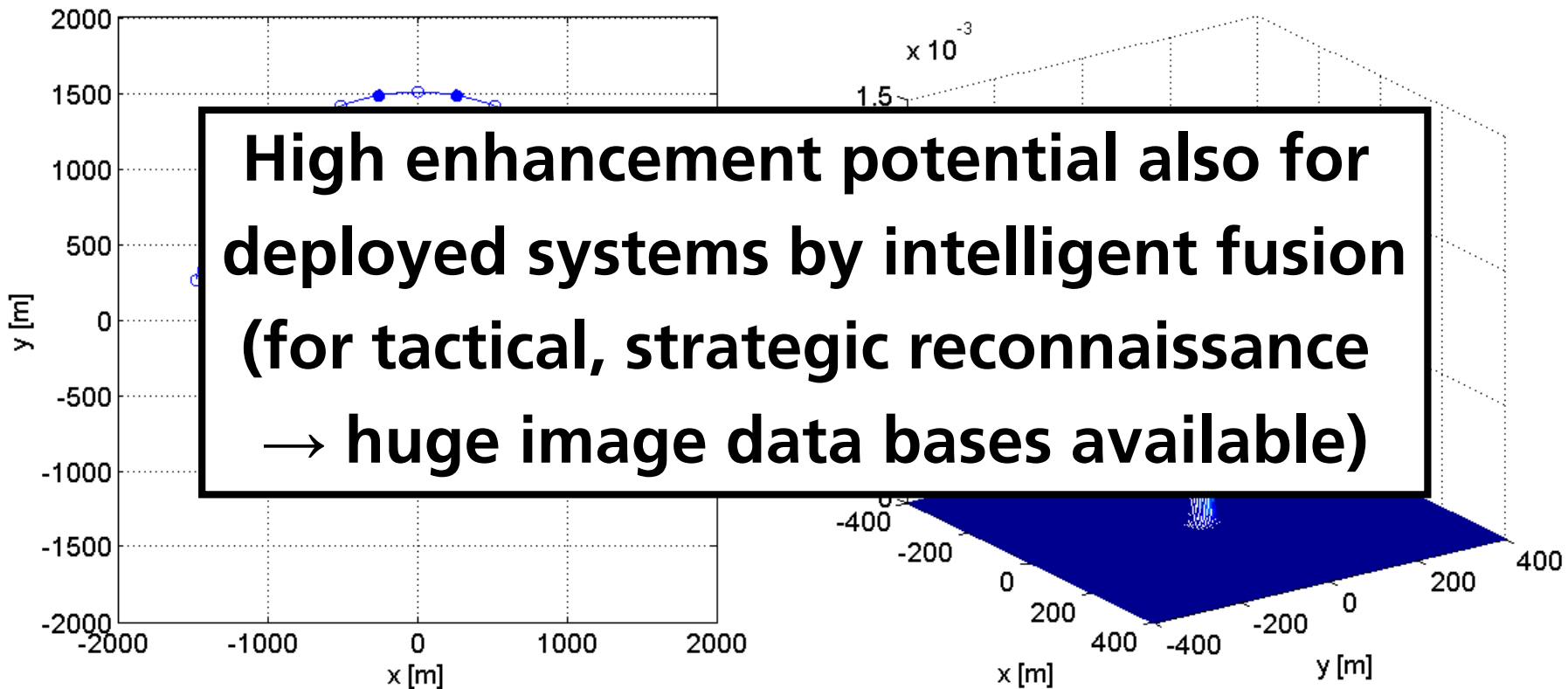
- observation point

Image sensor

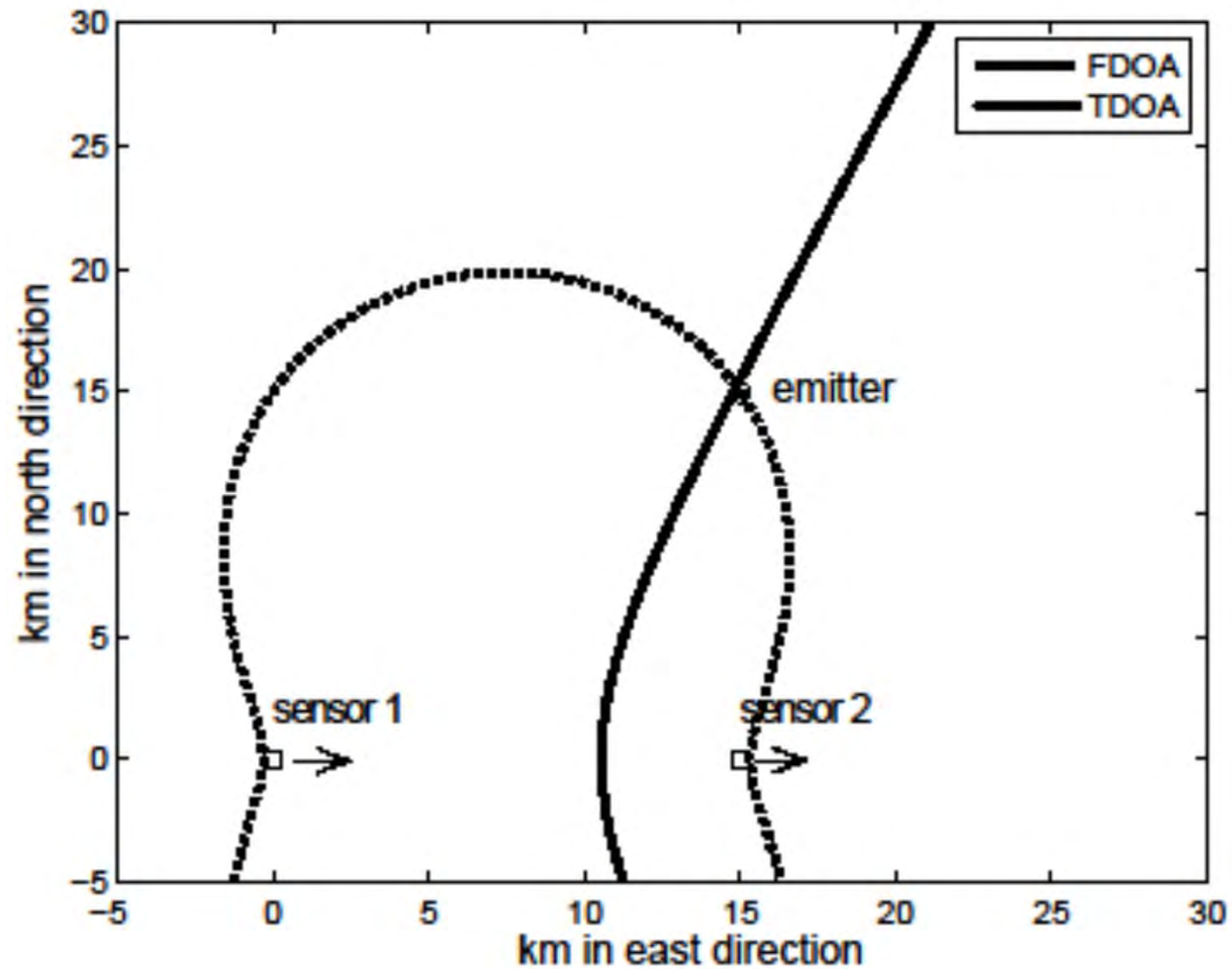
- observation point

- field of view

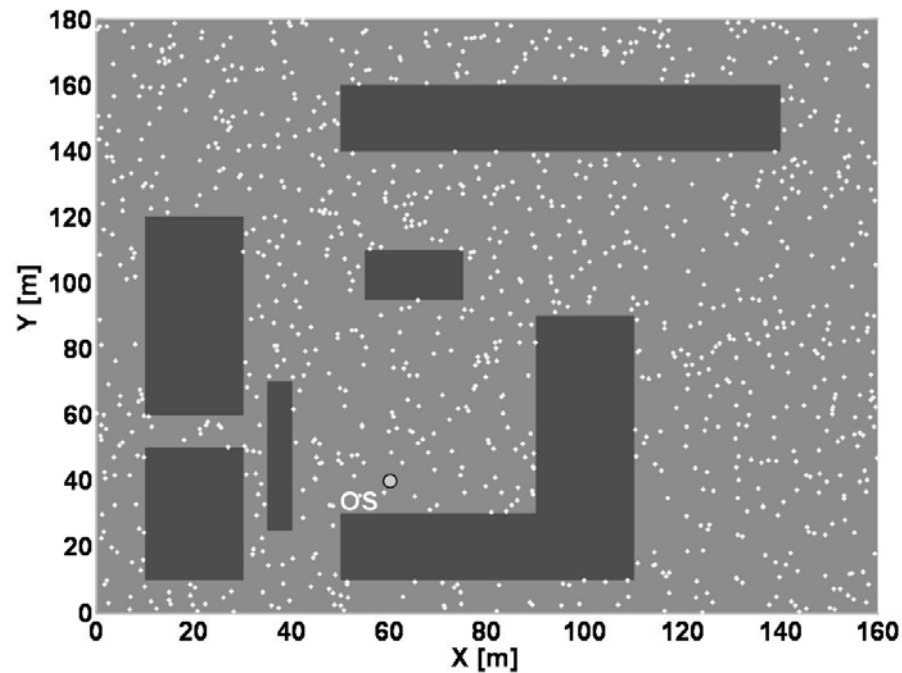
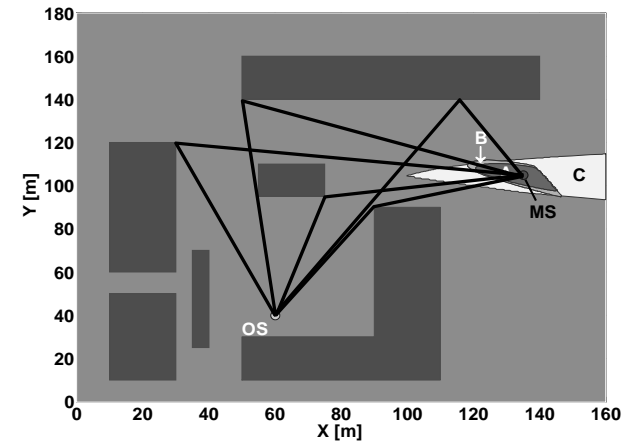
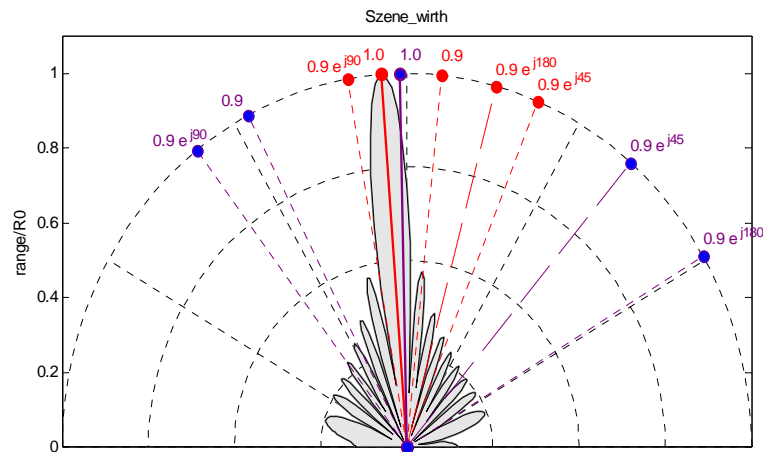
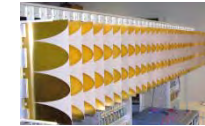
} localization



