An interval-based target tracking approach for range-only multistatic radar

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Main objective

What
Presentation of TIBA, an interval approach to solve the problem of maneuvering target tracking, using range-only multistatic radar.

Why
The radar process is plagued by several uncertainty sources that affect directly the receivers’ measures. As a result, the radar system can be both imprecise and unreliable. Usually, interval methods handle uncertainty easily . . .

How
By computation of the all feasible configurations for the target which are consistent with the measures.
Summary

1. Introduction
2. Problem description
3. TIBA
4. Numerical results
5. Conclusions
Scenario

Radar applications

- airspace monitoring, marine surveillance
- weather prediction, ground imaging
Scenario

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Radar systems can face
- noise in measurements
- outliers, missing measures
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...thus, the radar system can be unprecise and unreliable.
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...thus, the radar system can be unprecise and unreliable.

...then, we present TIBA as an alternative to traditional tracking algorithms.
Problem description

Details
- multistatic radar
- range-only measures
- one transmitter, three receivers
- monotarget

state: \( \mathbf{X}_n = [x_n, y_n, \dot{x}_n, \dot{y}_n]^t \)

evolution: \( \mathbf{X}_{n+1} = f(\mathbf{X}_n) + \mathbf{V}_n \)
Problem description

\[ X_{n+1} = AX_n + BN_n, \]

where matrices \( A \) and \( B \) are given by:

\[ A = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} \frac{\Delta t^2}{2} & 0 \\ 0 & \frac{\Delta t^2}{2} \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix} \]
Tracking using an Interval-Based Approach (TIBA)

- Initialization
  \[ [X]_1, [X]_2 \]

- Prediction
  \[ [X]_{n+1} | n \]

- Inversion
  \[ [h^{-1}] \]

- SIVIA

- Inversion
  \[ \tilde{Y}_{n+1} \]

- Observation
  \[ Y_{n+1} \]

(*) used if incoherent observations

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Interval Evolutionary Algorithms
SIVIA to solve $[r_n^i - \epsilon, r_n^i + \epsilon] = [d]_E[z] + [d]_zR_i$
Zoom on the region where the solution lies.

\[(\text{CPU time } = 0.7 \text{s}; [z] = [0, 25] \text{ km } \times [0, 10] \text{ km}; \varepsilon = 2 \text{ m}, \epsilon = 12 \text{ m})\]
Tracking using an Interval-Based Approach (TIBA)

\[
\begin{align*}
[X]_1, [X]_2 \\ [X]_{n+1} \\
\hat{Y}_{n+1} \\
[Y]_{n+1}
\end{align*}
\]

(*) used if incoherent observations
Tracking using an Interval-Based Approach (TIBA)

\[ [X]_{n+1|n} = A[X]_n + B[N]_n \]

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Interval Evolutionary Algorithms
Tracking using an Interval-Based Approach (TIBA)

\[
[X]_{n+1} = A[X]_n + B[N]_n
\]

\[
\tilde{Y}_{n+1} = [d]_E[z] + [d]_R[z]R_i
\]

(*) used if incoherent observations
Tracking using an Interval-Based Approach (TIBA)

\[
[X]_{n+1} = [X]_{n+1} | n^{(*)}
\]

\[
[Y]_{n+1} = \hat{Y}_{n+1} = [d]_{E[z]} + [d]_{[z]R_i}
\]

(*) used if incoherent observations

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Interval Evolutionary Algorithms
Trajectory generation

- $Y_n = AX_n + BW_n$,
  - $Y_n$ is Gaussian, mean 0 and $\sigma_Y = 4m$
  - $W_n$ is Gaussian, mean 0 and $\sigma_W = 100m.s^{-2}$

- delay between the observations: $\Delta t = 0.1$

- outliers and missing measures: 10%

- sample: 1000 observations
Experiments - approaches details

TIBA
- radar range: \([0, 25] km \times [0, 10] km\)
- maximal error in measurements: \(\epsilon = 12 m\)
- SIVIA’s accuracy: \(\epsilon = 2 m\)
- interval noise: \(N_n = [-90, 90]\)

Particle filtering
- particles: 1000
- Regularization noise: \([10, 10, 10, 10]\);
Experiments - Trajectory

Target trajectory

X position (km)
Y position (km)

R₁
R₂
R₃

E=R₁
Experiments - Observation example

Measured distance for receiver 3

Distance (km) vs. Iteration number for receiver 3.
Experiments - TIBA’s output
Experiments - TIBA’s output

Valid measurement

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Experiments - PF’s output

Iteration 1000/1000 after resampling

x position (km)
y position (m)

0 0.5 1 1.5 2 2.5

x 10^4

4000 4500 5000 5500 6000 6500 7000 7500 8000

TIBA
Numerical results
Conclusions
Experiments - TIBA’s estimation

TIBA’s estimation vs. real target position

- Estimation in detail (a)
- Estimation in detail (b)
Experiments - TIBA x Particle filtering

Tracking performance for the particle filtering

Tracking performance for TIBA

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Experiments - Error difference TIBA x PF
Conclusions

TIBA is a deterministic, interval-based technique while particle filtering is a stochastic method. The experiments provide the following comparison:

<table>
<thead>
<tr>
<th>Criteria</th>
<th>TIBA</th>
<th>PF</th>
</tr>
</thead>
<tbody>
<tr>
<td>fast cpu time</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>no parameter tuning</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>convergence</td>
<td>✓</td>
<td>not guaranteed</td>
</tr>
<tr>
<td>small maximal error</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>good estimation</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>