Fusion of Radar and Secondary Sensor Data using Kinematic Models of Multiple Simultaneous Targets

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Introduction

- We present a method for fusion of radar and secondary sensor data, e.g.
  - AIS (Automatic Identification System)
  - ADS-B (Automatic Dependent Surveillance – Broadcast) or
  - IFF (Identification, Friend or Foe) data.
- The method is based on fusion of kinematic models of target trajectories from the two sensors into kinematic models of the associations.
- The method can handle several hundred simultaneous targets (demonstrated for 529 x 529 targets + 1600 clutter plots and shown for a real world scenario).
- It does not require several iterations through the data set in order to find associations, and it includes track history from the two sensors.
- The mathematical framework of the method is based on Kalman filters, maximum likelihood and probability theory as well as kinematics.
- Our method is a specialization of multiple-hypothesis tracking with pruning [1] applied to data from two types of sensors after tracking.

Assumptions

- AIS is always valid: Each AIS message contains correct position (with some uncertainty), time and identifier. If an AIS transmitter is switched off the target is still present.
- The radar tracker tracks the target correctly given the observations.
- There is at most one correct AIS track for each radar track and vice versa, i.e. there are no overlapping pairs.
- The use of a cartesian coordinate system here takes place under the assumption of high resolution in radar azimuth ($< 1°$ beamwidth) and it serves as a first order approximation to the range-bearing coordinate system of the radar.

Conclusion

We have presented a method for fusion of radar data and AIS data. The method shows expected behaviour in terms of track distance dependency. The method is able to fuse data from highly complex scenarios with several hundred tracks from both sensors in real time (demonstrated for 529 tracks from each + 1600 clutter plots and shown for a real world scenario). The method is based on kinematic models of the tracks from each sensor, which are fused into kinematic models of the associations between the sensor tracks. The selection of the accepted associations is made using likelihoods and probability theory. The method is fast and scalable and includes the history of the underlying tracks.

References

[1] S. S. Blackman, *Multi-Hypothesis Tracking for Multiple Target Tracking*, IEEE A&E Systems Magazine Vol. 19, no. 1, pp. 5-18, January 2004

Method

1. Construct kinematic track models (e.g. Kalman filters) of each target as radar observations (o) and AIS messages (m) arrive from each sensor.
2. For each new radar observation o in a radar track τ
   (a) Extract the probability density $\Lambda(o,\tau) = \mathcal{N}\left[\Delta\boldsymbol{\zeta}; \mathbf{0}, \boldsymbol{\rho}_d\right]$ of $o \in \tau$ using the kinematic model of τ, where $\boldsymbol{\rho}_d$ is the residual filter covariance and $\Delta\boldsymbol{\zeta}$ is the cartesian difference between o and the filter prediction.
   (b) Update the association likelihood $\tilde{L}(a,\tau)$ between an AIS track a and a radar track τ as follows:

	Radar	AIS
New track:	$\tilde{L}(a,\tau) = \frac{\Lambda(o,a)}{\Lambda(o,0)}$	$\tilde{L}(a,\tau) = \frac{\Lambda(m,\tau)}{\Lambda(m,0)}$
Update:	$\tilde{L}(a,\tau) \leftarrow \frac{\Lambda(o,(a,\tau))}{\Lambda(o,\tau)}\tilde{L}(a,\tau)$	$\tilde{L}(a,\tau) \leftarrow \frac{\Lambda(m,(a,\tau))}{\Lambda(m,a)}\tilde{L}(a,\tau)$

   where $o \in \tau$, $m \in a$, (a,τ) is an association and $\Lambda(o,0)$ and $\Lambda(m,0)$ are scaling constants.
   (c) Include o in the kinematic model of the association (a,τ) if the Mahalanobis distance between the observation and the predicted position satisfies the following criterion:

$$D_M^2(o,(a,\tau)) = \Delta\boldsymbol{\zeta}^T \cdot \boldsymbol{\rho}_d^{-1} \cdot \Delta\boldsymbol{\zeta} \le [D_M^{\max}]^2$$

   where $D_M(o,(a,\tau))$ is the Mahalanobis distance and $[D_M^{\max}]^2$ is maximum allowed distance (constant). If this criterion is not met, the association in question is removed from the pool of candidate associations.
3. For each potential association
   (a) Calculate the probability of associating an AIS track a with a radar track τ as

$$p((a,\tau)) \equiv \frac{\tilde{L}(a,\tau)}{1 + \sum_{(a',\tau')} \tilde{L}(a',\tau')} ,$$