Emitter Localization: Fusion of AoA, TDoA, FDoA

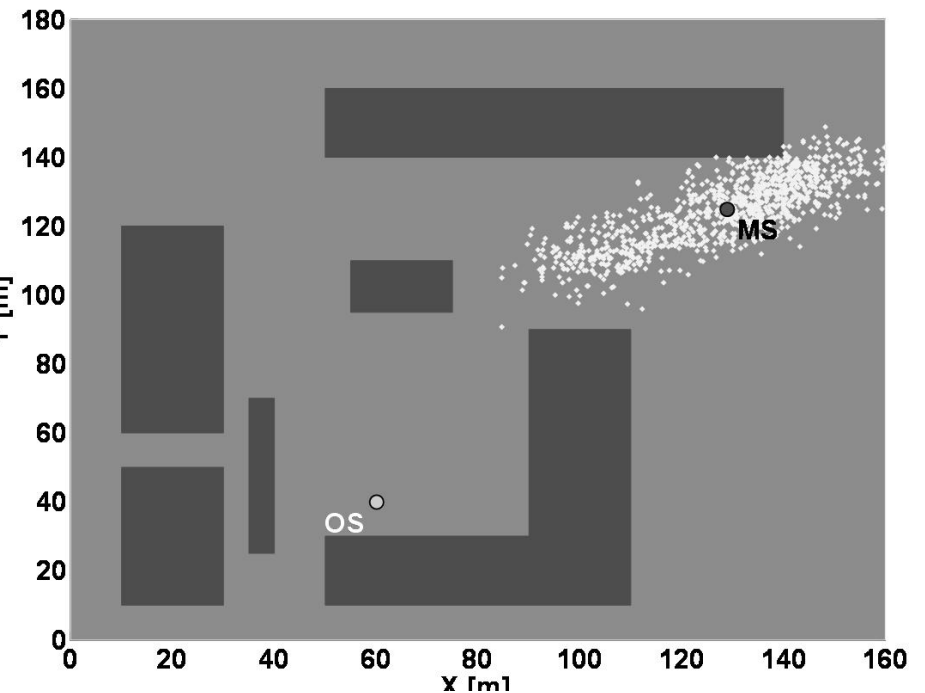
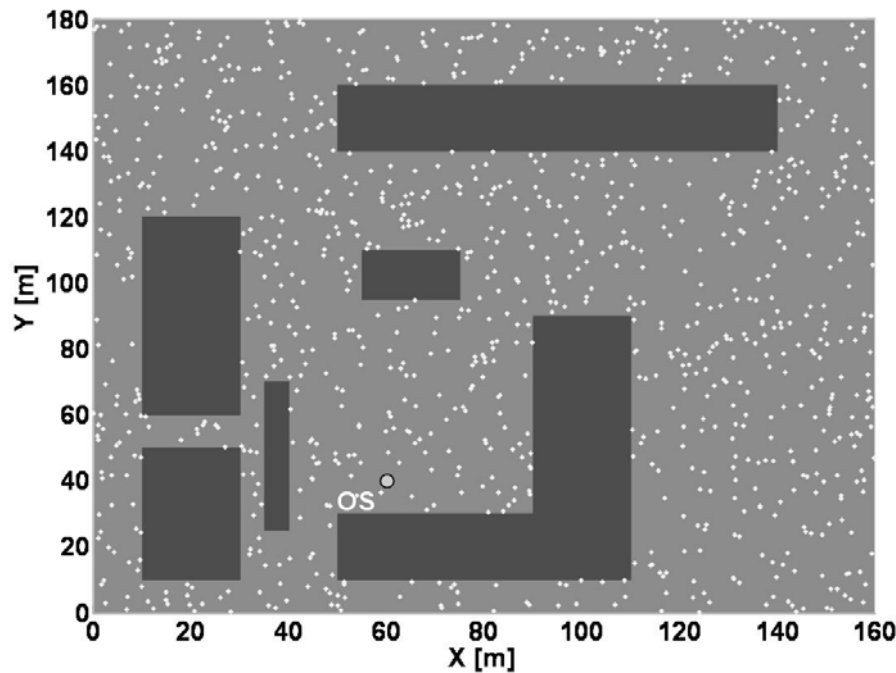
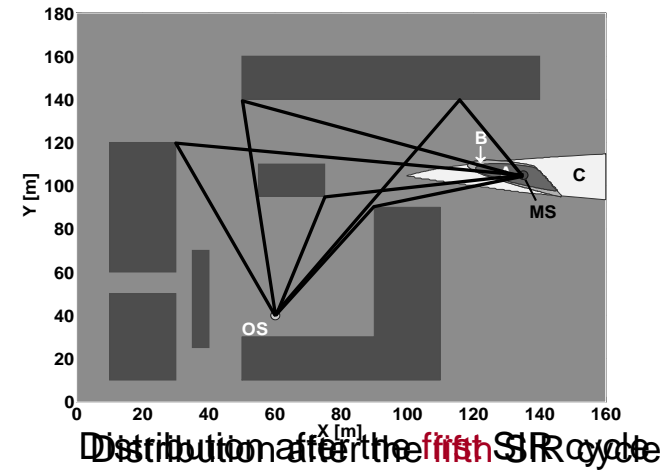
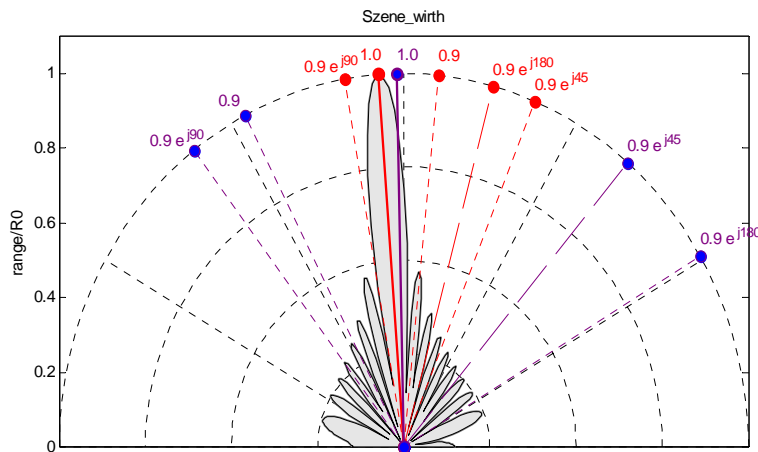


GAMMA: Urban Emitter Localization



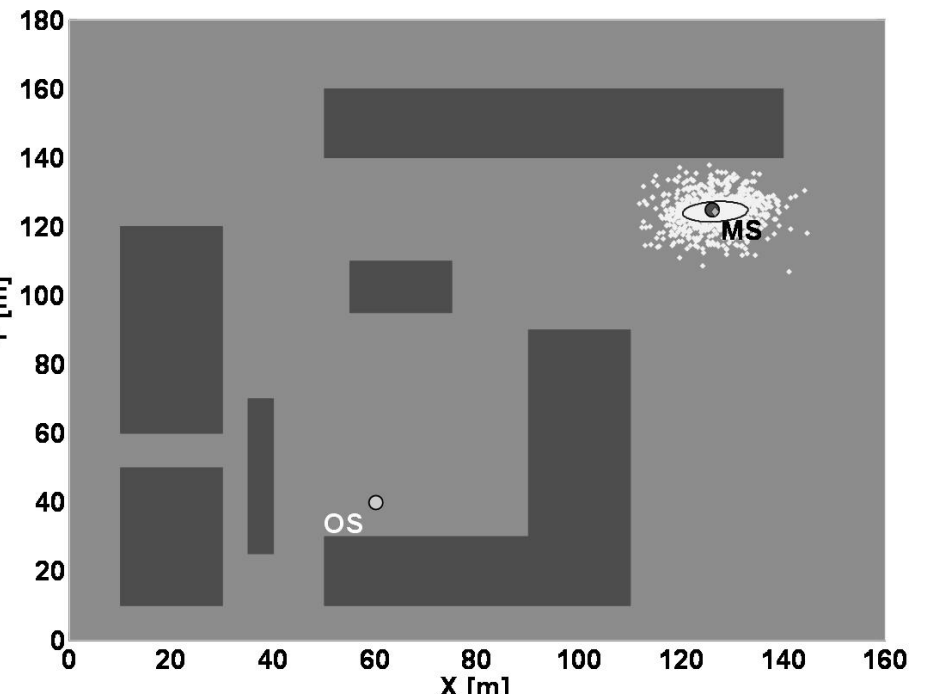
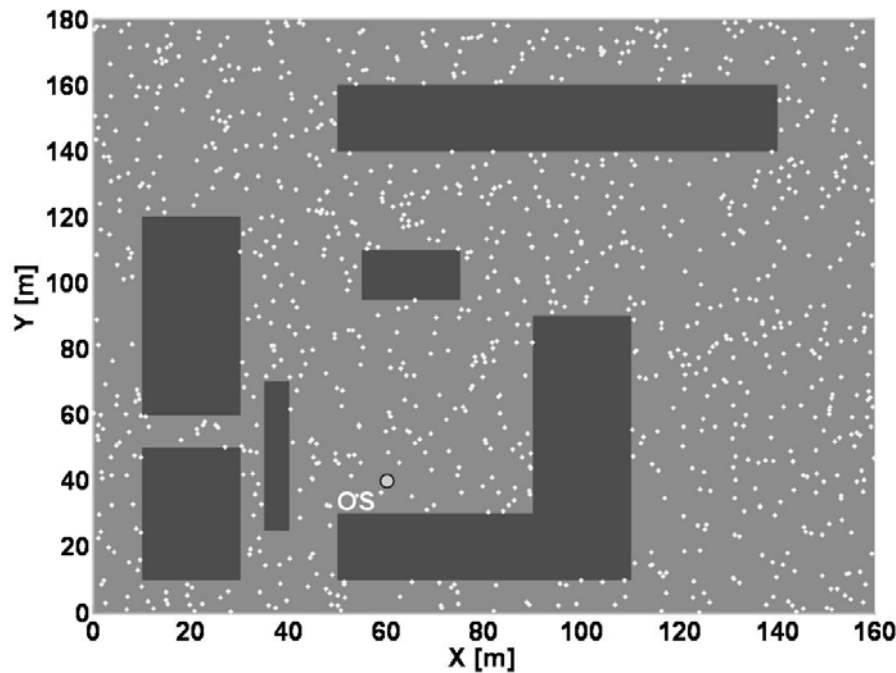
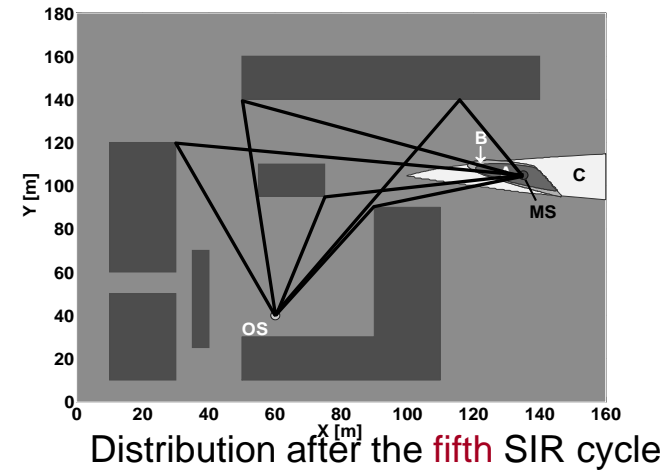
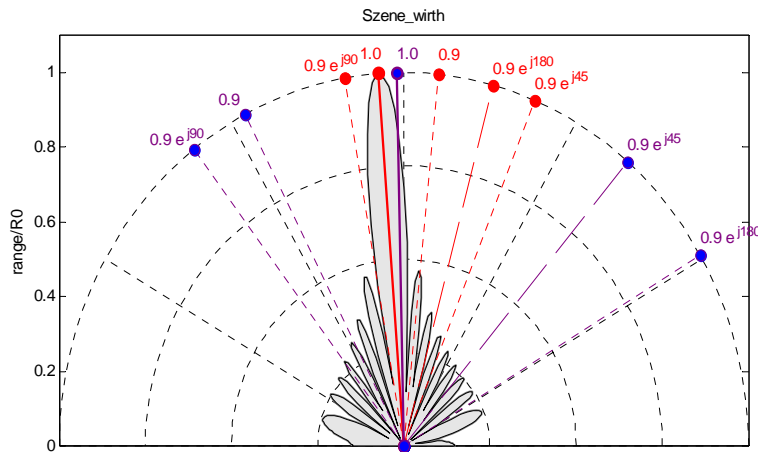
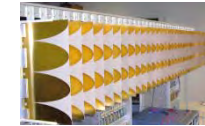
Algeier, V., Demissie, B., Koch, W., Thomä, R., State Space Initiation for Blind Mobile Terminal Position Tracking. *EURASIP Journal on Advances in Signal Processing, Special Issue on Track-before-Detect Algorithms, Volume 2008 (2008), ID 394219.*

GAMMA: Urban Emitter Localization

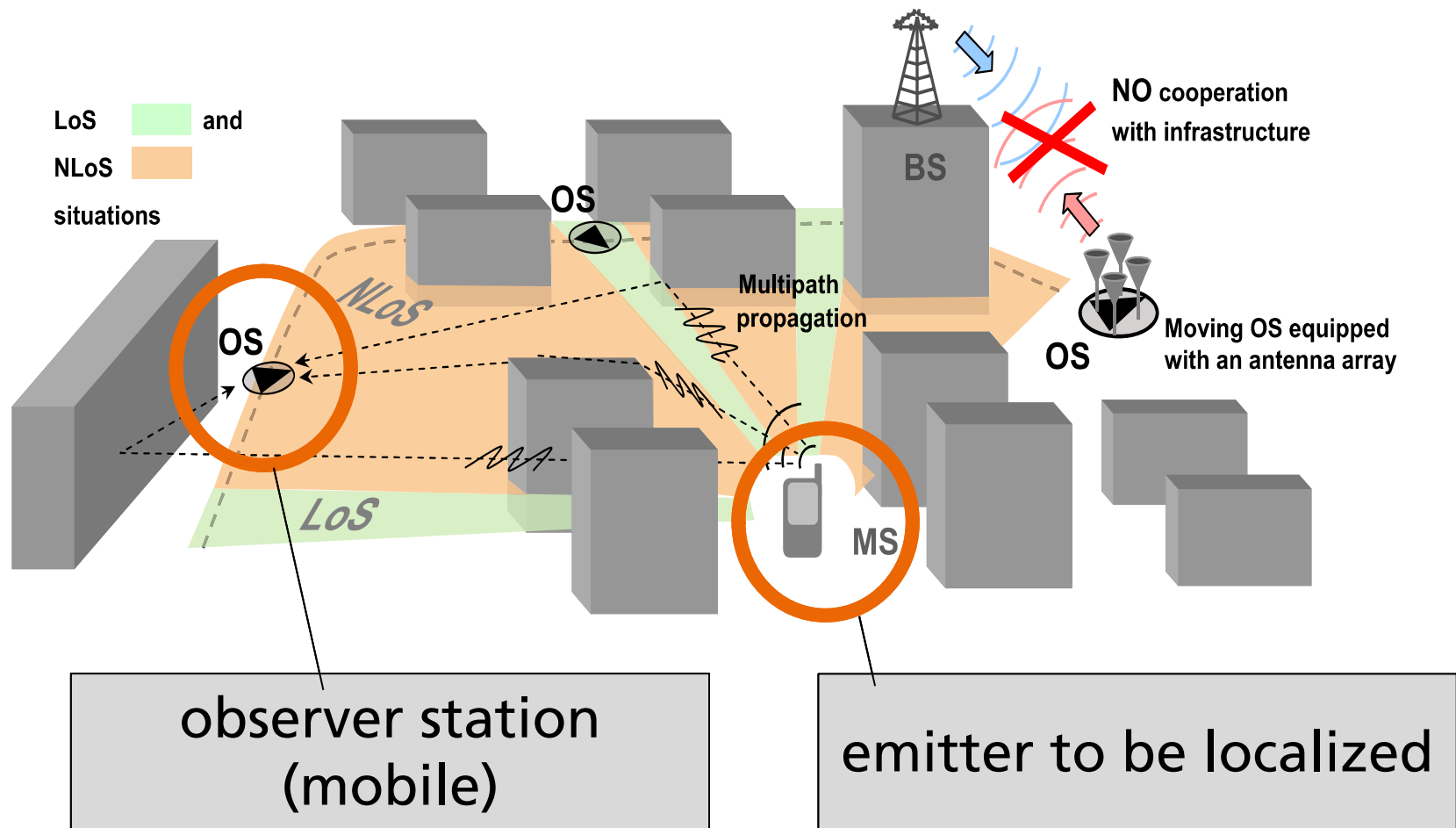


Algeier, V., Demissie, B., Koch, W., Thomä, R., State Space Initiation for Blind Mobile Terminal Position Tracking. *EURASIP Journal on Advances in Signal Processing, Special Issue on Track-before-Detect Algorithms, Volume 2008 (2008), ID 394219.*

