# TARGET TRACKING AND DATA FUSION: How to Get the Most Out of Your Sensors

and make a living out of it

AN OVERVIEW OF TRACKING ALGORITHMS FOR CLUTTERED AND MULTITARGET-MULTISENSOR ENVIRONMENTS

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- *Quantify* the corresponding uncertainties.
- Fuse the information from the various sources accounting for their uncertainties.

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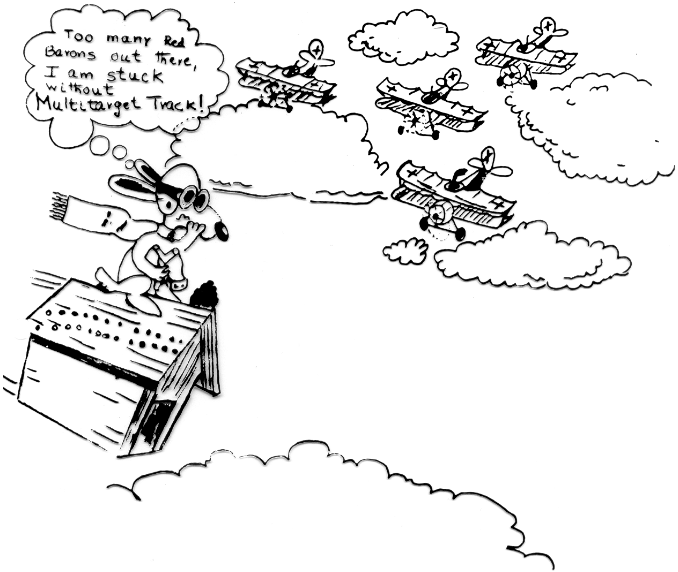
**Method of approach**

Make things as simple as possible, but not simpler.

A. Einstein

- The evolution of the technology of tracking targets (objects of interest) in a cluttered environment starting from the Kalman filter (recursive LMMSE estimator for Markovian dynamic systems), the backbone of most current systems.
- Approaches for handling target maneuvers (unpredictable motion, including thrusting/ballistic targets) and false measurements (clutter).
- Advanced robust techniques with moderate complexity.
- Tracking of multiple targets.
- Tracking with multiple sensors: Fusion architectures.

# SNOOPY: ORIGINAL MOTIVATION OF MTT



# MTT IN THE ANIMAL WORLD

# TRACKING WITH UNCERTAIN MOTION MODELS AND UNCERTAIN MEASUREMENTS

TRACKING consists of:

- Estimation of the current state of a target (i.e., filtering) based on uncertain measurements to reduce the effect of the various noises.
- Calculation of the accuracy/credibility associated with the state estimate.

TARGET MODEL UNCERTAINTIES — motion is subject to:

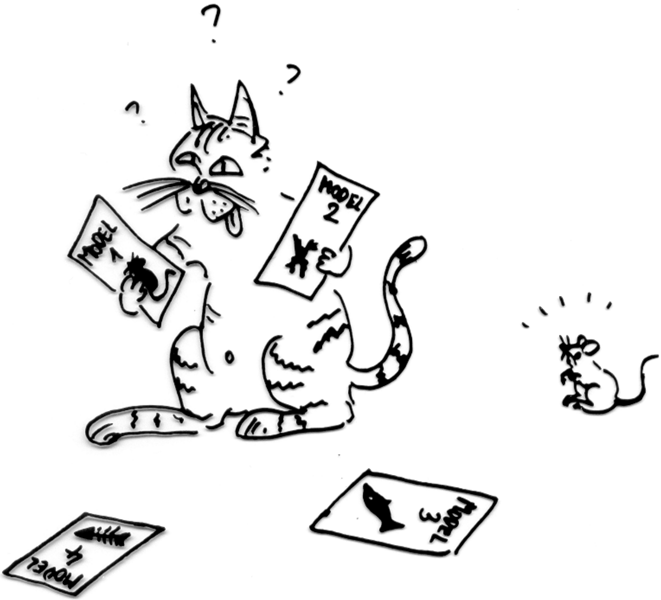
- Random perturbations and/or
- Unknown maneuvers or motion model changes.

Multiple models are needed to describe different target behavior modes.

MEASUREMENT UNCERTAINTIES:

- Measured values from the target are inaccurate (noisy)
- Origin of the measurements is not perfectly certain — the measurement(s) can be from the target of interest, false alarms, clutter or other targets — data association is necessary.

