Distributed Sensor Networks –

Current Projects & Research Perspectives

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Sensor Signal Processing for Defence

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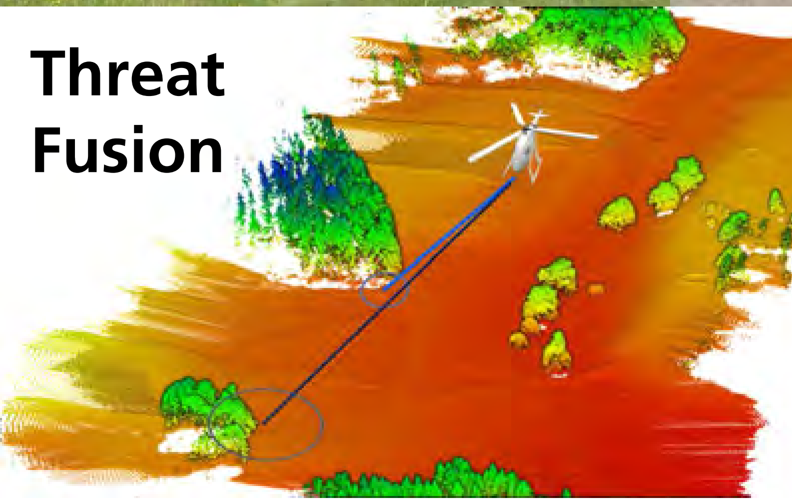
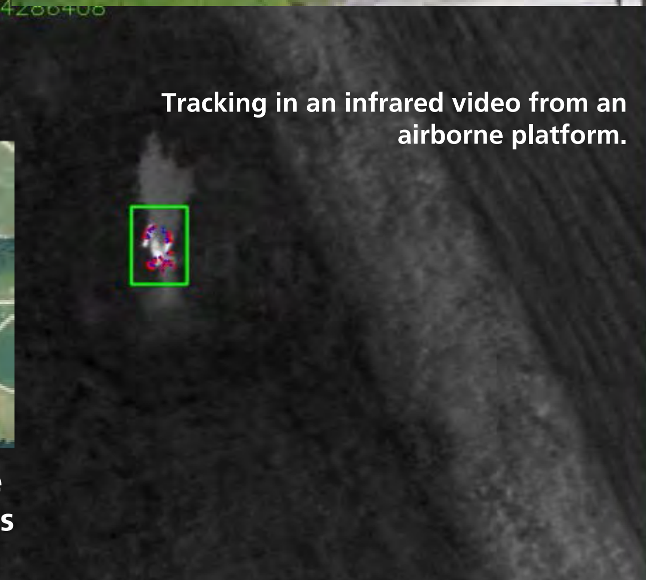
UAV AMOS-X6 with EO/IR camera payload.

Soldiers line up for a patrol mission with an UGV moving in front as advance guard.

Threat Fusion





Tracking in an infrared video from an airborne platform.

Ellipses are used to compensate for localizing errors in track fusion. The size of a ellipse increases with distance from detection to UAV.

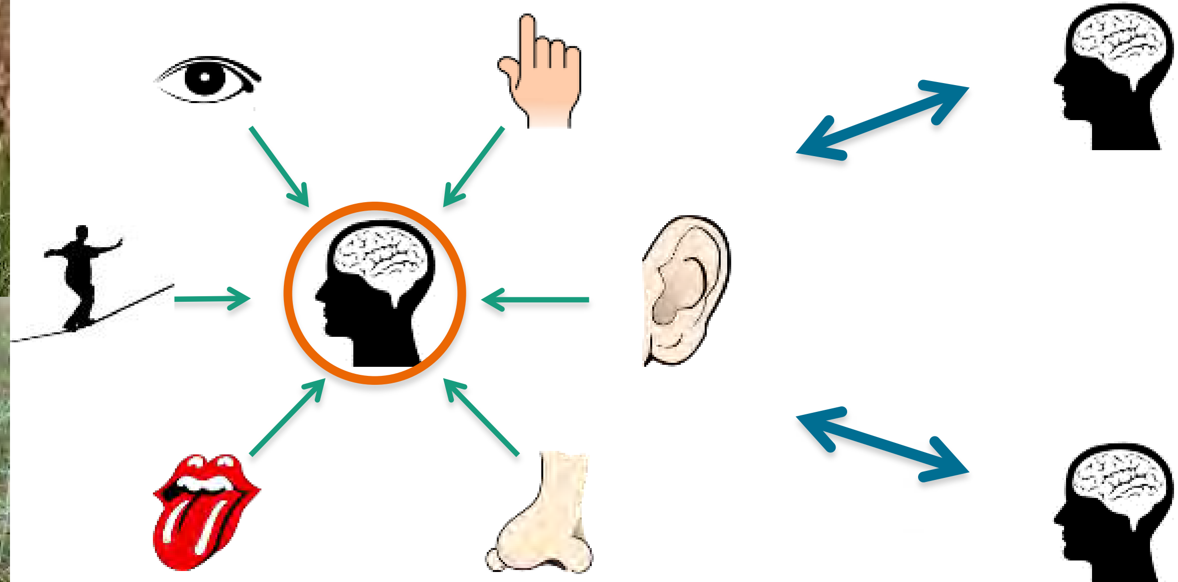
Bearing angle measurements for gunshots.

Soldiers command an unmanned system to reconnaissance an area.

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

Sensor Data Fusion – A Pillar of Natural Intelligence

All creatures "fuse" mutually complementary sense organs with prior information / communications: prerequisites for orientation, action, protection.



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

Sensor Data Fusion – A Pillar of Artificial Intelligence

A Branch of "Weak AI" providing *cognitive assistance*:

1. **Understand, automate, enhance.**
2. **Integrate new sources / platforms.**
   - networking sensor technology: sensitivity, range
     new dimensions of apprehension otherwise hidden
   - Data base systems with vast context information
   - Unmanned mobile platform in all ISR dimensions
   - Interaction with humans: exploit natural intellicence
3. **Information basis: manned/unmanned teaming**