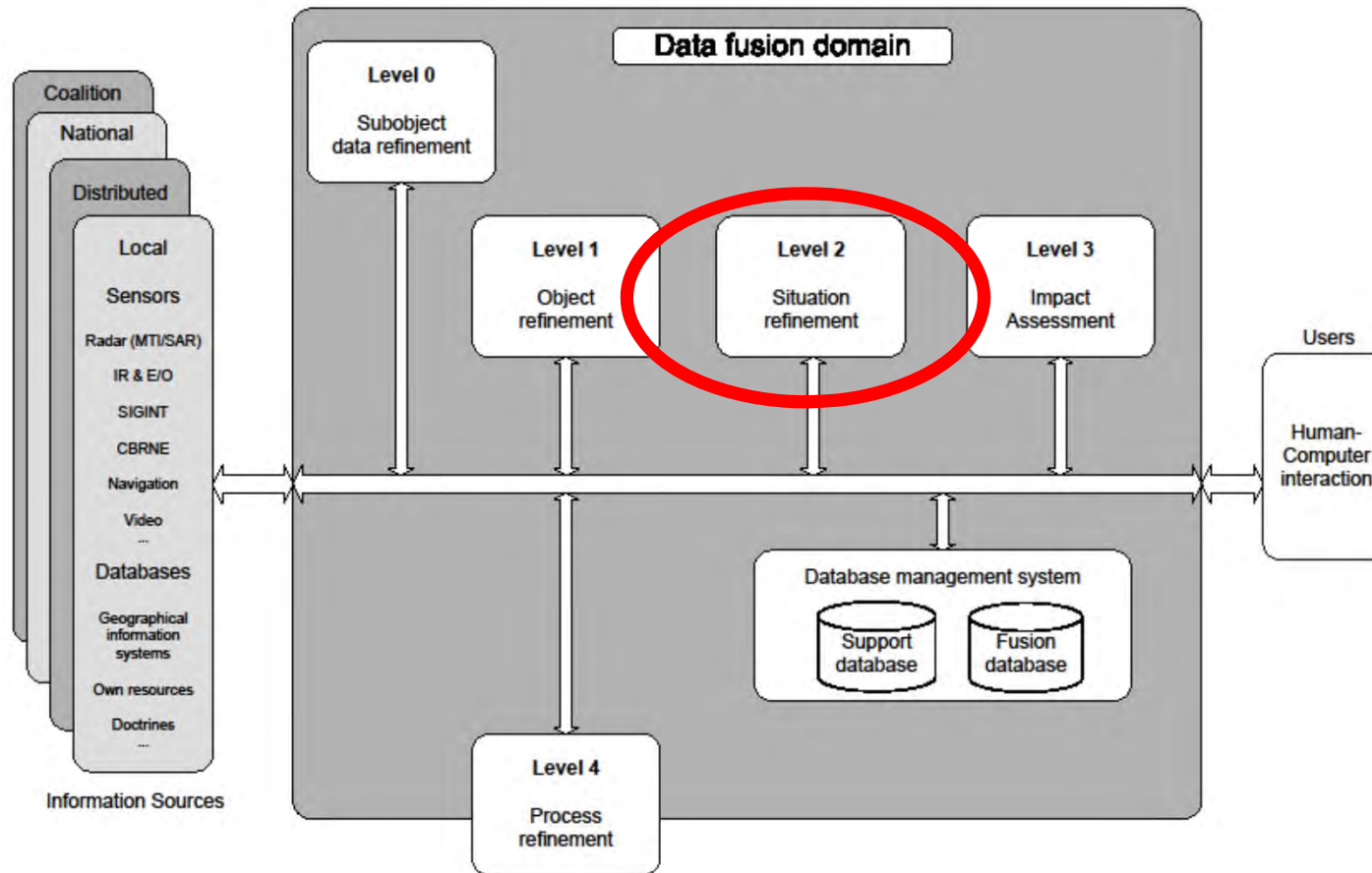
GAMMA: Urban Emitter Localization



Algeier, V., Demissie, B., Koch, W., Thomä, R., State Space Initiation for Blind Mobile Terminal Position Tracking. *EURASIP Journal on Advances in Signal Processing, Special Issue on Track-before-Detect Algorithms, Volume 2008 (2008), ID 394219.*

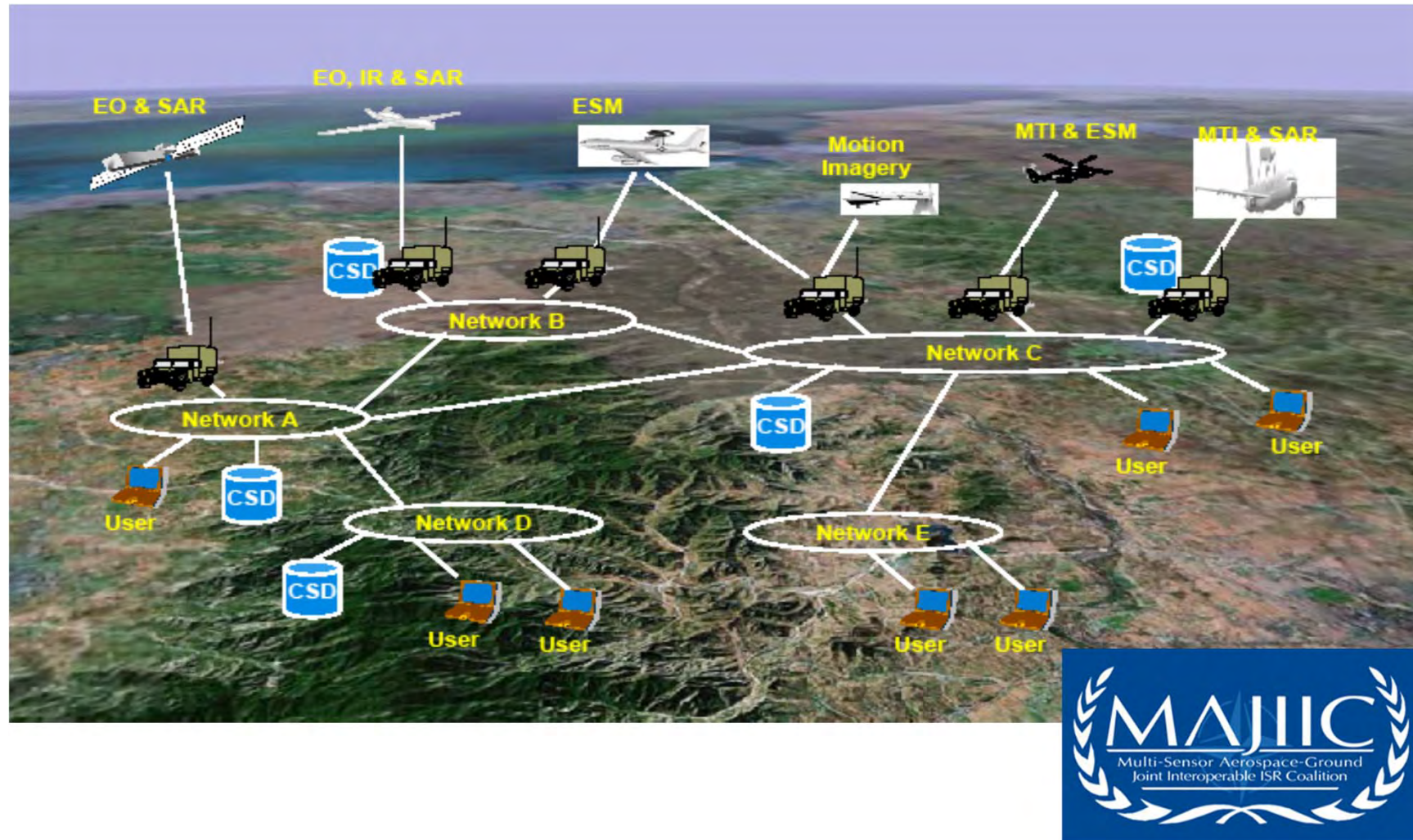


[1] V. Algeier, "Blind Localization of Mobile Terminals in Urban Scenarios", Dissertation TU Ilmenau, 2010.



Level 2 processing (situation refinement) dynamically develops a description of current relationships among entities and events in the context of their environment (clustering & relational analysis: force structure, cross-force relations, communications,...).

NEC: Situational Awareness for ISR Coalitions



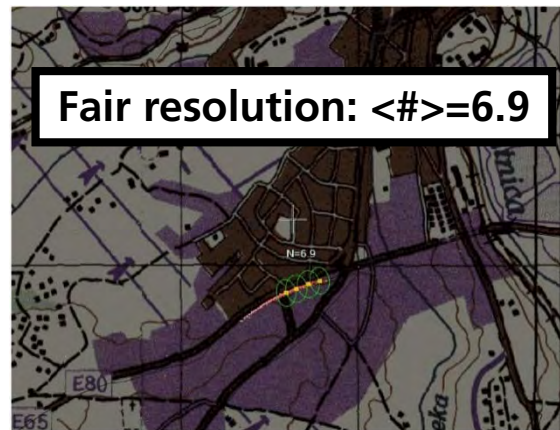
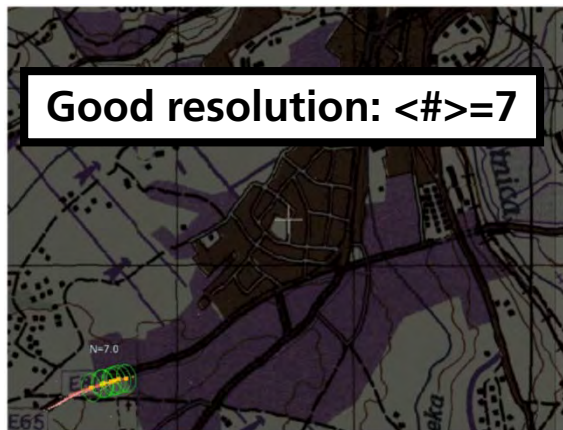
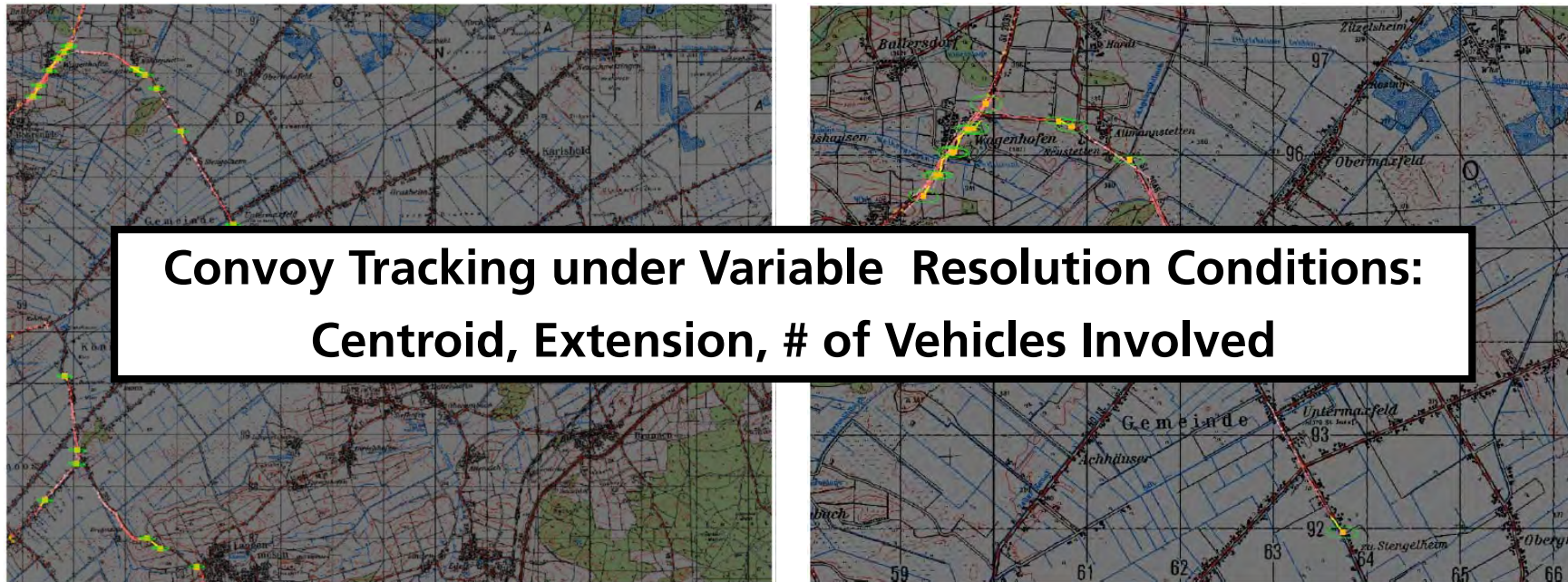
Multi-Target Tracking: Examples from MAJIC



Automated Track Extraction, Track Maintenance, Target # Estimates

Road maps: fast extraction, precise, continuous, off-on-road classification,...