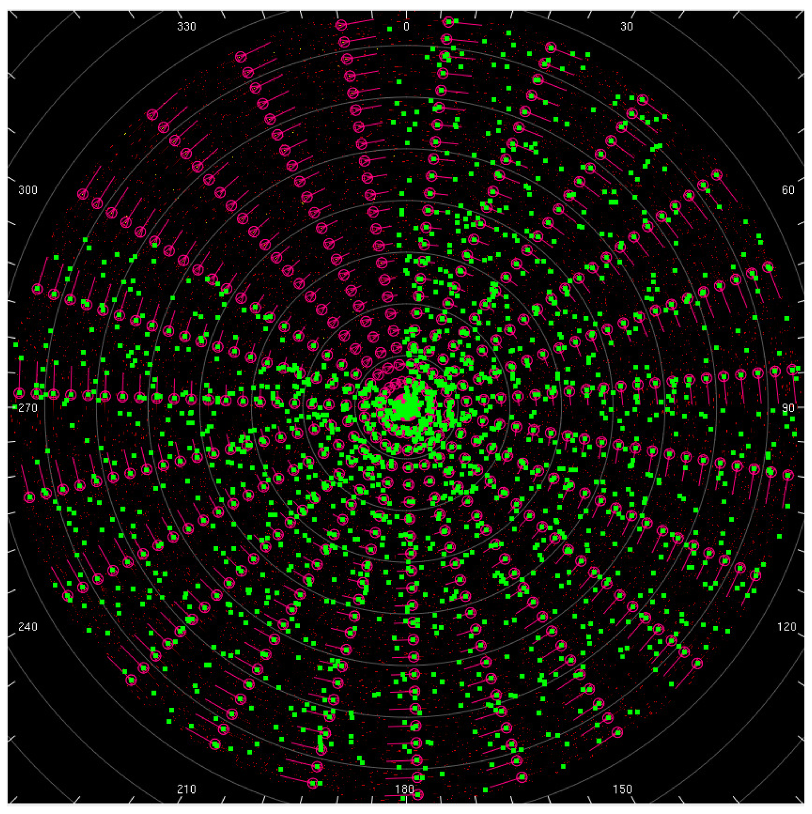
   i.e. (a',τ') iterates over all the conflicting associations of (a,τ) including itself.
   (b) The criterion for acceptance and removal of an association are then

$$\text{Accept:} \quad \max_{(a',\tau')} p((a',\tau')) > p_T \qquad \text{Remove:} \quad p((a,\tau)) < p_{\min}$$

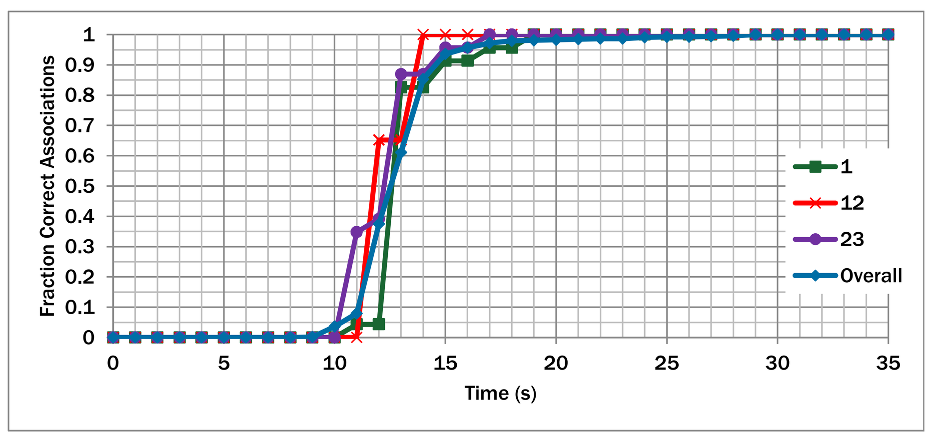
   where p_T is a probability threshold usually set to 0.9 and $p_{\min} = 0.1$.

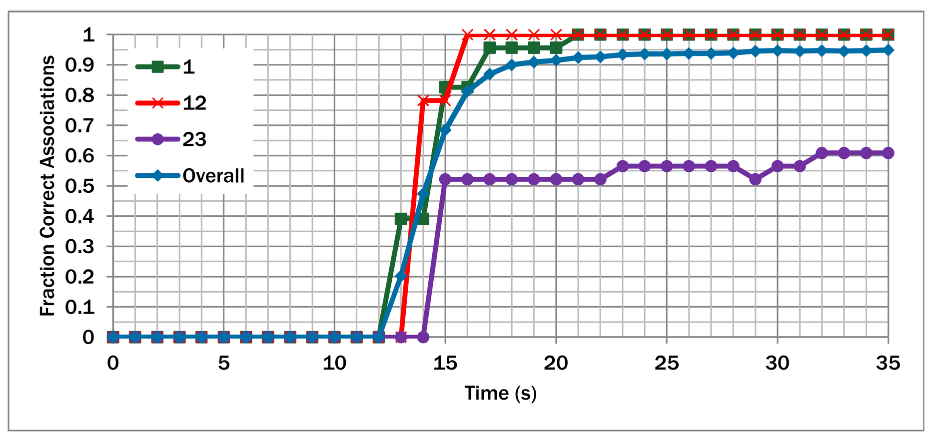
Results

- Simulations - baseline and displaced scenario with gradually increasing distance (0-500 m)



Baseline scenario with 529 AIS targets and 529 radar targets plus 1600 radar noise plots with random intensity.





Fraction of correct fusions over time in the baseline (above) and in the displaced scenario (below).

- Real world scenario - Port of London - +1600 radar tracks and +30 AIS tracks and ≈ 20 associations. Recorded without land masks and zones.