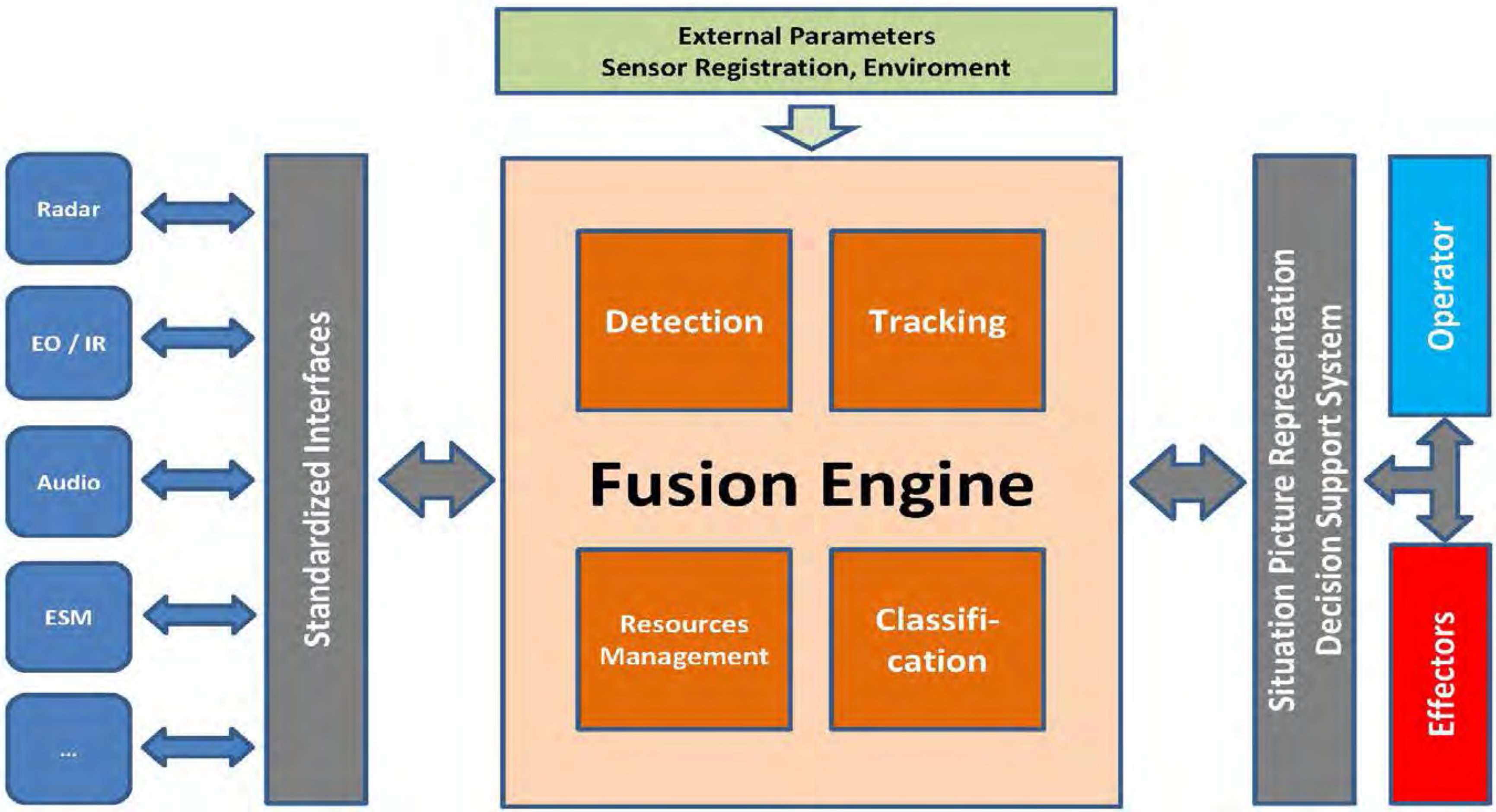
Distributed Sensor Networks – Backbone of ISR

Defence applications need reliable assistance that

- exploits large sensor data streams,
- makes context information accessible,
- optimizes the use of the ISR resources,
- checks plausibility of ISR information,
- suggests options to act properly,
- helps respecting constraints of action,
- adapts to the intention of the user,

in general: unburden humans from routine and mass task to let them do what only humans can do – acting responsibly.

Fusion Engines – Link between Sensors, Context, Action



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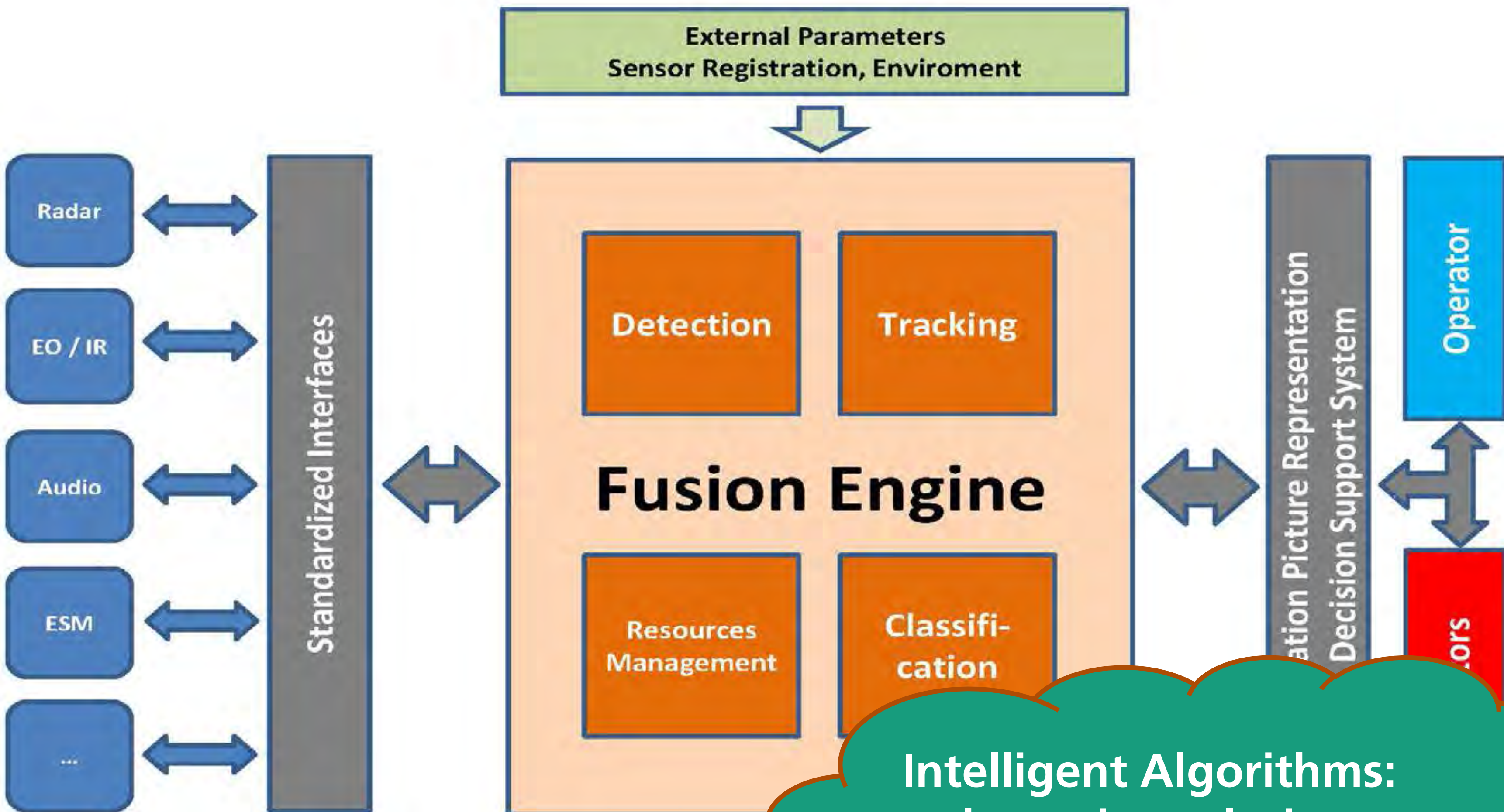


Intelligent Algorithms:
dynamic evolution
→ modular frame

An often implicitly assumed, but *decisive* prerequisite:

Integrity of Sensor and Context Data

Do the data correspond to the expectations?