Multi-Target Tracking: Examples from MAJIC



Joint Multitarget Probability Density (JMPD)

Multiple Target Tracking: Iterative Calculation of $p(\mathbf{X}_k|\mathbf{Z}^k)$

Joint Kinematical Target State Vector: $\mathbf{X}_k = (\mathbf{x}_k^{(1)}, \dots, \mathbf{x}_k^{(n)})^\top$

$$p(\mathbf{X}_{k+1}|\mathbf{Z}^k) = \int d\mathbf{X}_k p(\mathbf{X}_{k+1}|\mathbf{X}_k) p(\mathbf{X}_k|\mathbf{Z}^k)$$
$$p(\mathbf{X}_{k+1}|\mathbf{Z}^{k+1}) \propto p(\mathbf{Z}_{k+1}|\mathbf{X}_k) p(\mathbf{X}_{k+1}|\mathbf{Z}^k)$$

Kinematical model: potentially complex, correlated target dynamics

Likelihood function: # associations grows exponentially in n and m

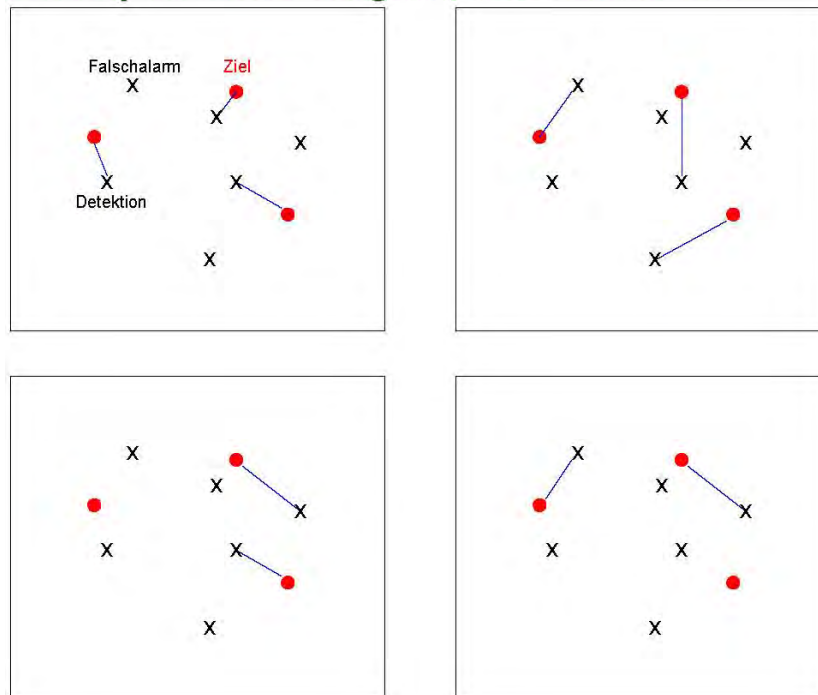
Approximations: Gating, NN, (J)PDAF, MHT, Particle Filtering, ...

JMPD reasonably tractable for well-separated target groups with $n \leq 5$

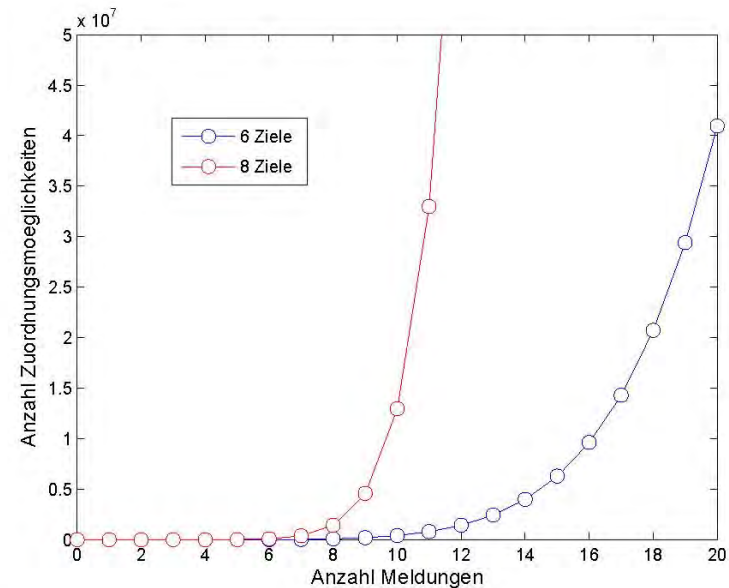
Problem: Complexity due to Associations

Number of possible associations grows exponentially with number of targets n and number of detections m .

Example: Three targets, six detections



Example: Six and eight targets



...

$$N(m, n) = \sum_{j=0}^{\min\{m, n\}} j! \binom{m}{j} \binom{n}{j}$$

A Different Point of View: Probability Hypothesis Density (PHD)

Measure of the probability that a target exists in a certain “region”

Identity of targets often irrelevant

For a multitarget PDF (identical targets): $p(\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)})$:

$$\begin{aligned} v(\mathbf{x}|n) &= \int d\mathbf{y}^{(1)} \dots d\mathbf{y}^{(n-1)} p(\mathbf{x}, \mathbf{y}^{(1)}, \dots, \mathbf{y}^{(n-1)}) \\ &\quad + \int d\mathbf{y}^{(1)} \dots d\mathbf{y}^{(n-1)} p(\mathbf{y}^{(1)}, \mathbf{x}, \dots, \mathbf{y}^{(n-1)}) + \dots \\ &= n \int d\mathbf{y}^{(1)} \dots d\mathbf{y}^{(n-1)} p(\mathbf{x}, \mathbf{y}^{(1)}, \dots, \mathbf{y}^{(n-1)}) \end{aligned}$$

JMPD symmetric under target permutations

PHD: $v(\mathbf{x}) = \sum_{n=0}^{\infty} v(\mathbf{x}|n) P(n)$

Dimension of a single target density

PHD: Is a target “here”?

“Cardinality” distribution: $P(n)$

In a region: $\int d\mathbf{x} v(\mathbf{x}) = \sum_{n=0}^{\infty} n P(n) = \langle n \rangle$ (target number estimator)

If $P(n) = 0$ for $n > 1$: $v(\mathbf{x}) = P(1) p(\mathbf{x})$ (single target pdf)

Cardinalized PHD Filtering: Properties

**Bayes Rule &
Combinatorics:**

$$v_{k|k}(\mathbf{x}) = \mathcal{F} \left[v_{k|k-1}(\mathbf{x}), P_{k|k-1}(n), \mathbf{Z}_k \right]$$
$$P_{k|k}(n) = \mathcal{G} \left[v_{k|k-1}(\mathbf{x}), P_{k|k-1}(n), \mathbf{Z}_k \right]$$

PHD: Is a target “here”?

Cardinality Distribution

- **Independent targets; target-independent, Poisson-distributed clutter**
- **Number of false measurements / targets are mutually independent**
- **Avoidance of combinatorial disaster / curse of dimensionality**

Cardinalized PHD Filtering: Properties

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Cardinality Distribution

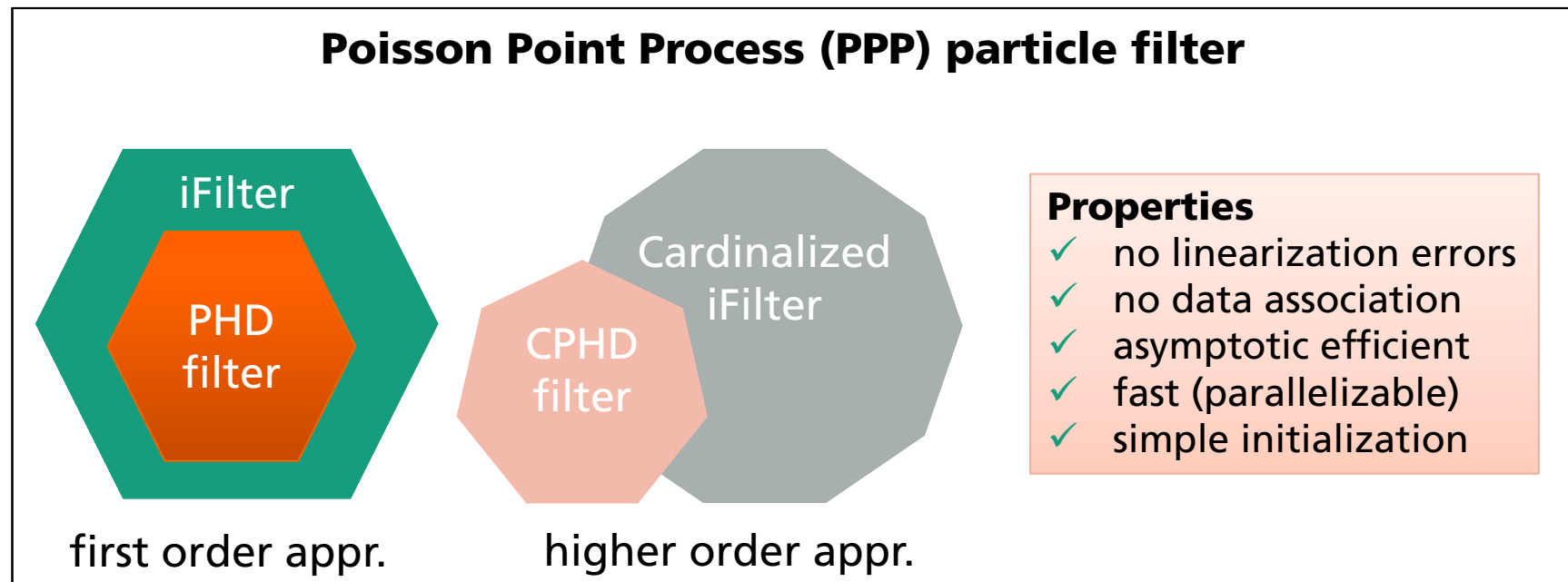
- Independent targets; target-independent, Poisson-distributed clutter
- Number of false measurements / targets are mutually independent
- Avoidance of combinatorial disaster / curse of dimensionality
- **Gaussian Mixture approximation:** *Vo; Erdinc, Willett (UConn); Ulmke (FKIE)*
 - “real time” multiple target tracking: $T_{\text{CPU}} \propto J m^3, \quad J \propto n$
 - simple target number / single target state estimation
 - simple extension to EKF, IMM, Gaussian mixture filtering
 - **for $n=0, 1$: GMCPHD identical to Bayesian MHT with LR sequential initiation**

Multi-object localization and tracking

Input: $Z_k = \{ \mathbf{z}_i \}_{i=1}^M$, with $\mathbf{z}_i = (\alpha_i, \varepsilon_i)^T$

Output: $X_k = \{ \mathbf{x}_j \}_{j=1}^N$, with $\mathbf{x}_j = (x, y, z, v_x, v_y, v_z)^T$

Method: Approximation of the multi-object multi-sensor Bayes filter

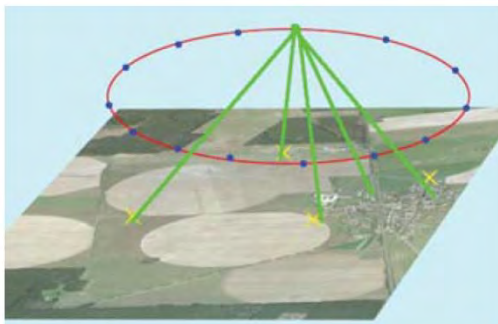


Sequential Monte Carlo Method for the iFilter

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Abstract—Poisson point processes (PPP's) are very useful theoretical models for diverse applications. One of those is multi-target tracking of an unknown number of targets, leading to the intensity filter (iFilter) as a generalization of the probability hypothesis density (PHD) filter. This article develops a sequential Monte Carlo (SMC) implementation of the iFilter. In theory it was shown that the iFilter can estimate a clutter model from the measurements and thus does not need it as a-priori knowledge, like the PHD filter does. Our studies show that this property holds not only in simulations but also in real world applications. In addition it can be shown, that the performance of the PHD filter decreases substantially if the a-priori knowledge of the clutter intensity is chosen incorrectly.

Keywords: Intensity Filter, Sequential Monte Carlo, Multi-target tracking, PHD Filter, Poisson point processes (PPP's)

I. INTRODUCTION

Multi-target tracking is a challenging task in many applications. Classical approaches like the Joint Probabilistic Data Association filter (JPDAF) [2] and multi hypothesis tracking (MHT) [3] need in general the knowledge of the expected target number. In recent time the intensity filter (iFilter) [4], [5] has been presented as a generalization of the probability density hypothesis (PHD) filter [6]. Both filters use multi-target and multi-measurement states along with the estimation of the number of target. While the PHD filter was originally derived using finite set statistics the iFilter was

a performance analysis of this new filter is illustrated on simulated and real data. To obtain an objective judgement the PHD filter is also used for the same scenarios. This article is structured as follows: Firstly, some basic theory about PPP's is described to make the article self-contained. Secondly, the iFilter and its SMC implementation is derived. Followed by numerical studies on simulated and real data for linear and not linear scenarios. We close with a discussion about the results. In the appendix the relationship between the iFilter and the PHD filter is presented.