# UNCERTAINTIES



# TYPES OF DATA ASSOCIATION

MEASUREMENT-TO-MEASUREMENT association (Start-up).

MEASUREMENT-TO-TRACK association (Continuation).

Gating is done in the measurement space consisting of kinematic variables (position, Doppler, etc.) as well as feature components (signal strength, frequency, etc.).

TRACK-TO-TRACK association (in the decentralized multisensor case)

Given two tracks, each based on the data from a different sensor, are they from the same target?

- Common origin hypothesis test
- Combination (fusion) of the estimates if common origin hypothesis is accepted — for improved accuracy.

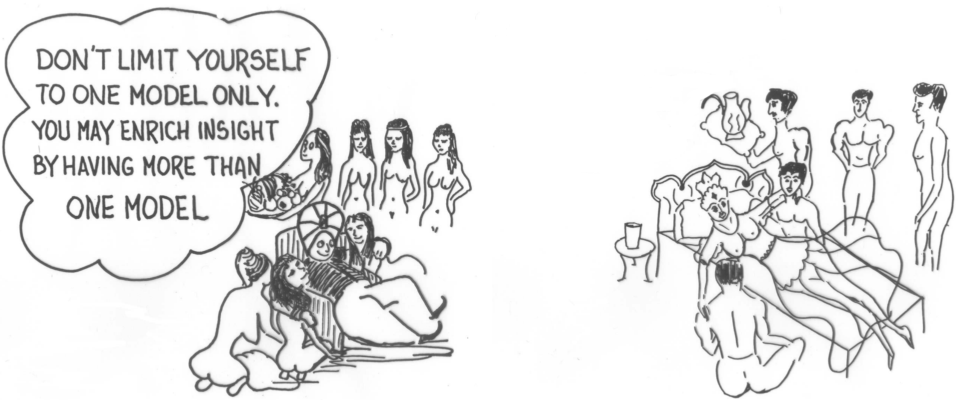
Gating is done in the state space with a weighted Cartesian norm and the *dependence* of the state estimation errors (across independent sensors!) has to be accounted for.

The true measurement of a kinematic variable can be far from the predicted location — this can cause problems in data association.

Modeling of maneuvers:

- PROCESS NOISE (assumed by the filter — “pseudo noise" — white or from a subsystem driven by white noise)
  [Q: why white?]
  - with a single high level (conservative)
  - with several discrete levels with heuristic “hard” switching based on the norm of the innovations (not practical in clutter)
- MULTIPLE MODELS — use various models that differ in state equation and/or process noise levels, state dimension (e.g., add turn rate or thrust for thrusting/ballistic targets)
  - with hard switching (based on some logic — not practical in clutter)
  - with soft (probabilistic) switching — Interacting Multiple Model (IMM) estimator — works in clutter.

# THE MORE MODELS THE BETTER — PC on the average!



**The $\alpha$-$\beta$ Filter**

- Uses *fixed gains* and *fixed association gates* (with possible simple logic of switching between several sets — gain scheduling)
- It does not yield state estimation accuracies (covariances)
- This filter is actually the *steady-state Kalman filter* for a kinematic model (2nd order with acceleration as white process noise) with a given set of parameters. A similar filter ($\alpha$-$\beta$-$\gamma$) is available for a 3rd order model

**Handling of measurement ambiguities**
Measurement selection

- “nearest neighbor" (following thresholding of the signal)
- “strongest neighbor" (following gating).

This is then used in the state update as if it was the correct one.

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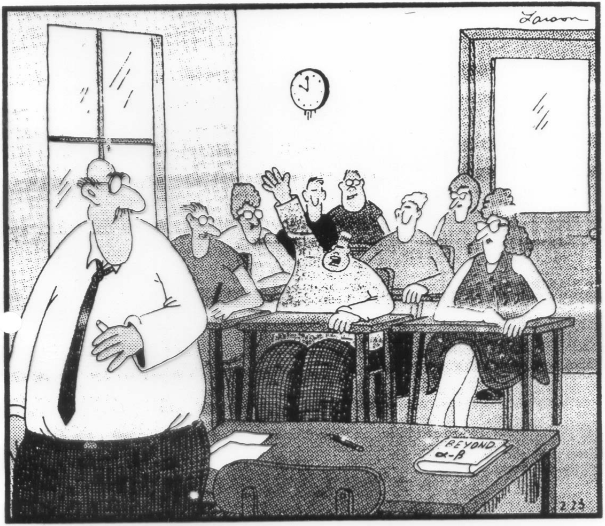
Q: How can one improve on the $\alpha$-$\beta$ filter in clutter?