- Signals
- Measurements
- Classifified tracks
- Situation vignettes
- Mission data

Fusion may turn to confusion, management to mismanagement.

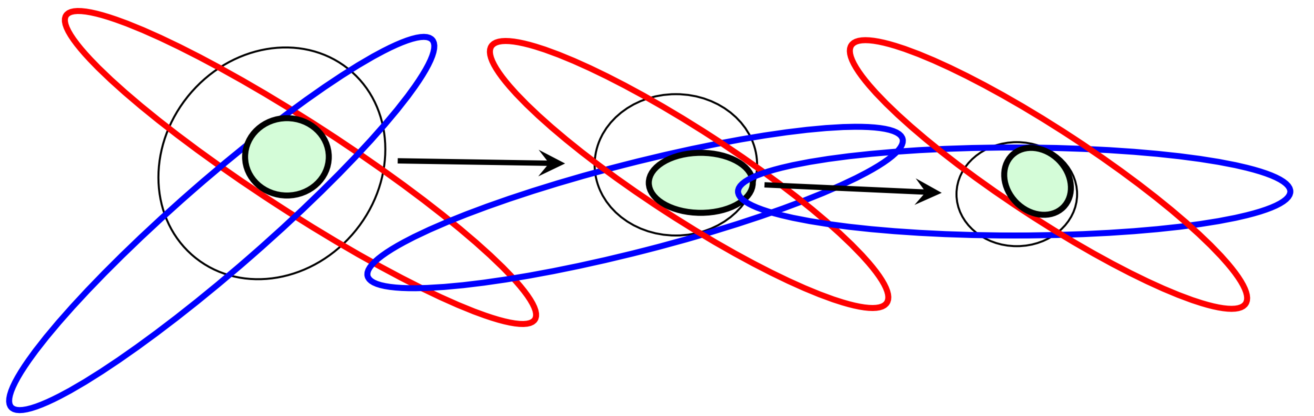
- unintended malfunction
- malign intervention
- unreal artefacts
- blind spots of AI

Fusion when sensor data are potentially corrupted

Data from distributed sensor:
radar, sonar, camera, AIS, microphone …

Learn, check
sensor models.

Fuse
sensor data.



Five Pillars of Distributed Sensor Data Fusion

- Statistical Estimation
- Combinatorial Optimization
- Statistical Decision Making
- Machine Learning
- Control and Game Theory

Highly developed, mathematically founded knowledge

Boosting: ***ITC and Platform Technologies***

economy-driven: deep learning

Quo vadis, Distributed FUSION?
Guessing its future development

... continuous practice, progress in theory

- **Need for mathematically exact results**
- **Fusion-dominated sensor networks**
- **Fusing sensor and context information**
- **Demand for resources management**

Predictions are difficult, especially when dealing with the future. Karl Valentin (1882-1948)

Need for more mathematically exact results for Information Fusion

„Nothing is as practical as a good theory.“

James Clerk Maxwell
Werner Heisenberg
Roy Streit
and probably many others

Examples:

- Exact formulae for distributed fusion
- Using Accumulated State Densities

Bayesian Approach: Multiple Sensor Tracking

Tracks: Conditional PDFs representing available knowledge on the targets

Kinematic state: x_k, **accumulated plots from** S **sensors:** $\mathcal{Z}^k = \{\{\mathrm{z}_k^s\}_{s=1}^S, \mathcal{Z}^{k-1}\}$

Prediction:	$p(\mathrm{x}_{k-1}\|\mathcal{Z}^{k-1})$	$\xrightarrow[p(\mathrm{x}_k\|\mathrm{x}_{k-1})]{\text{dynamics model}}$	$p(\mathrm{x}_k\|\mathcal{Z}^{k-1})$
Filtering:	$p(\mathrm{x}_k\|\mathcal{Z}^{k-1})$	$\xrightarrow[\ell(\mathrm{x}_k; Z_k, n_k)]{\text{sensor model}}$	$p(\mathrm{x}_k\|\mathcal{Z}^k)$
Retrodiction:	$p(\mathrm{x}_l\|\mathcal{Z}^k)$	$\xleftarrow[\text{filtering}]{\text{dynamics model}}$	$p(\mathrm{x}_{l+1}\|\mathcal{Z}^k)$

The likelihood function $\ell(\mathrm{x}_k; \{\mathrm{z}_k^s\}_{s=1}^S)$ **contains the full sensor information:**

***current* sensor data + *context* information on the sensor performance.**

$p(\mathrm{x}_k|\mathrm{x}_{k-1})$ **contains context information on the object's kinematic properties.**

Some Remarks on Distributed Fusion

Reconstruct $p(\mathrm{x}_k|\mathcal{Z}^k) = p(\mathrm{x}_k|\{\mathcal{Z}_s^k\}_{s=1}^S)$ **from local tracks** $p(\mathrm{x}_k|\mathcal{Z}_s^k)$.

$$\left\{p(\mathrm{x}_l|\mathcal{Z}_s^l)\right\}_{s,l=1}^{S,k} \xrightarrow[\text{fusion}]{\text{track-to-track}} \left\{p(\mathrm{x}_l|\{\mathcal{Z}_s^l\}_{s=1}^S)\right\}_{l=1}^{k}$$

+ Communications is less overloaded with false tracks (local processing).
+ Less sensible to registration errors: local tracking is inherently robust.
+ Disturbances of sensor nodes do not lead to total system function loss.

— Often suboptimal performance: system reaction time and track quality.
— Lacking profit from redundancy and data rate (e.g. local track initiation).
— Relies on local track existence: critical in fusing active / passive data.