II. POISSON POINT PROCESSES (PPP'S)

This section gives a short introduction to basics of PPP's, which are used in the following. For further background see [7]. Every PPP defined on a general set \mathcal{S} is parametrized by a non-negative function g , called the intensity, with $\int_{\mathcal{S}} g(s) ds < \infty$. In multi-target tracking applications g is not constant, so

First published SMC realization and experimental evaluation of the iFilter!

$$\Pr\{n\} = \exp\left(-\int_{\mathcal{S}} g(s) ds\right) \frac{\left(\int_{\mathcal{S}} g(s) ds\right)^n}{n!}, n = 0, 1, 2, \dots \quad (1)$$

Take into account that

$$E\{n\} = \int_{\mathcal{S}} g(s) ds. \quad (2)$$

The n points in \mathcal{S} are obtained as independent and identically

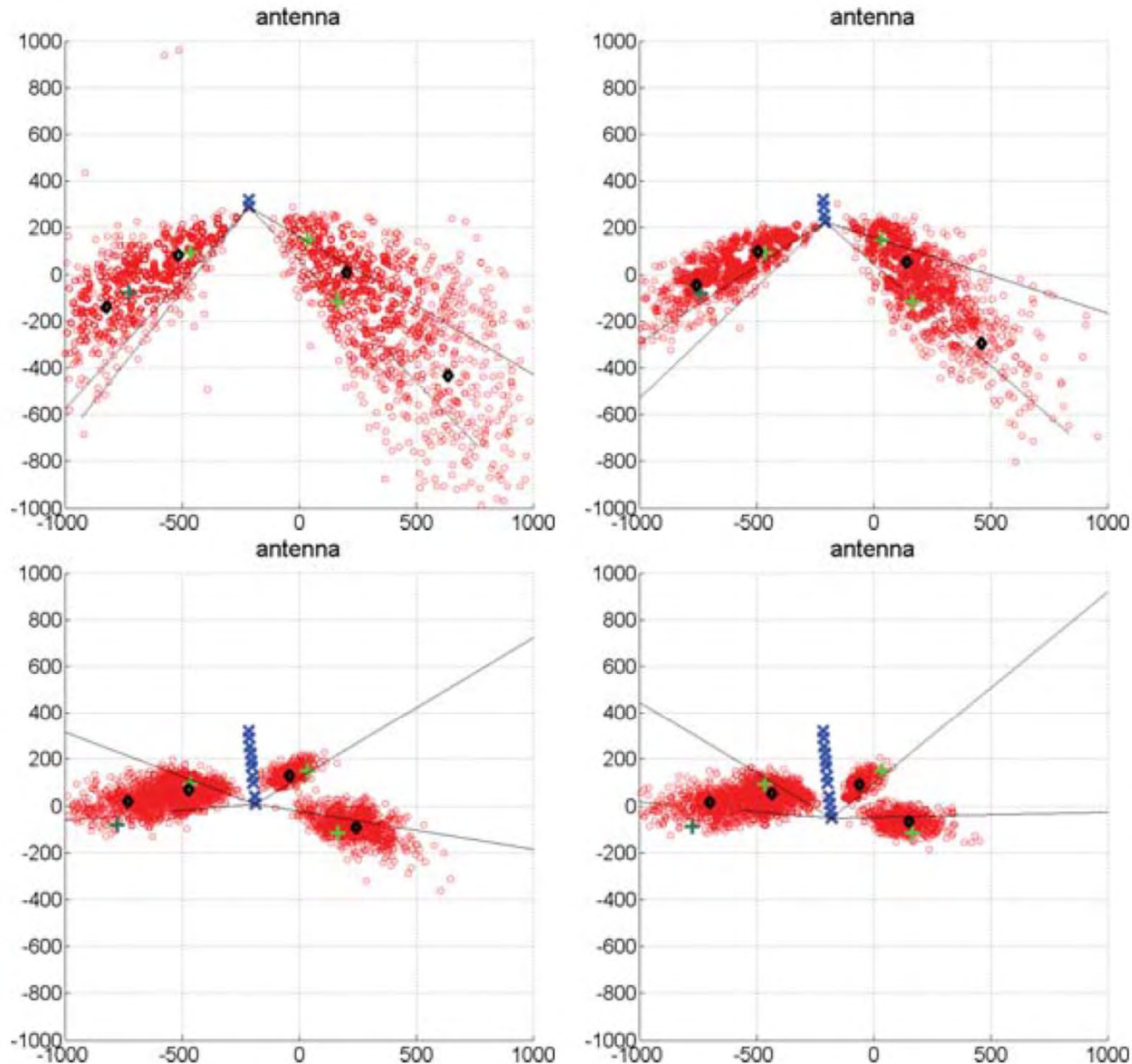
Field trials for emitter localization with PPP's

Zellendorf (July 2010)

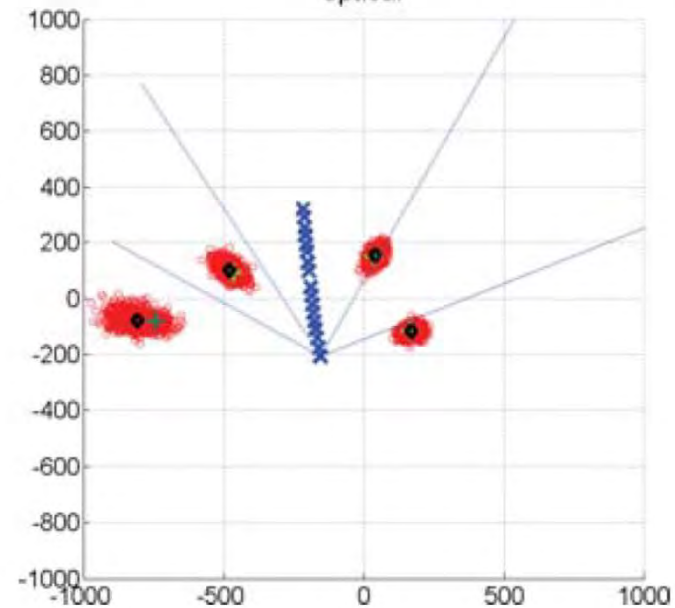
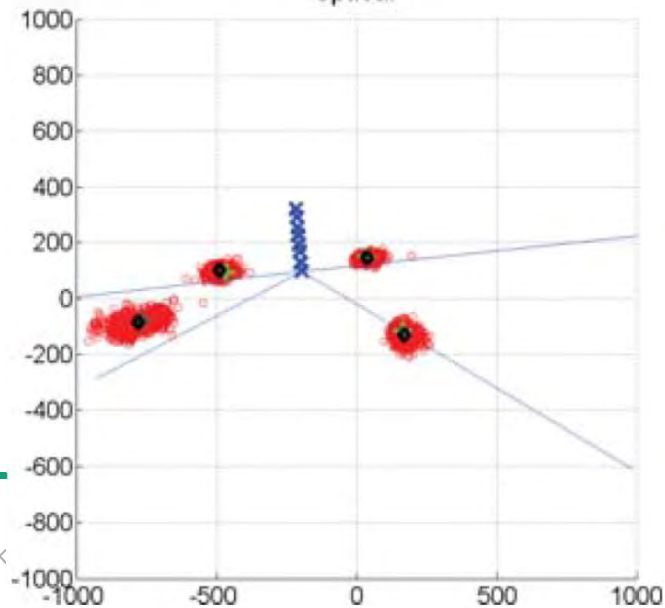
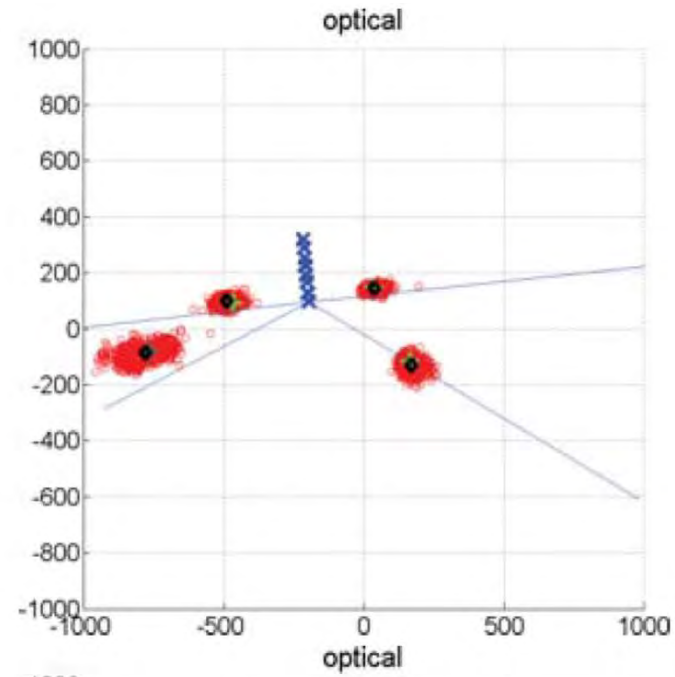
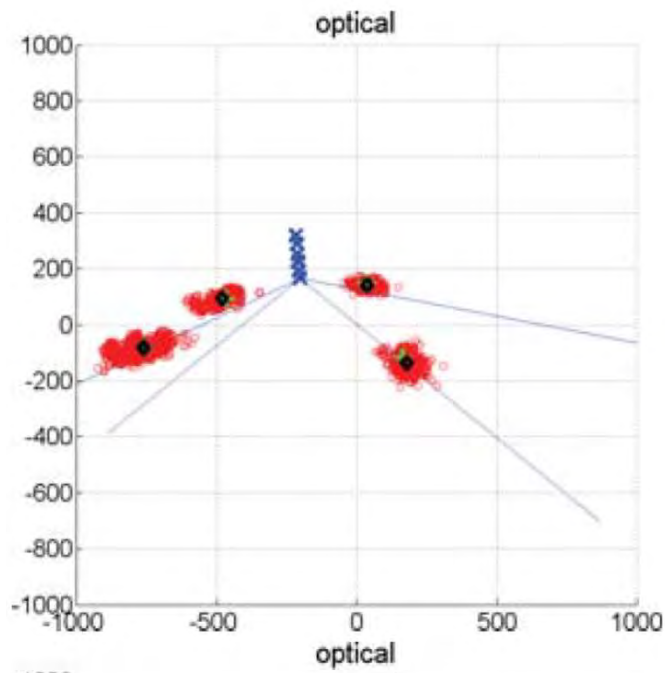
- Localization with UAS demonstrator **Smaragd**
- Three stationary and one moving emitter
- Bearing measurements from 4-element antenna array and camera system

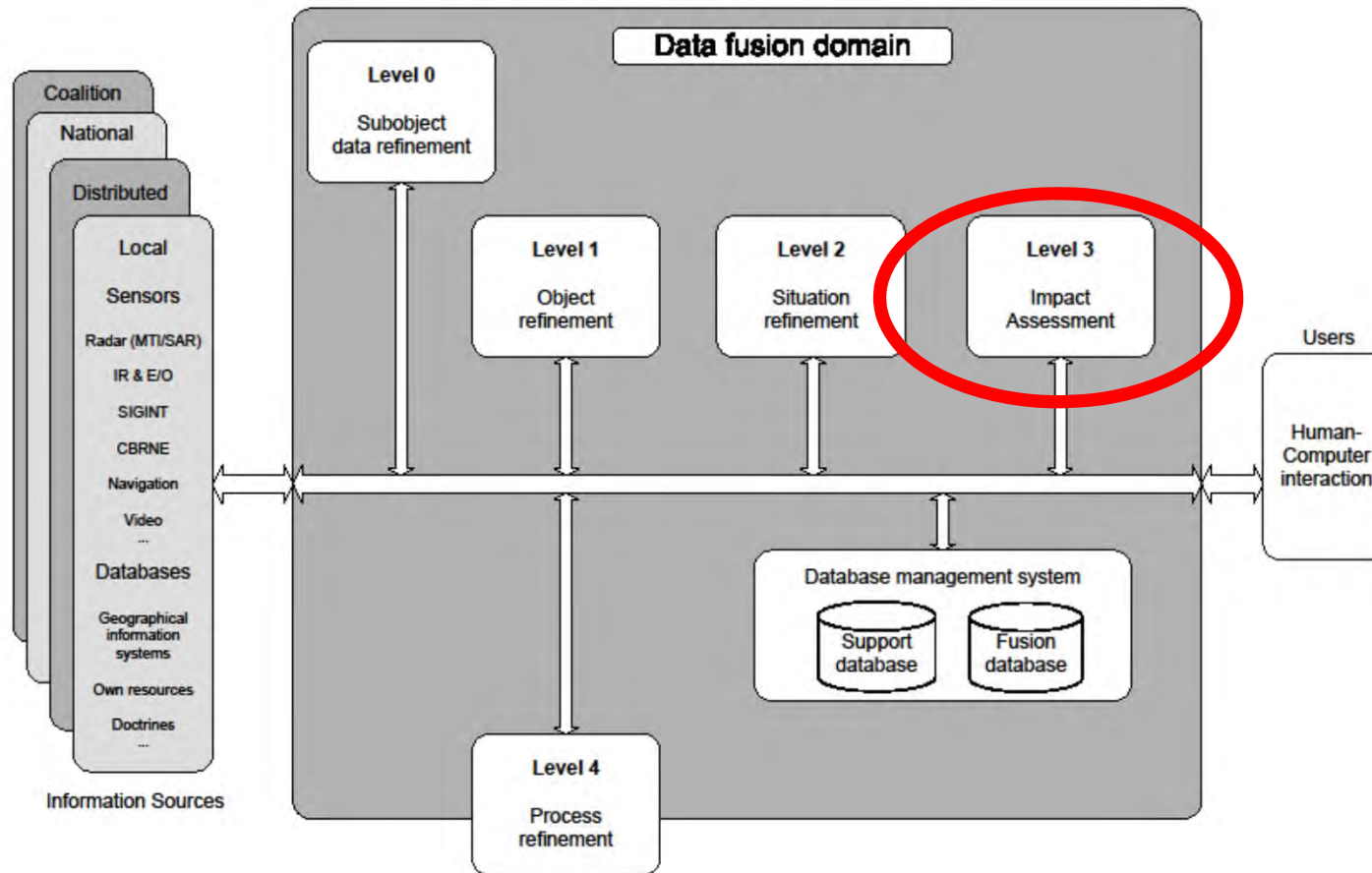


iFilter Results: Multiple Emitter Localization: RF Sensor Only



iFilter Results: Multiple Emitter Localization: RF + E/O Sensor





Level 3 processing (impact assessment, significance estimation)

projects the current situation into the future to draw inferences about enemy threats, friend and foe vulnerabilities, and opportunities for operation.