(outlw)




"Mr. Osborne, may I be excused? My brain is full."

Selection of the measurement (from the gate) for state update is done according to

- A “minimum distance rule" — Nearest-Neighbor (NNSKF), or
- A feature, e.g., the signal strength — Strongest Neighbor (SNSKF).

The update is done with a time-varying gain (as opposed to the $\alpha$-$\beta$ filter), which is optimal if

- the assumed motion model parameters are correct and
- the selected measurement is the correct one.

No accounting is made of the possibility that a clutter measurement might have been selected — it is a “standard” filter.

A logic can be used to effect a switching between several process noise levels (“spaghetti logic” unless the SNR is very high).

For nonlinear state or measurement models: Extended KF uses linearization.

(KF workhrs; $\alpha - \beta$ mule)

- This filter calculates for all the current measurements from the gate the *association probability* of having originated from the target in track based on their locations/features — time depth 1.
- The state is then updated with a *weighted combination* of these measurements with the weights being the above association probabilities — “soft” association decision.
- The covariance associated with the resulting state estimate includes a term due to the measurement origin uncertainty.
- This algorithm is suboptimal since it “lumps" all the measurements in a single state estimate — it replaces a Gaussian mixture by a single Gaussian using moment matching
- It is simple ($1.3\times$ the NNSKF) and yields significantly improved tracking performance.

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**Some implementations of the PDAF**

- Jindalee over-the-horizon radar in Australia — the only algorithm that was capable of working in very heavy clutter
- At Raytheon: Hawk SAM, ROTHR, THAAD, ASDE, GBR
- At EUROCONTROL (combined with the IMM).

This (most comprehensive) algorithm, with time depth $> 1$

- splits the existing track (within a sliding window) whenever there is an association ambiguity and follows each branch (sequence of measurements) with a probability calculation
- updates the tracks for each hypothesis with a KF/IMM
- has built-in track initiation capability.

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Disadvantages

- Computational and memory requirements (NP-hard)
- Very complex data management and debugging
- Multitude of the output — all the hypotheses are put out and it is very complicated to present an overall picture: one can display the most likely hypothesis (questionable/optimistic) or composite tracks.

# THE INTERACTING MULTIPLE MODEL (IMM) ESTIMATOR

- The Interacting Multiple Model estimation algorithm is a very efficient recursive scheme with fixed requirements for systems with switching models (hybrid systems) — a self-adjusting variable-BW estimator.
- The IMM estimator runs Kalman filter (or EKF) modules *simultaneously* based on several target models (e.g., non-maneuvering and maneuvering models or thrusting and ballistic)
  - in an interacting manner — constantly exchanging information
  - yields the "current model" probability conditioned on the available data.
- The output consists of mode probabilities, combined state estimate weighted by the mode probabilities and covariance of the combined state estimate.
- The IMM was the key that made it possible for an off-the-shelf torpedo to intercept and attacking torpedo in a sea test.

The IMM, which has a modular architecture, has been extended (**IMMPDAF**) for tracking a target in clutter by

- using the PDAF as the basic filter module and
- making suitable changes in the model probability calculation to account for the target $P_D$ and the clutter.
- Major advantages
  - simplicity of implementation
  - modest and fixed computational and memory requirements
  - effects soft switching between the models — “never totally right, never totally wrong”

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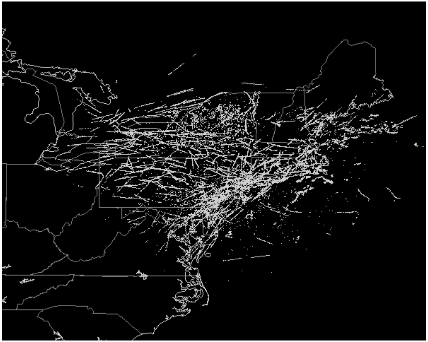
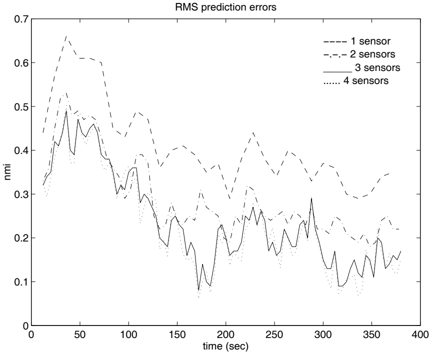
The IMMPDAF has been fielded in an active hull mounted sonar to track low-SNR maneuvering targets.