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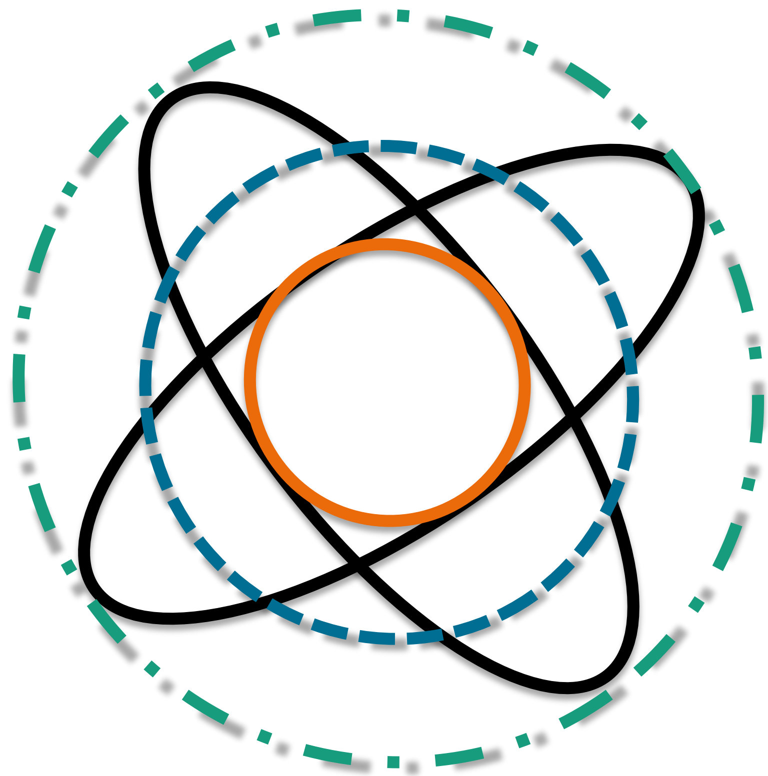
Distributed Estimation

- **Centralized Fusion (CKF)**
  - requires full communication
  - single point of failure
- **Bar-Shalom-Campo-Formula**
  - requires cross-correlation
  - analytical approach
- **Exact Track-to-Track Fusion**
  - requires cross-covariances
- **Naïve Fusion (Convex combination)**
  - too optimistic, ignores cross-correlation
- **Covariance Intersection**
  - simple solution
  - too pessimistic
- **Tracklet Fusion**
  - requires full communication
  - reconstructs the equivalent measurements
- **Federated Kalman Filter**
  - decorrelation by decompensation in process noise
- **Distributed Kalman Filter**
  - keeps local tracks decorrelated



Decorrelated Distributed Kalman Filter (D-DKF)

If the local tracks were not correlated (they are!), T2TF would be trivial:

$$\mathbf{P}_{l|k}^{-1} = \sum_{s=1}^{S} \mathbf{P}_{l|k}^{s\ -1},$$

$$\mathbf{x}_{l|k} = \mathbf{P}_{l|k}\Big(\sum_{s=1}^{S} \mathbf{P}_{l|k}^{s\ -1}\mathbf{x}_{l|k}^{s}\Big).$$

i.e. just a convex combination.

If Kalman filter assumptions hold, decorrelation of tracks is possible.

- Initialization is independent.
- Observation is independent.
- Prediction by using : "globalized covariances"

- However, the locally produced, decorrelated "tracks" are no longer *locally* optimal.

Fusion at Arbitrary Communication Times

Consider Gaussian *products*: $p(\mathrm{x}_l|Z^k) \propto \prod_{s=1}^{S} \mathcal{N}(\mathrm{x}_l;\, \mathrm{x}^s_{l|k},\, \mathrm{P}^s_{l|k})$.

Whenever a fusion result is requested, transform the product into a single Gaussian, $p(\mathrm{x}_l|Z^k) = \mathcal{N}(\mathrm{x}_l;\, \mathrm{x}_{l|k},\, \mathrm{P}_{l|k})$**, by a convex combination of** $\mathrm{x}^s_{l|k}$**,** $\mathrm{P}^s_{l|k}$**:**

$$\mathrm{P}^{-1}_{l|k} = \sum_{s=1}^{S} \mathrm{P}^{s\;-1}_{l|k}, \quad \mathrm{x}_{l|k} = \mathrm{P}_{l|k}\Big(\sum_{s=1}^{S} \mathrm{P}^{s\;-1}_{l|k}\mathrm{x}^s_{l|k}\Big).$$

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A key question: **Can $\mathrm{x}^s_{l|k}$ be calculated by using only measurements of sensor s, i.e. locally at each node of a distributed sensor network?**

The answer: **YES — at least under conditions where Kalman filtering is strictly applicable (e.g. measurement error covariances known, $P_D = 1$).**

DKF at Optimal Conditions

Given Kalman filter assumptions + *error covariances of the remote sensors are known* ➔ DKF is exact.

$$\begin{aligned}\mathbf{x}_{k|k} &= \sum_{s=1}^{S} \mathbf{P}_{k|k} \left(\mathbf{P}^{-1}_{k|k-1} \mathbf{x}^{s}_{k|k-1} + \mathbf{H}_k^{\top} \mathbf{R}_k^{s\,-1} \mathbf{z}_k \right) \\ &=: \sum_{s=1}^{S} \mathbf{x}^{s}_{k|k}\end{aligned}$$

$$\mathbf{P}_{k|k} = \left(\mathbf{P}^{-1}_{k|k-1} + \sum_{s=1}^{S} \mathbf{H}_k^{\top} \mathbf{R}_k^{s\,-1} \mathbf{H}_k \right)^{-1}$$

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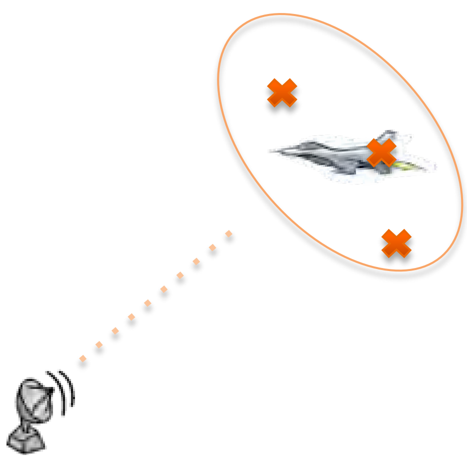
$$\mathbf{P}_{k|k} = \left(\mathbf{P}_{k|k-1}^{-1} + \sum_{s=1}^{S} \mathbf{H}_k^\top \mathbf{R}_k^{s\,-1}\mathbf{H}_k\right)^{-1}$$



In many practical applications, these assumptions are not given.

- **Measurement error covariance dependent on the *sensor-target-geometry.***
- **Sensors have *non-detections* and (gated) *clutter*.**

In certain applications *<u>A</u>ccumulated <u>S</u>tate <u>D</u>ensities* (ASDs) can be very useful!