Multiple Sensor Security Assistance Systems

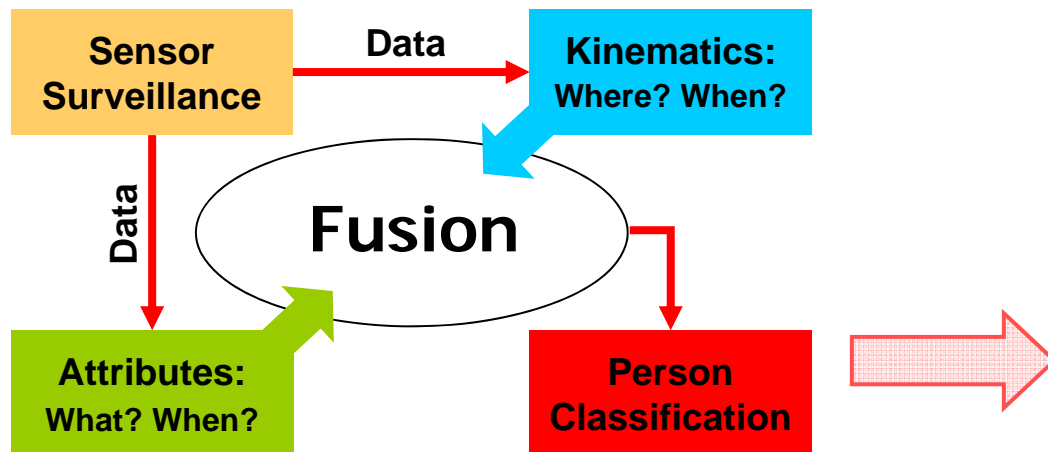


General Task

Covert & Automated Surveillance of a Person Stream:
Identification of **Anomalous Behavior**

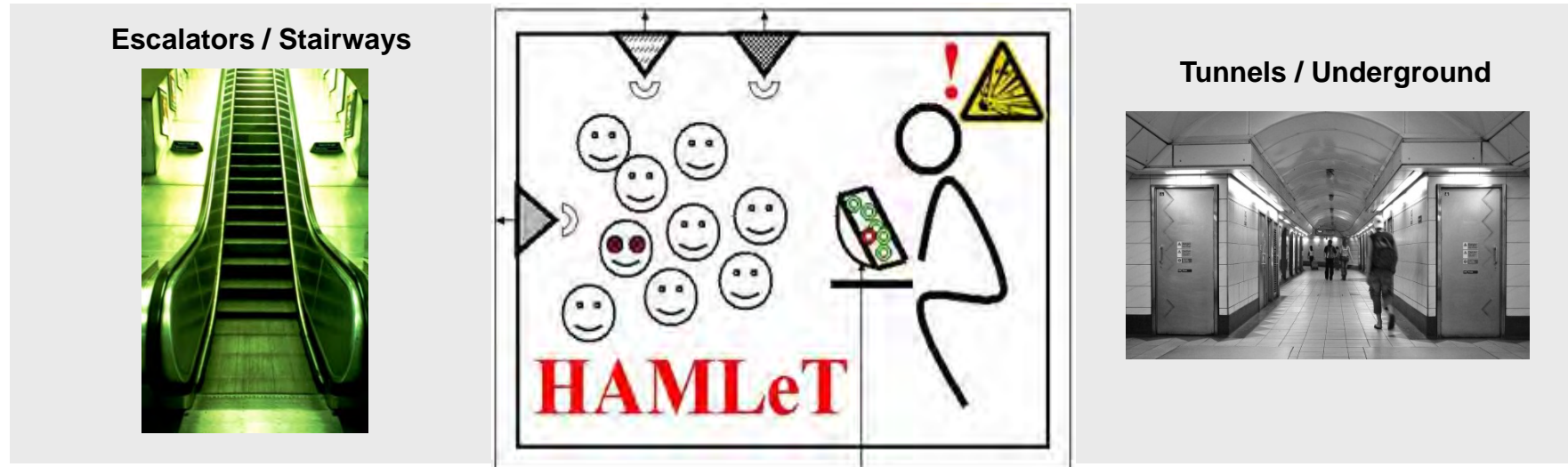
Towards a Solution

Exploit **Heterogeneous** Multiple Sensor Systems.



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

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



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

Fusion: Kinematics Attributes

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^{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 				

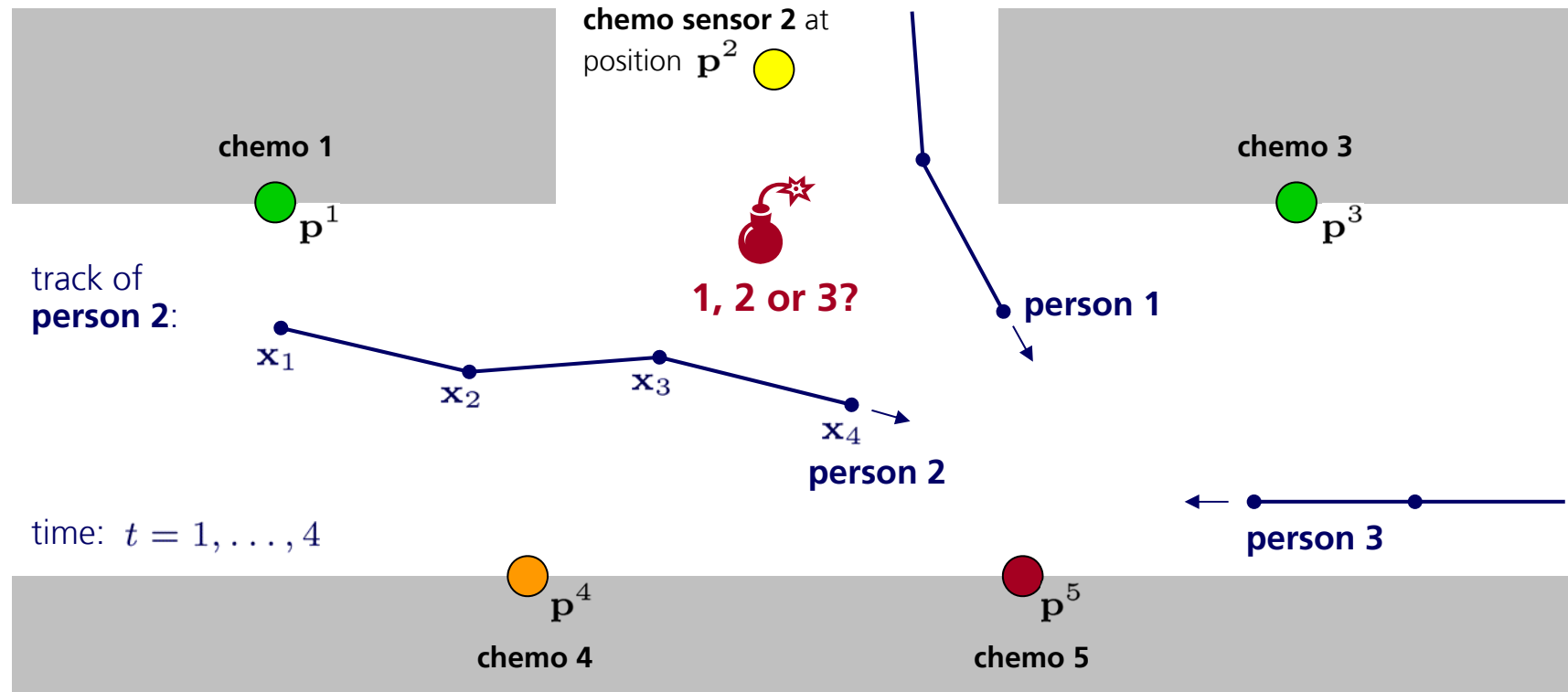
Probability that Person 3 has Attribute 

Classification problem: Why carries the bomb?

Fuse all position and signature measurements over time!

Position measurements: reconstruction of the kinematic behaviour

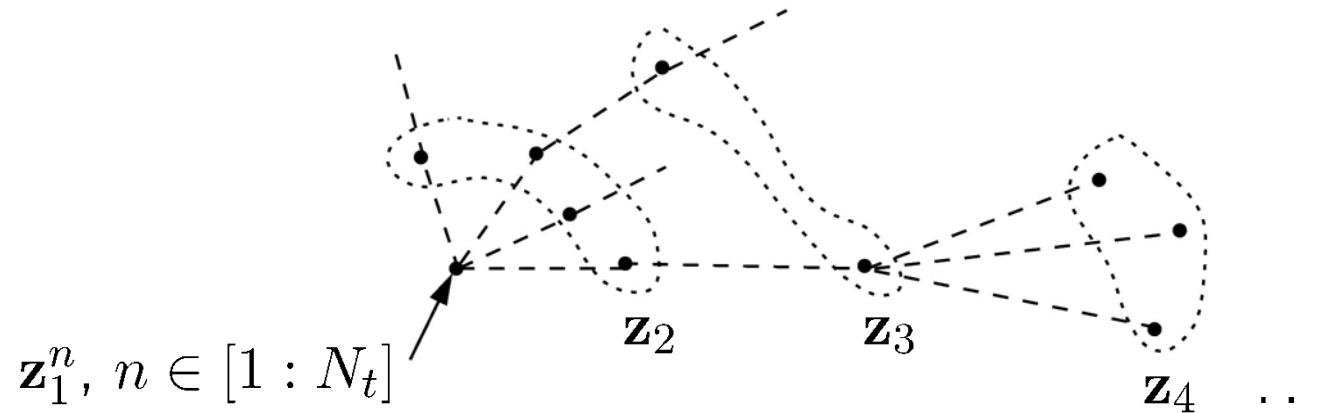
CBRNE signatures: low space-time resolution → non-trivial association



Multiple Person Tracking

Association Problem

Multitude of possible Interpretations

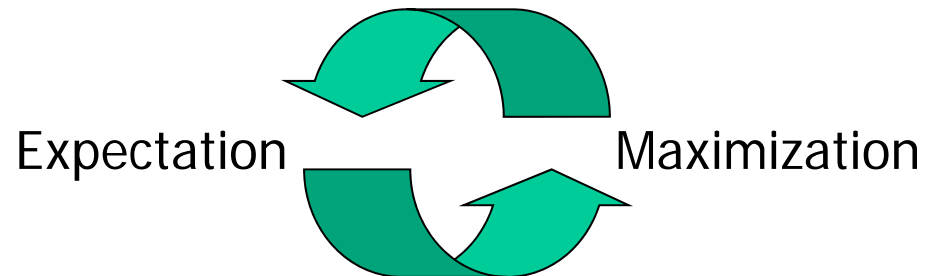


Solution

Probabilistic Multiple Hypotheses Tracking (PMHT)

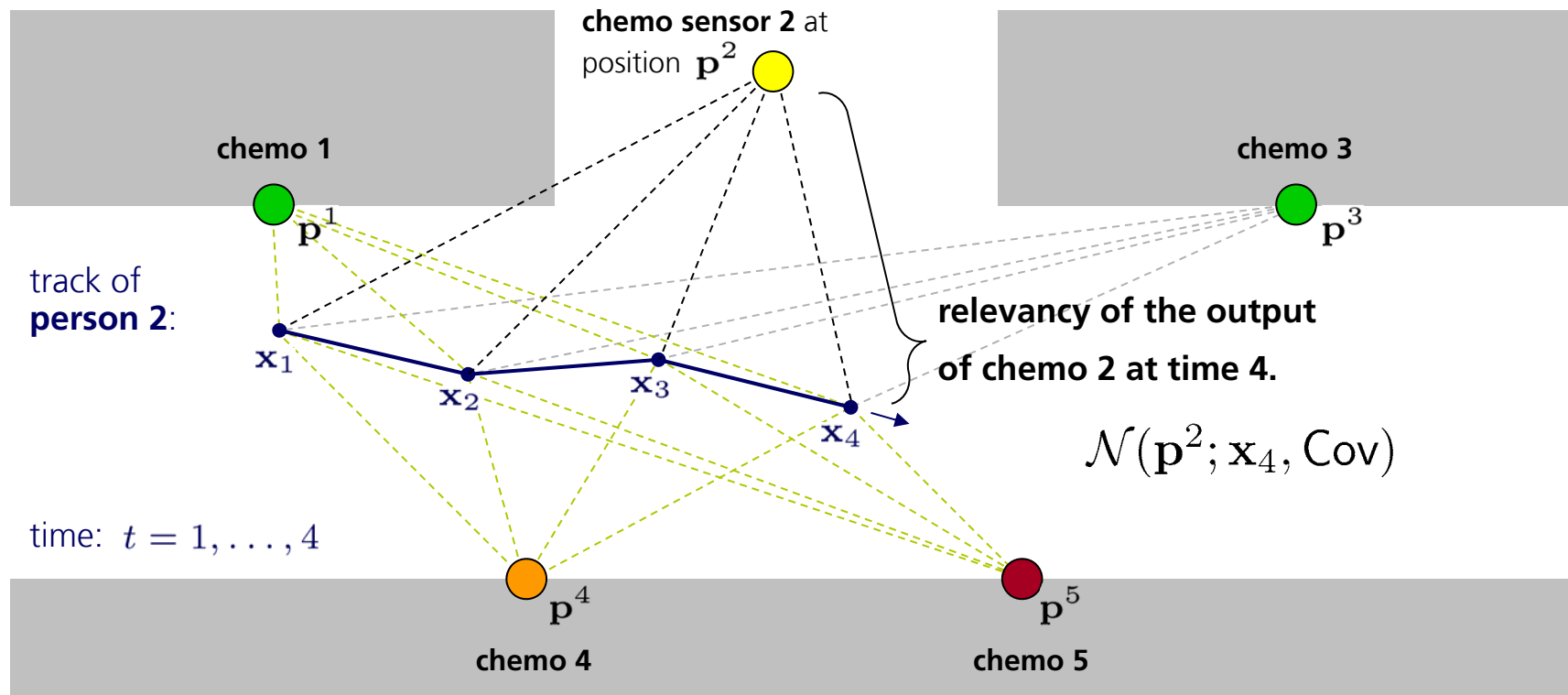
(Streit 1995, Willett et al. 2002/04, Davey, Gray, Luginbuhl ...)