The IMM has been successfully used in combination with assignment — "hard" association decision — for real ATC data (800 targets, 5 radars).






- Scenario: 5 FAA/JSS radars, 800 targets
- Solution: 2-D assignment algorithm for data association in conjunction with the IMM estimator for tracking
- Real-time capability: IMM/Assignment tracker processed 5 minutes worth of data in less than one minute

Major issue: Is there enough information in the data?

*Information in the sense of Fisher*: a matrix whose inverse, if it exists, yields the lowest achievable covariance in estimation (the CRLB; in general there is no guarantee that one can achieve this bound).

If $P_D < 1$ and $P_{FA} > 0$, one has a new situation: an *information reduction factor (IRF)* has been quantified — there is less information and the **CRLB in clutter (CRLBiC)** is higher than the conventional CRLB.

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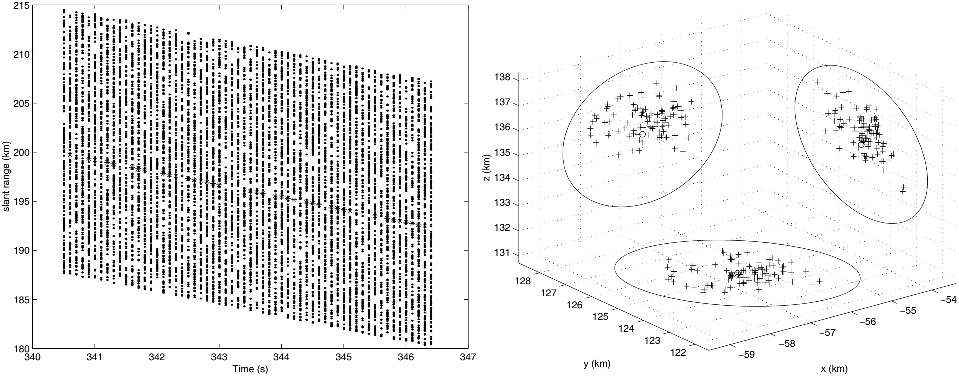
In real world problems

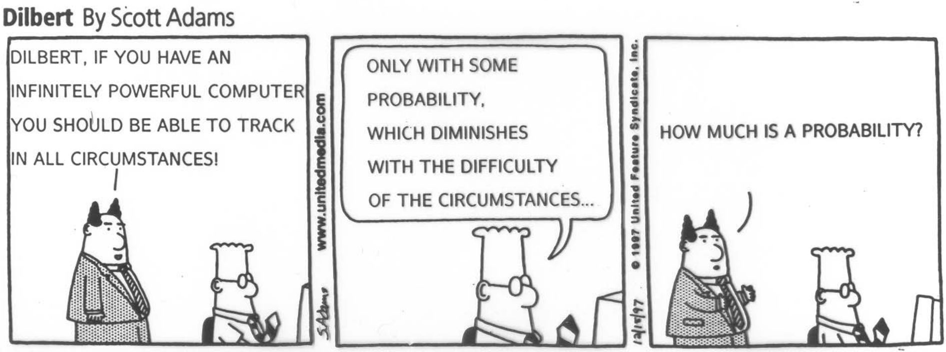
- we have to understand the limits due to finite (perhaps insufficient) information in the sensor data — the **existing information**
- seek efficient algorithms — such that the **extracted information** is equal to the existing information, or as close as possible to it, subject to implementation constraints.

Example: The ML-PDA for TBM acquisition is efficient for LO targets down to 4dB SNR in a cell — average signal strength is 1.6 times the average noise.

# LOW OBSERVABLE TBM ACQUISITION USING ML-PDA




- Scenario: 200-250 km missile acquisition range, data for 6 s at 10 Hz
- Difficulty: low SNR ⇒ high false alarm density (low observability)
- Solution: ML-PDA estimator with features to initialize tracks
- Efficient — meets the **CRLB in clutter (CRLBiC)** down to 4 dB SNR — extracts all available information.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HOW MUCH IS A PROBABILITY?