Object state vectors accumulated over a time window $t_k, t_{k-1}, \ldots, t_n$:

$$\mathrm{x}_{k:n} = (\mathrm{x}_k, \ldots, \mathrm{x}_n)$$

The full information on $\mathrm{x}_{k:n}$ based on a time series of sensor data $\mathcal{Z}^k$ is contained in the corresponding *accumulated state density (ASD):*

$$p(\mathrm{x}_k, \ldots, \mathrm{x}_n | \mathcal{Z}^k) = p(\mathrm{x}_{k:n} | \mathcal{Z}^k).$$

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- **a more comprehensive treatment of issues in particle filtering,**
- **Q-functions in PMHT applications to be maximized are ASDs,**
- **exact solution to the out-of-sequence measurement problem**
- **Here: exact solution of the distributed target tracking problem**

Via marginalizing over all object states in the window, excepting x_l, $n \leq l \leq k$,

$$\int \mathrm{d}\mathrm{x}_k, \ldots, \mathrm{d}\mathrm{x}_{l+1}, \mathrm{d}\mathrm{x}_{l-1}, \ldots, \mathrm{d}\mathrm{x}_n \, p(\mathrm{x}_k, \ldots, \mathrm{x}_n | \mathcal{Z}^k) = p(\mathrm{x}_l | \mathcal{Z}^k),$$

we obtain the pdfs for filtering & retrodiction; ASDs thus unify these notions.

In addition, all correlations between different instants of time are contained.

In a way an ASD ist *THE* tracking result!

Via marginalizing over all object states in the window, excepting x_l, $n \le l \le k$,

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In addition, all correlations between different instants of time are contained.

Bayes' Theorem: a recursion formula for updating ASDs:

$$\boxed{p(\mathrm{x}_{k:n} | \mathcal{Z}^k) = \frac{\ell(\mathrm{x}_k; Z_k) \, p(\mathrm{x}_k | \mathrm{x}_{k-1}) \, p(\mathrm{x}_{k-1:n} | \mathcal{Z}^{k-1})}{\int \mathrm{dx}_{k:n} \, \ell(\mathrm{x}_k; Z_k) \, p(\mathrm{x}_k | \mathrm{x}_{k-1}) \, p(\mathrm{x}_{k-1:n} | \mathcal{Z}^{k-1})}}$$

A little formalistically speaking, 'sensor data processing' means:

Make sure that the sensor data are no longer explicitly present.

Closed-form Representations for ASDs

Example: conditions, where Kalman filtering is applicable

likelihood function: $\ell(\mathrm{x}_k; Z_k) = \mathcal{N}(\mathrm{z}_k;\, \mathrm{H}_k \mathrm{x}_k,\, \mathrm{R}_k)$

evolution model: $p(\mathrm{x}_k|\mathrm{x}_{k-1}) = \mathcal{N}(\mathrm{x}_k;\, \mathrm{F}_{k|k-1}\mathrm{x}_{k-1},\, \mathrm{D}_{k|k-1})$

Induction argument (tedious, but elementary calculations):

The corresponding ASD is a Gaussian:

$$p(\mathrm{x}_{k:n}|Z^k) = \mathcal{N}(\mathrm{x}_{k:n};\, \mathrm{x}^k_{k:n},\, \mathrm{P}^k_{k:n})$$

with $\mathrm{x}^k_{k:n} = (\mathrm{x}^\top_{k|k}, \mathrm{x}^\top_{k-1|k}, \dots, \mathrm{x}^\top_{n|k})^\top$.

$\mathrm{x}_{k|k}$: standard Kalman filtering, $\mathrm{x}_{l|k}$, $l < k$: standard RTS smoothing

Block Matrix Representations of the ASD Covariance

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

products of Kalman filter gains

$$= \begin{pmatrix} \mathbf{T}_{k|k} & -\mathbf{W}^\top_{k-1|k}\mathbf{Q}^{-1}_{k-1|k} & \mathbf{O} & \cdots & \mathbf{O} \\ -\mathbf{Q}^{-1}_{k-1|k}\mathbf{W}_{k-1|k} & \mathbf{T}_{k-1|k} & -\mathbf{W}^\top_{k-2|k}\mathbf{Q}^{-1}_{k-2|k} & \ddots & \vdots \\ \mathbf{O} & -\mathbf{Q}^{-1}_{k-2|k}\mathbf{W}_{k-2|k} & \ddots & \ddots & \mathbf{O} \\ \vdots & \ddots & \ddots & \mathbf{T}_{m+1|k} & -\mathbf{W}^\top_{m|k}\mathbf{Q}_{m|k} \\ \mathbf{O} & \cdots & \mathbf{O} & -\mathbf{Q}_{m|k}\mathbf{W}_{m|k} & \mathbf{T}_{m|k} \end{pmatrix}^{-1}$$

Markov property: tridiagonal structure of the inverse ASD covariance

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MULTI SENSOR ASD FILTER

Multi Sensor ASD Posterior

For *S* sensors, we have

$$
\begin{aligned}
p(\mathbf{x}_{k:n}|\mathcal{Z}^k) &= \frac{p(Z_k^1,\ldots,Z_k^S|\mathbf{x}_k)\cdot p(\mathbf{x}_{k:n}|\mathcal{Z}^{k-1})}{\int \mathrm{d}\mathbf{x}_{k:n} p(Z_k^1,\ldots,Z_k^S|\mathbf{x}_k)\cdot p(\mathbf{x}_{k:n}|\mathcal{Z}^{k-1})} \\
&= \frac{\prod_{s=1}^S p(Z_k^s|\mathbf{x}_k)\cdot p(\mathbf{x}_{k:n}|\mathcal{Z}^{k-1})}{\int \mathrm{d}\mathbf{x}_{k:n} \prod_{s=1}^S p(Z_k^s|\mathbf{x}_k)\cdot p(\mathbf{x}_{k:n}|\mathcal{Z}^{k-1})} \\
&\propto \prod_{s=1}^S p(Z_k^s|\mathbf{x}_k)\cdot p(\mathbf{x}_k|\mathbf{x}_{k-1:n})p(\mathbf{x}_{k-1:n}|\mathcal{Z}^{k-1})
\end{aligned}
$$

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\end{aligned}
$$

***relaxed* evolution model**

An *extremely simple* observation:

$$
\boxed{\mathcal{N}\big(\mathbf{x}_k;\, \mathbf{F}_{k|k-1}\mathbf{x}_{k-1},\, \mathbf{Q}_{k|k-1}\big) \;\propto \mathcal{N}\big(\mathbf{x}_k;\, \mathbf{F}_{k|k-1}\mathbf{x}_{k-1},\, S\mathbf{Q}_{k|k-1}\big)^S}
$$

DASD Product Representation

Similar to the single sensor ASD we have

$$p(\mathbf{x}_{k:n}|\mathcal{Z}^k) \propto \prod_{l=n+1}^{k} \Big[\prod_{s=1}^{S} \big\{ \mathcal{N}\big(\mathbf{z}_l^s;\, \mathbf{H}_l^s \mathbf{x}_l,\, \mathbf{R}_l^s\big)\, \mathcal{N}\big(\mathbf{x}_l;\, \mathbf{F}_{l|l-1}\mathbf{x}_{l-1},\, S\mathbf{Q}_{l|l-1}\big)\big\} \Big] \cdot \mathcal{N}\big(\mathbf{x}_n;\, \mathbf{x}_{n|n},\, \mathbf{P}_{n|n}\big),$$

Assume furthermore an independent initialization at time *n.* Then:

$$p(\mathbf{x}_{k:n}|\mathcal{Z}^k) \propto \prod_{s=1}^{S} \mathcal{N}\big(\mathbf{x}_{k:n};\, \mathbf{x}_{k:n|k}^s,\, \mathbf{P}_{k:n|k}^s\big),$$

..only depends on local data and local error covariancs!