- ▶ Iterative Procedure
- ▶ Sliding Data Window
- ▶ Efficient

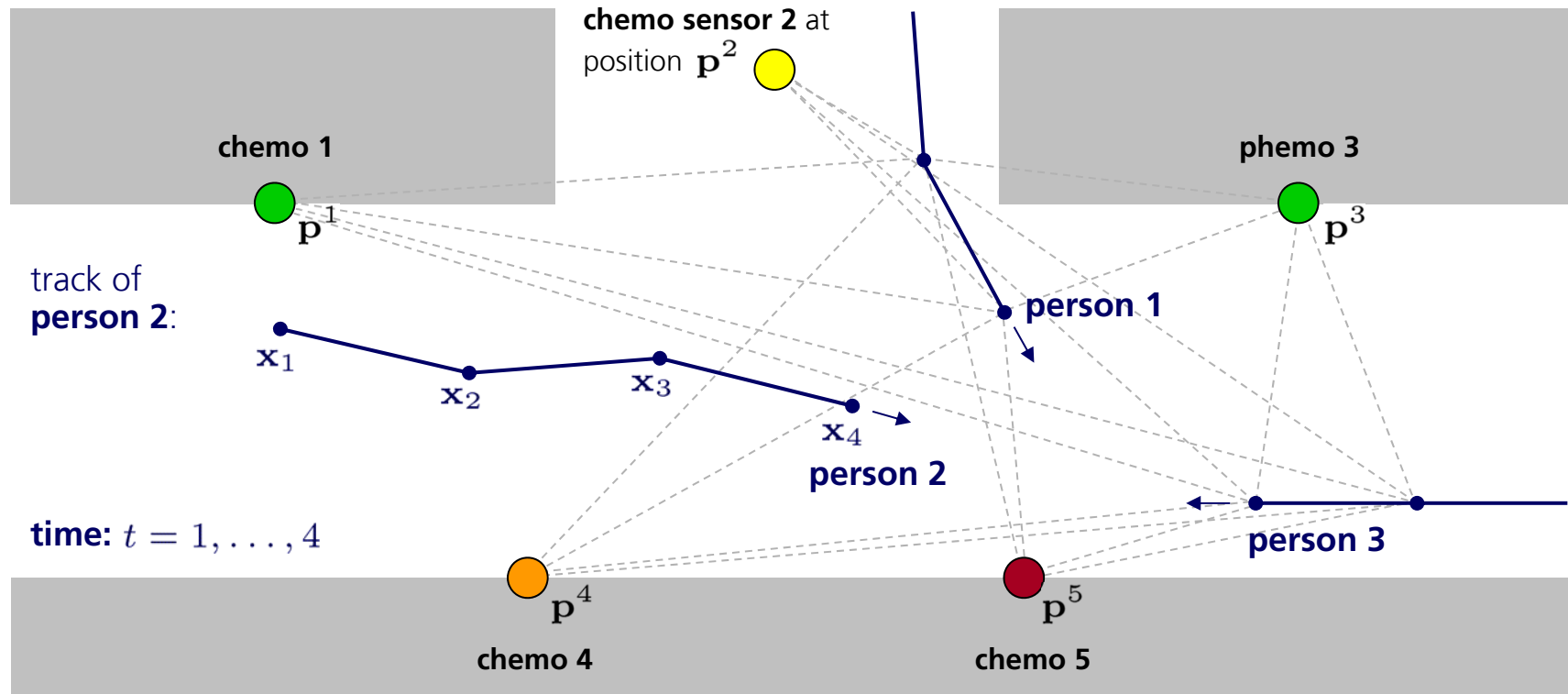


Solve the association problem via *Expectation-Maximization!*

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

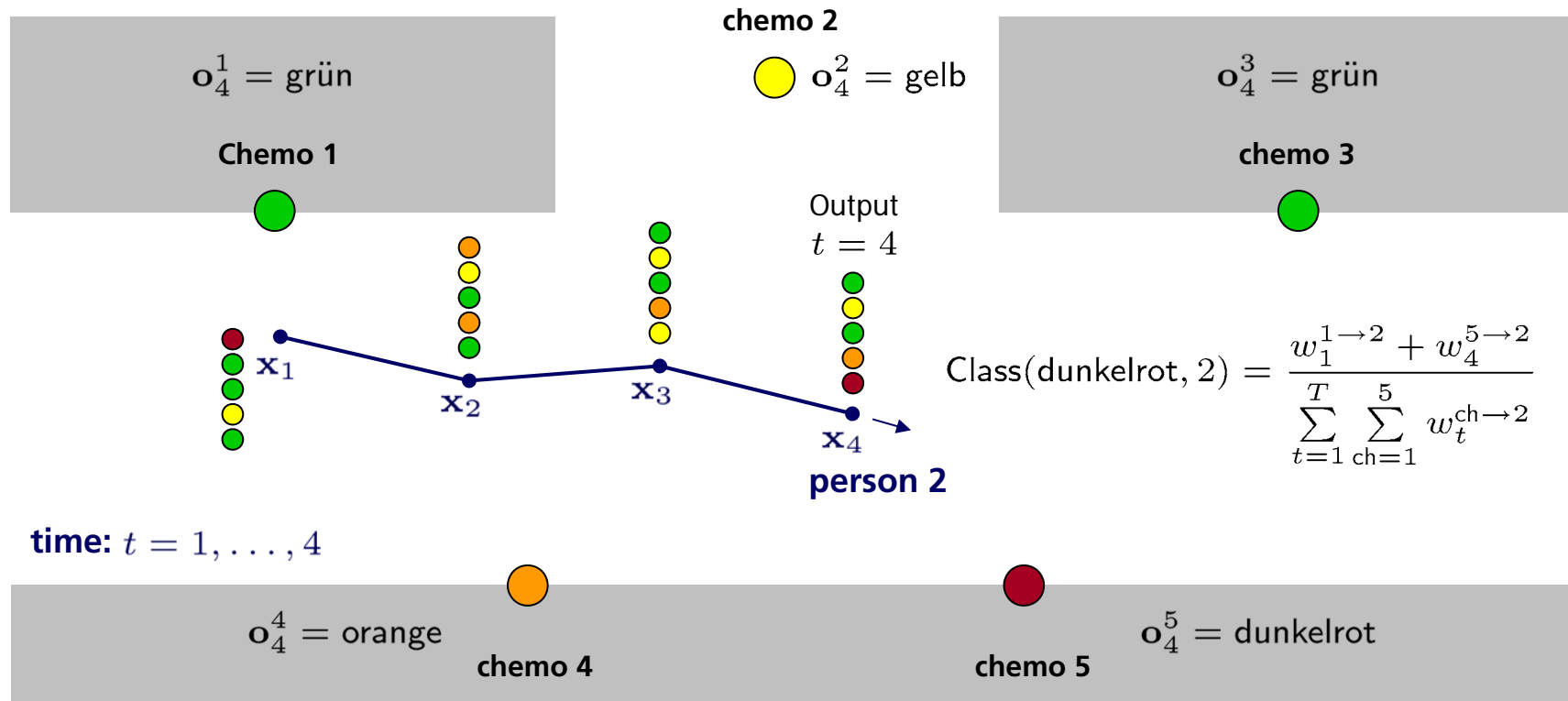


Individual relevancies of the signatures of all chemo sensors at all instants of time for persons 2 and 3 along their tracks:



Fusion of position attribut measurements

Iterative calculation of the classification matrix for each person



Fusion: Problems

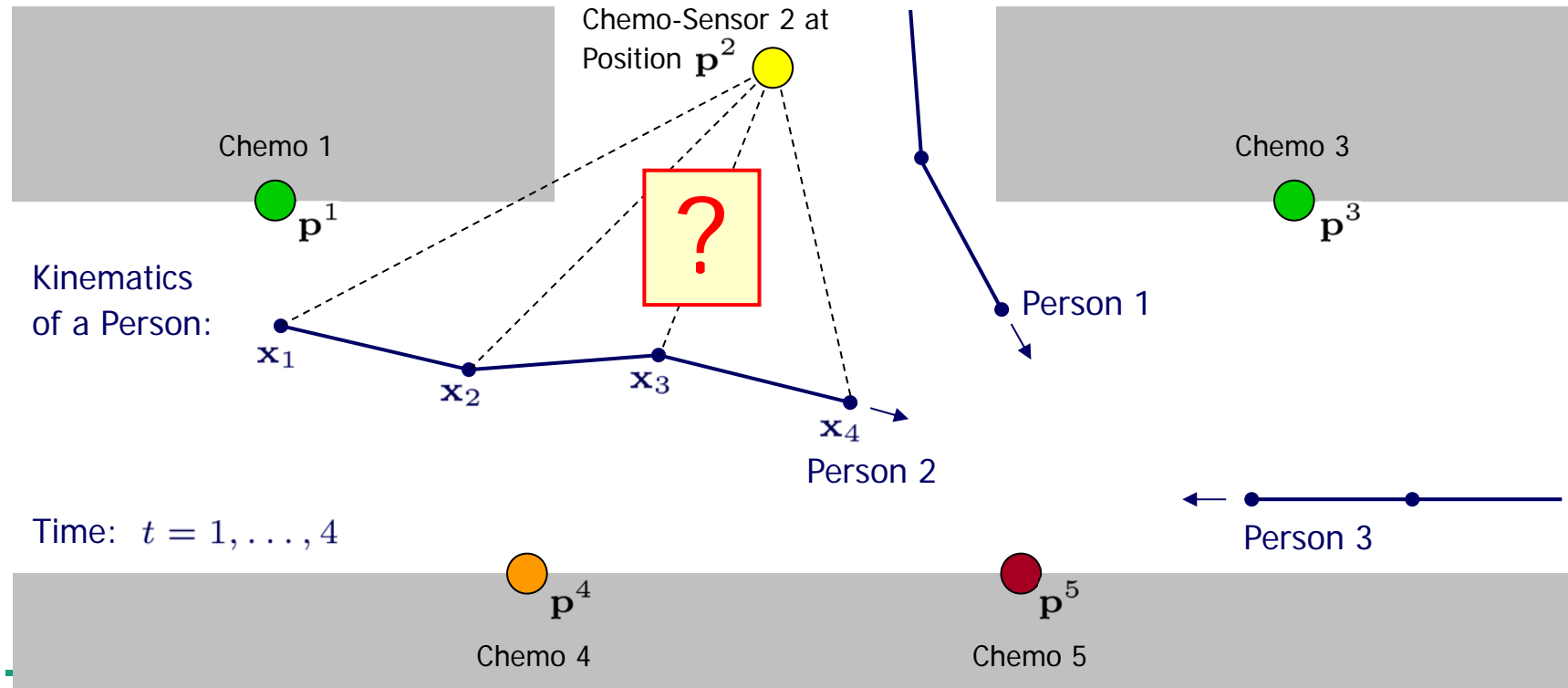
Remark

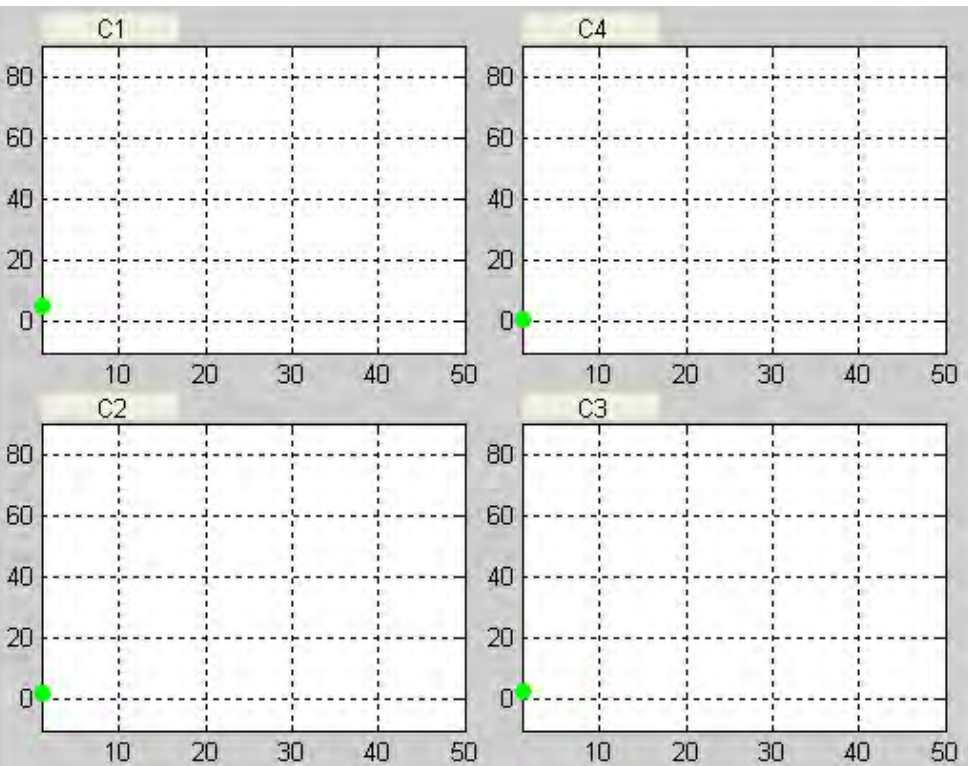
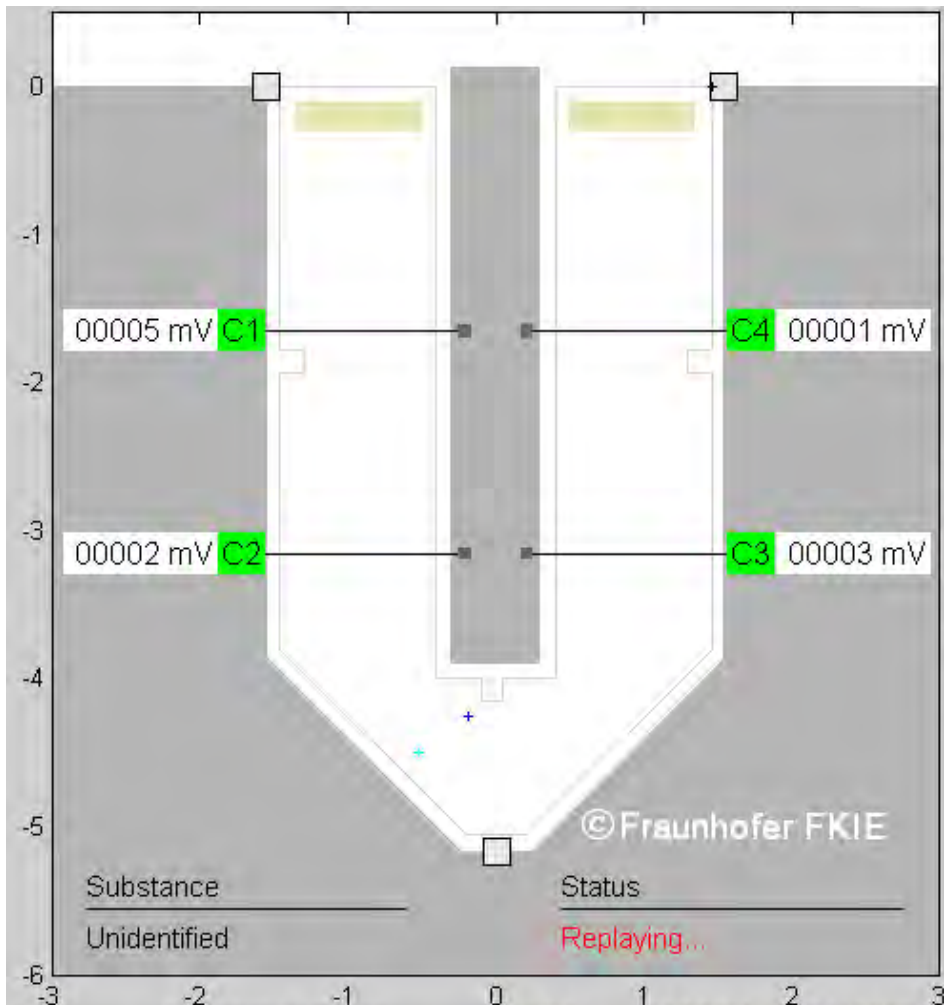
Assignment Weight Calculation is a difficult task!