Prerequisites for successful data fusion:

- Sensor registration (alignment)
- Reliable statistical description of the uncertainties in each sensor's data
- Reliable estimation accuracies — track error covariances.

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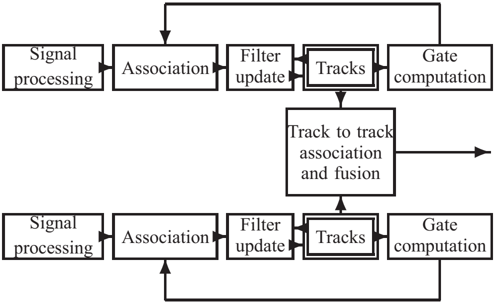
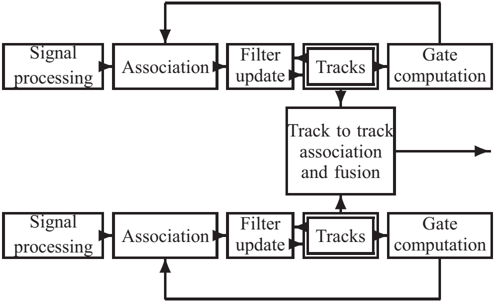
An interesting results in fusion from distributed local trackers is that local tracks using independent sensors have correlated errors.

This correlation is due to the "common process noise" — the motion uncertainty model is common, only the measurement uncertainties are independent across local trackers — and is quantified by "crosscovariances".




This fusion, even if performed optimally (with the exact cross-correlations between the local state estimation errors), is known to be slightly inferior (10–15%) compared to the centralized configuration.
Explanation: optimal fusion of locally optimal tracks is globally suboptimal — because the locally optimal filter gains are not globally optimal.

# SINGLE SENSOR TRACKING FOLLOWED BY TRACK FUSION W/O FEEDBACK

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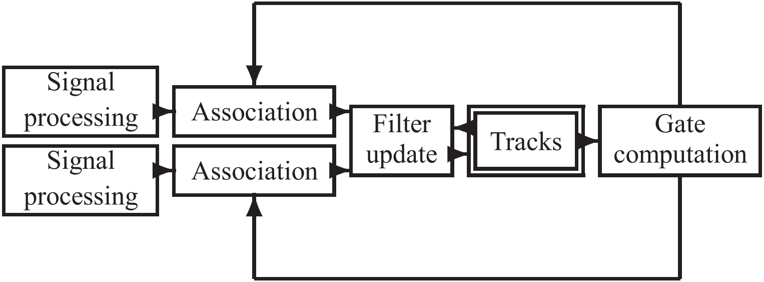
Explanation: optimal fusion of locally optimal tracks is globally suboptimal — because the locally optimal filter gains are not globally optimal.

It is critical that each estimate is consistent (has a covariance that is neither optimistic nor pessimistic).

In this configuration all the associations and tracking are carried out at a central location.




This provides the best performance but it has high communication bandwidth requirements.

- The $\alpha$-$\beta$ and the NNSKF/SNSKF approaches are overly simplistic and outdated.
- At the other extreme, the MHT technique is very complex. The use of discrete optimization (rather than enumerative hypothesis evaluation) makes it more efficient and brings it to the stage where real-time implementation is feasible.
- For a single target, the IMMPDAF is believed to be the best available compromise between complexity and performance. Its capabilities in a realistic cluttered environment have been shown in a series of Navy Benchmark problems.
- The use of the IMM (combined with PDAF or MHT) has, with its built-in auto-tuning, the potential of overcoming the problem that many filters cannot be tuned for a wide enough range of situations.
- For VLO targets the ML-PDA is the best algorithm because it can extract all the relevant information from the data — it meets the CRLB in clutter down to 4dB SNR.

# SUMMARY (Cont'd)

- For multisensor track-to-track fusion, the cross-correlations between local tracking errors have to be accounted for.
- Optimal track-to-track fusion on demand is slightly inferior to optimal centralized tracking but can save communication BW.
- Sensor alignment (registration) hinges on observability, which is not always guaranteed.
- Sensor resolution modeling still needs work.

# SOMETHING WRONG