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..only depends on local data and local error covariancs!

and the fused estimate parameters are given by

$$\mathbf{P}_{k:n|k} = \left(\sum_{s=1}^{S} \mathbf{P}_{k:n|k}^{s\;-1} \right)^{-1} \qquad \mathbf{x}_{k:n|k} = \mathbf{P}_{k:n|k} \sum_{s=1}^{S} \mathbf{P}_{k:n|k}^{s\;-1} \mathbf{x}_{k:n|k}^s$$

DASD Prediction

The prior parameters at sensor node *s* is given by

$$\mathbf{x}^s_{k:n|k-1} = \begin{pmatrix} \mathbf{x}^s_{k|k-1} \\ \mathbf{x}^s_{k-1|k-1} \\ \vdots \\ \mathbf{x}^s_{n|k-1} \end{pmatrix}, \quad \mathbf{P}^s_{k:n|k-1} = \begin{pmatrix} \mathbf{P}^s_{k|k-1} & \mathbf{P}^s_{k|k-1} \mathbf{W}^{s\,\top}_{k-1:n} \\ \mathbf{W}^s_{k-1:n} \mathbf{P}^s_{k|k-1} & \mathbf{P}^s_{k-1:n|k-1} \end{pmatrix}$$

known from previous posterior!

DASD Prediction

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$$\mathbf{x}^s_{k|k-1} = \mathbf{F}_{k|k-1} \mathbf{x}^s_{k-1|k-1}$$

$$\mathbf{P}^s_{k|k-1} = \mathbf{F}_{k|k-1} \mathbf{P}^s_{k-1|k-1} \mathbf{F}^\top_{k|k-1} + S\mathbf{Q}_{k|k-1}$$

DASD Filtering

Define a projection onto the current state:

Measurement function

then:

$$\begin{aligned} p(\mathbf{z}_k^s|\mathbf{x}_k) &= p(\mathbf{z}_k^s|\mathbf{\Pi}_k\mathbf{x}_{k:n}) \\ &= \mathcal{N}\left(\mathbf{z}_k^s; \mathbf{\Pi}_k\mathbf{H}_k^s\mathbf{x}_{k:n}, \mathbf{R}_k^s\right) \end{aligned}$$

➔ Kalman filter update possible!

Sliding Window Implementation

Delete row and column such that

k-*n* = const.

The approximation error at time *k* decreases exponentially with the time window length since the cross-covariance is given by

$$\begin{aligned}\mathrm{cov}\left[\mathbf{x}_n, \mathbf{x}_k \middle| \mathcal{Z}^k\right] &= \mathbf{W}_{n|k} \cdot \mathbf{P}_{k|k} \\ &= \prod_{l=n}^{k-1} \mathbf{W}_{l|l+1} \cdot \mathbf{P}_{k|k}\end{aligned}$$

Product of Kaman gains, each of which has Eigenvalues < 1.

Conclusions and Ongoing Work

- **Distributed Kalman Filtering Problem:**

  relaxed ASDs: a mathematically **exact** ***solution!***

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Conclusions and Ongoing Work

- **Distributed Kalman Filtering Problem:**

  relaxed ASDs: a mathematically* exact *solution!

- **+ no global knowledge on sensor model needed**
- **- increasing state vector**
- **Fixed length ASD works well (*not* mathematically exact)**
- **Systematic investigation of acceptable errors possible**
- **Future work:**
  - **Extend to more advanced local trackers**
  - **Systematic comparison to existing approaches**

Quo vadis, Distributed FUSION?
Guessing its future development

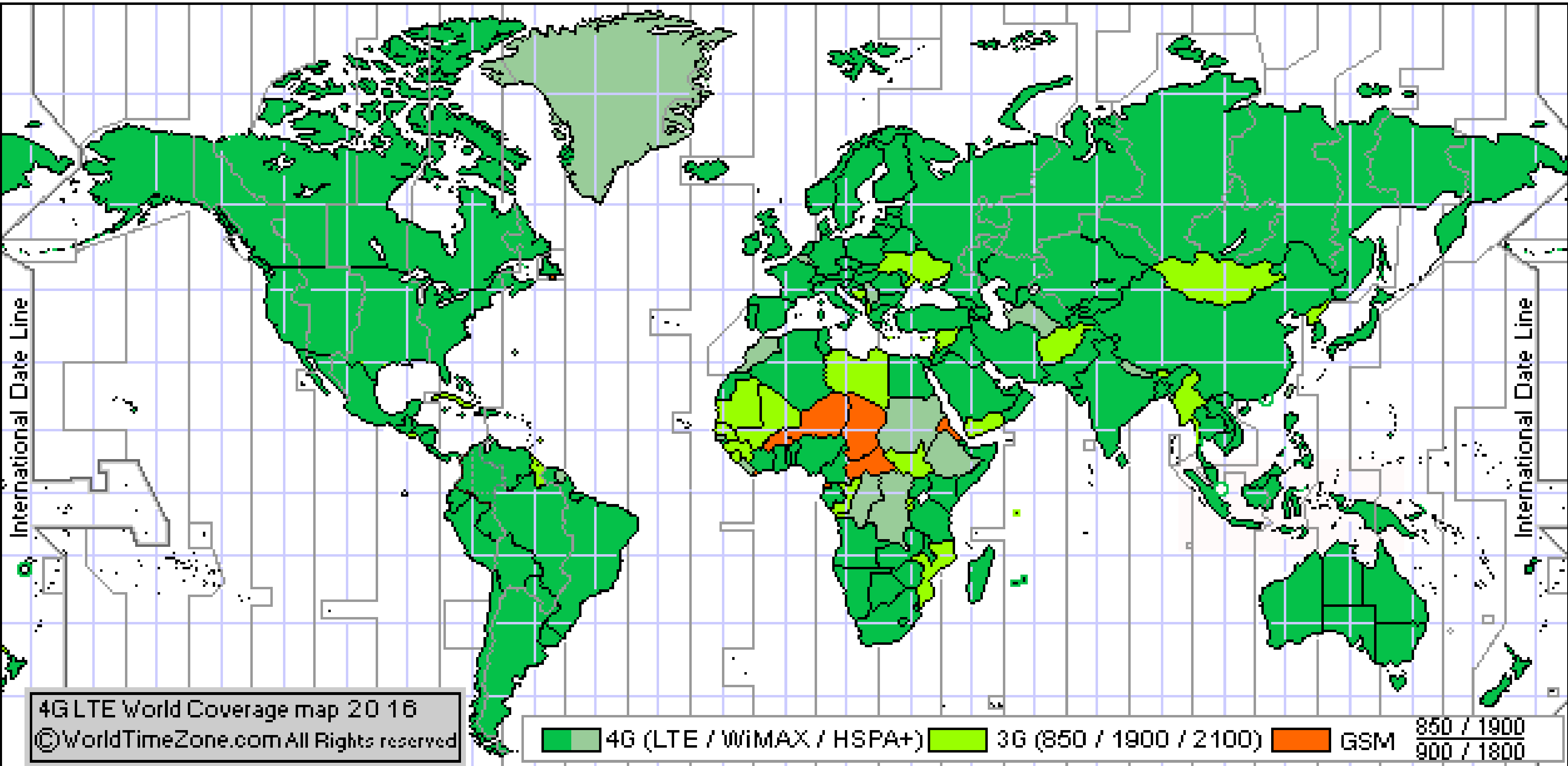
... continuous practice, progress in theory