Requires Knowledge about the Behavior of Chemo-Sensors

Influences

Not only Distance, but also Velocity, Temperature, **Delay**





Docu: (20): 5 P, beliebige Bewegung, Quelle normal von rechts nach links

Start Stop Close

Substance: Unidentified

Status: **Replaying...**

Recorded Data Files:

- Log_20101129_141205171
- Log_20101129_141533718
- Log_20101129_142010000
- Log_20101129_142429562
- Log_20101129_142927656
- Log_20101129_143655328
- Log_20101129_144347343

LSR: 00000001 51270765

CHM: 00000001 51270765

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

Radioactive Material as Potential Terrorist Threat



Dirty Bomb

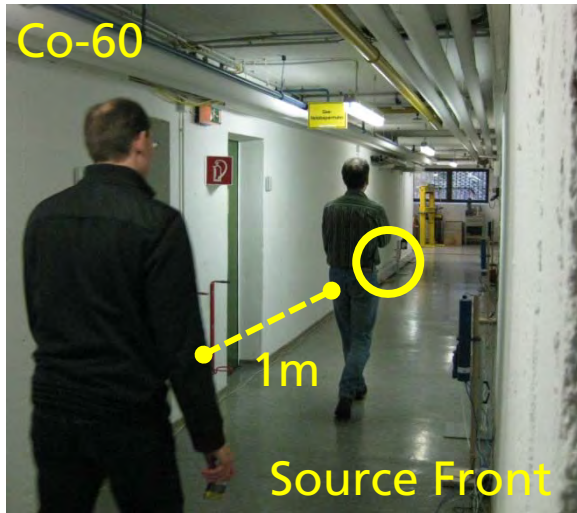


Localization?

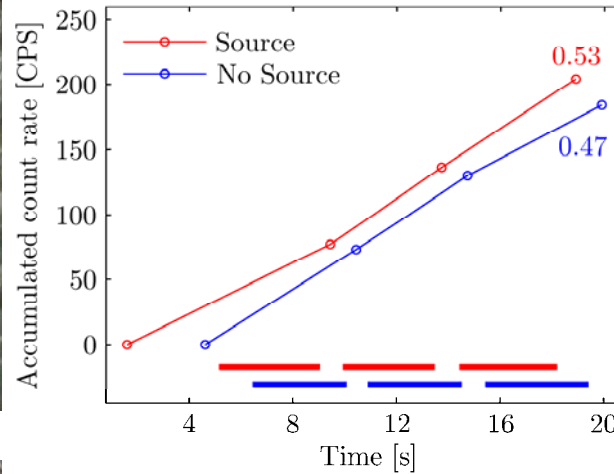


- **Radioactive Dispersion Devices (RDD / Dirty Bomb)**
 - ⇒ Combination of Conventional Explosive with Radioactive Material
 - ⇒ High Damage Potential: Contaminated Areas, Health Damage
- **RDD not yet applied but Growing Concerns**
 - ⇒ Radioactive material readily available for medical / commercial use
 - ⇒ Numerous accidents involving loss or theft of radioactive sources
- **Early Localization of Radioactive Material in Public Spaces**

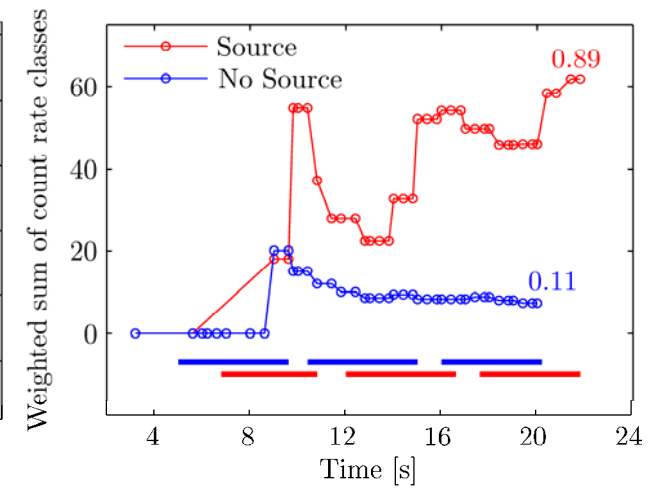
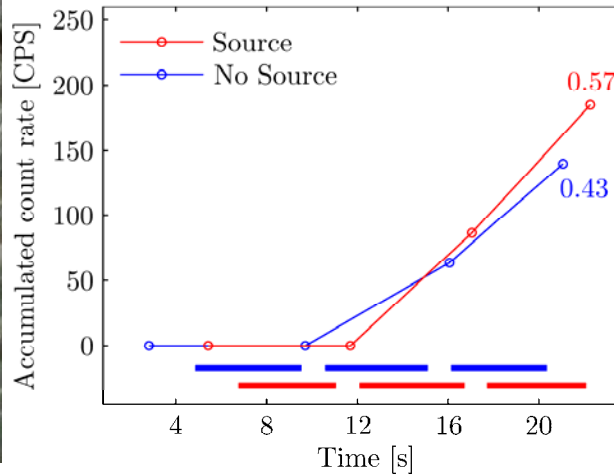
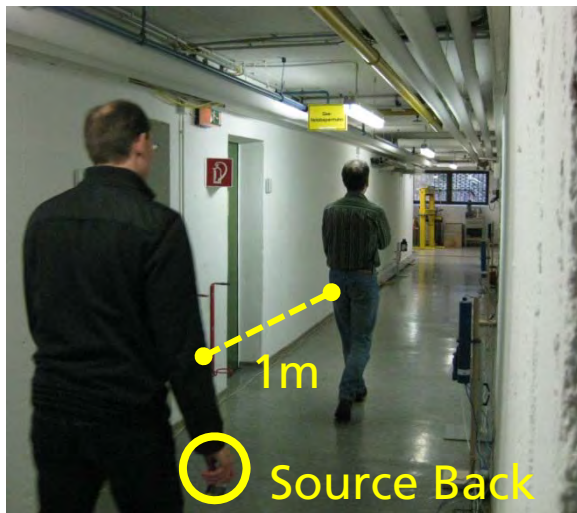
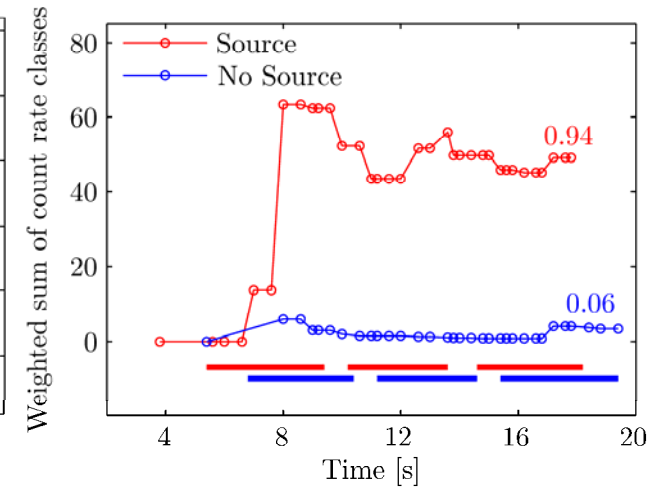
Experimental Results

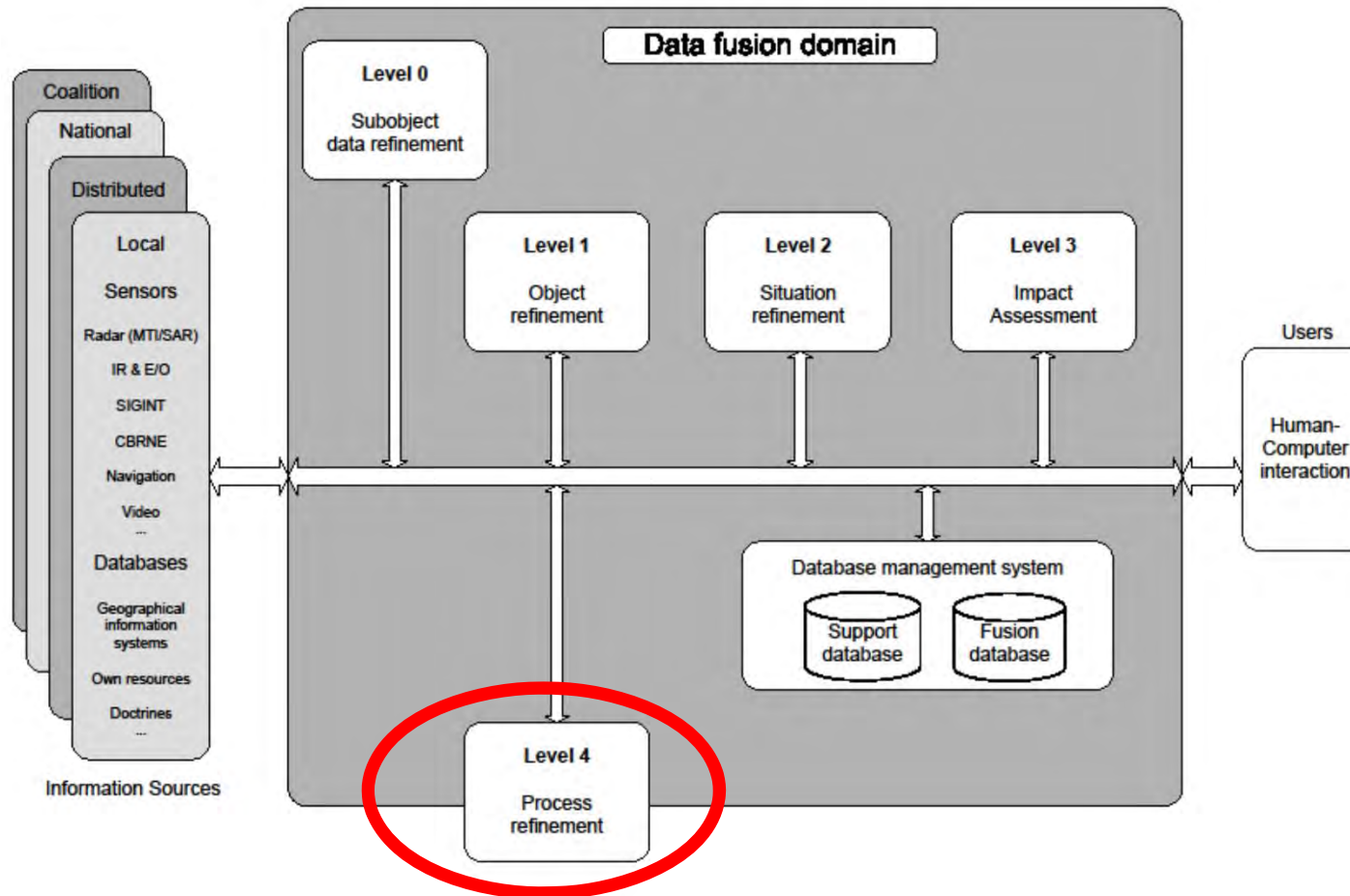


Accum-C



PMHT-C





Level 4 processing (process refinement) is a meta-process that monitors the overall data fusion process to assess and improve real-time system performance (resource management).

Joint Directors of Laboratories Data Fusion Model