- Need for mathematically exact results
- Fusion-dominated sensor networks
- Fusing sensor and context information
- Demand for resources management

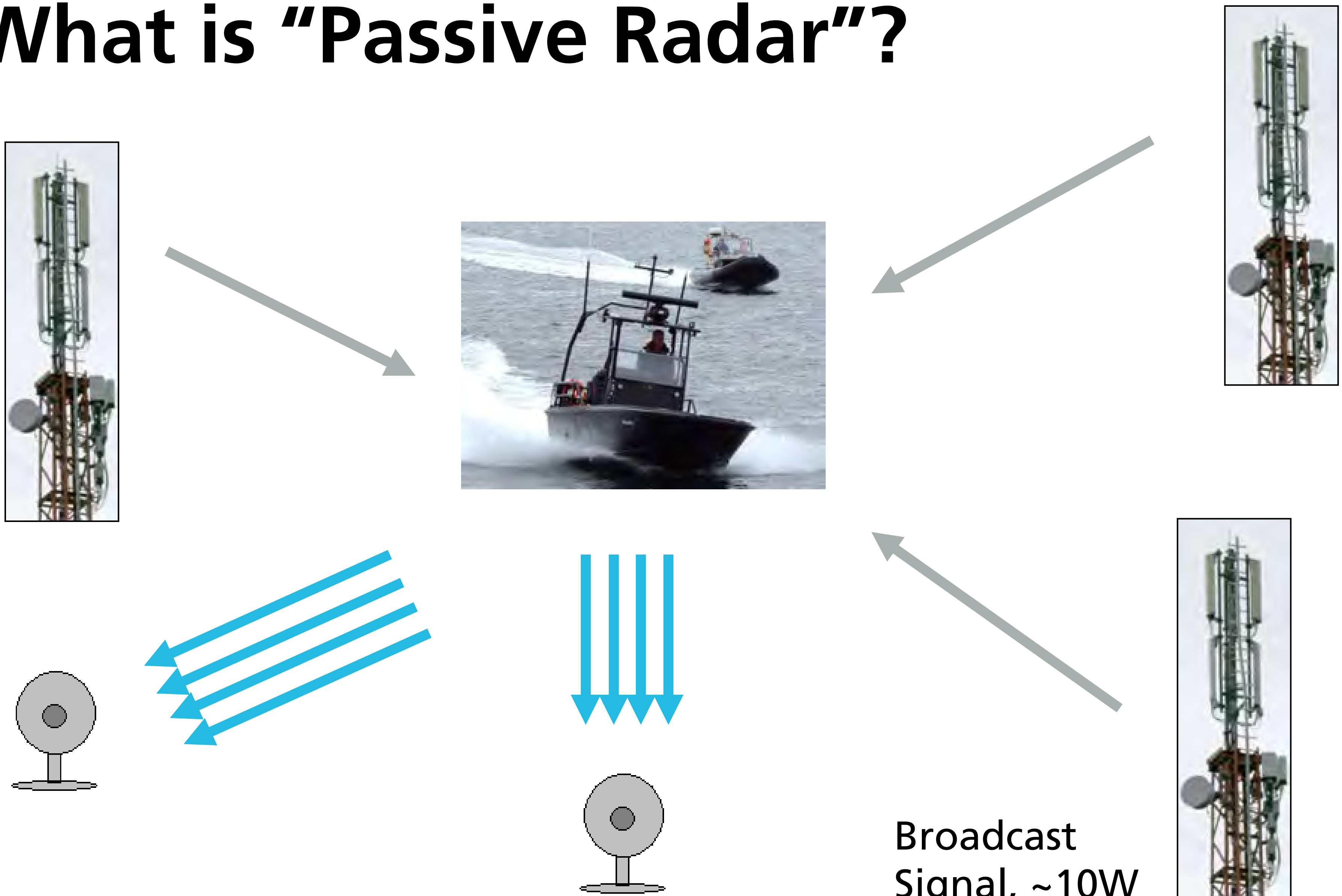
Predictions are difficult, especially when dealing with the future. Karl Valentin (1882-1948)

Globally available mobile phone infrastructure

Use mobile phone base stations as illuminators for passive radar!



What is “Passive Radar”?



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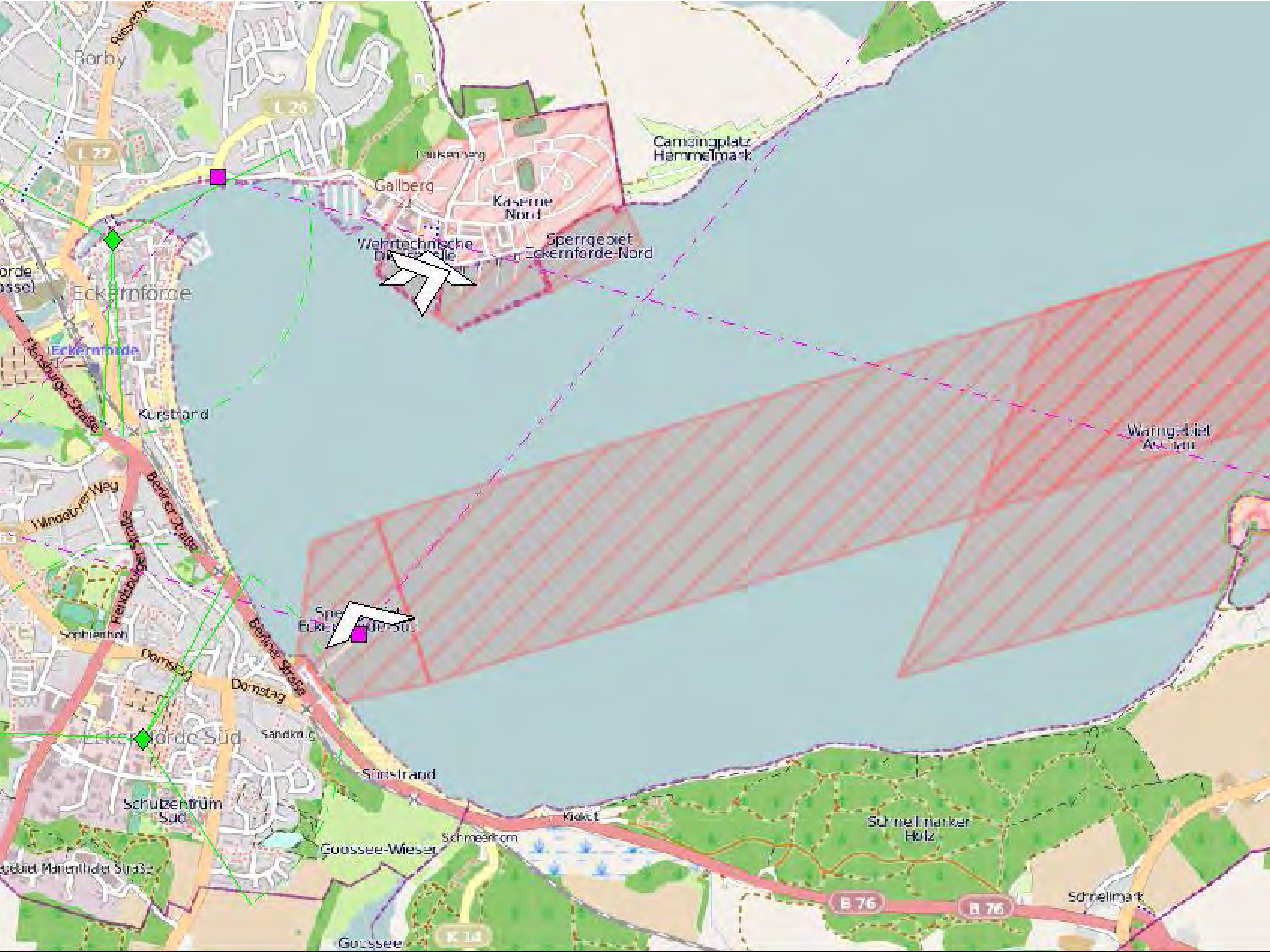
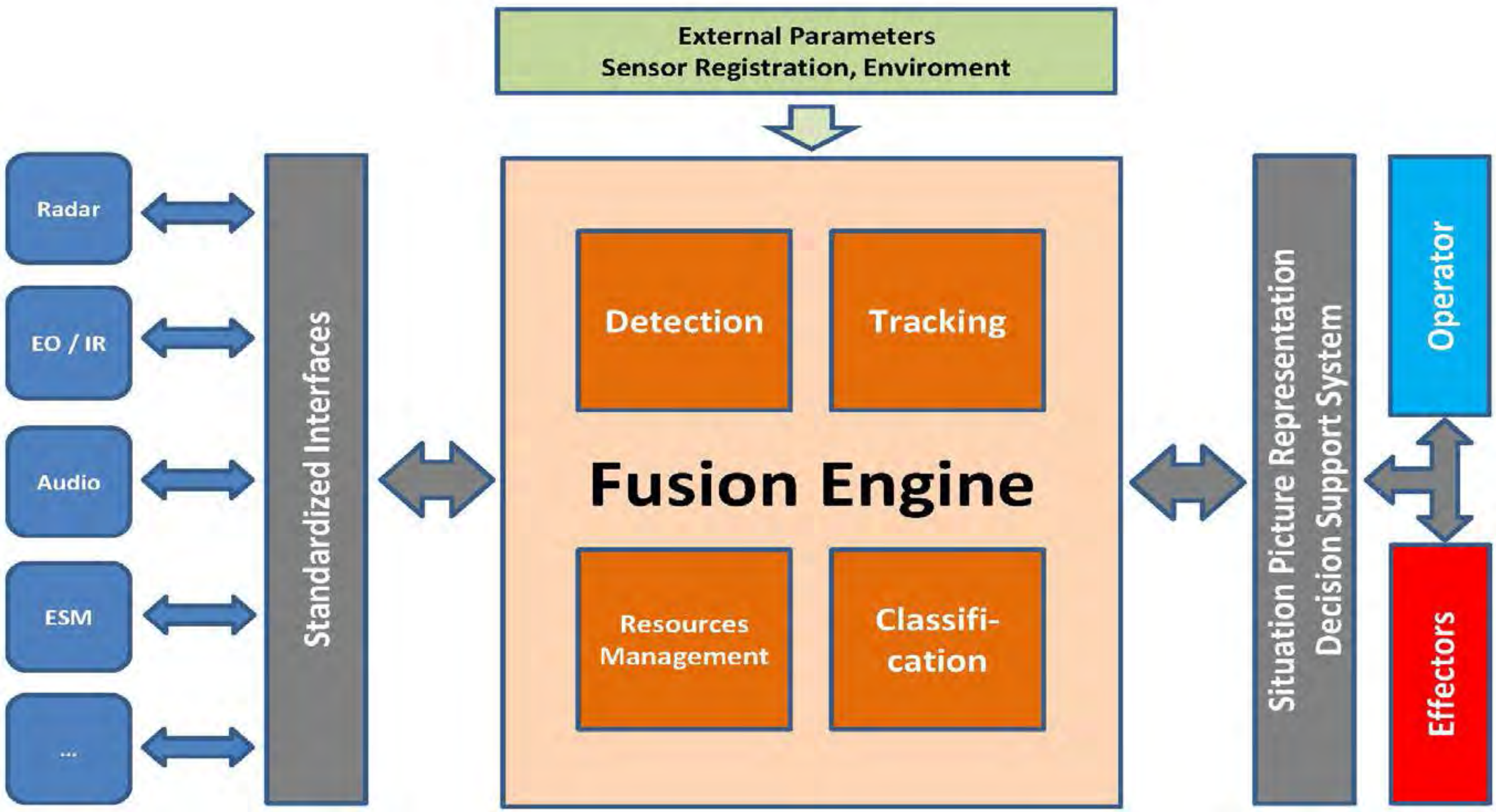


Borby
L 26
L 27
Campingplatz
Hammelmark
Gallberg
Kaserne
Nord
Sperrgebiet
Eckernförde-Nord
Eckernförde
Kurstrand
Warngebiet
Aschau
Berliner Straße
Domstag
Eckernförde Süd
Schulzentrum
Süd
Südstrand
Goossee-Wiesen
Schnellmarker
Holz
Kiekut
B 76
B 76
Schnellmark
K 14
Goossee

Fusion Engines – Link between Sensors, Context, Action



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