GMTI Tracking Performance

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Presentation Outline

- ♦ **GMTI Tracking Issues**
  - **GMTI itself**
  - **Infrastructure Definition.**
- ♦ **Scenario Context**
  - **Normalized Density**
  - **Normalized Mobility – Prediction Error**
- ♦ **MOPs**
  - **Accuracy**
  - **Maintenance**
- ♦ **Samples**

Largest efforts are not associated with MOPs, but rather with interfaces & timing (coordinates, validity, etc.), and scenario definition.

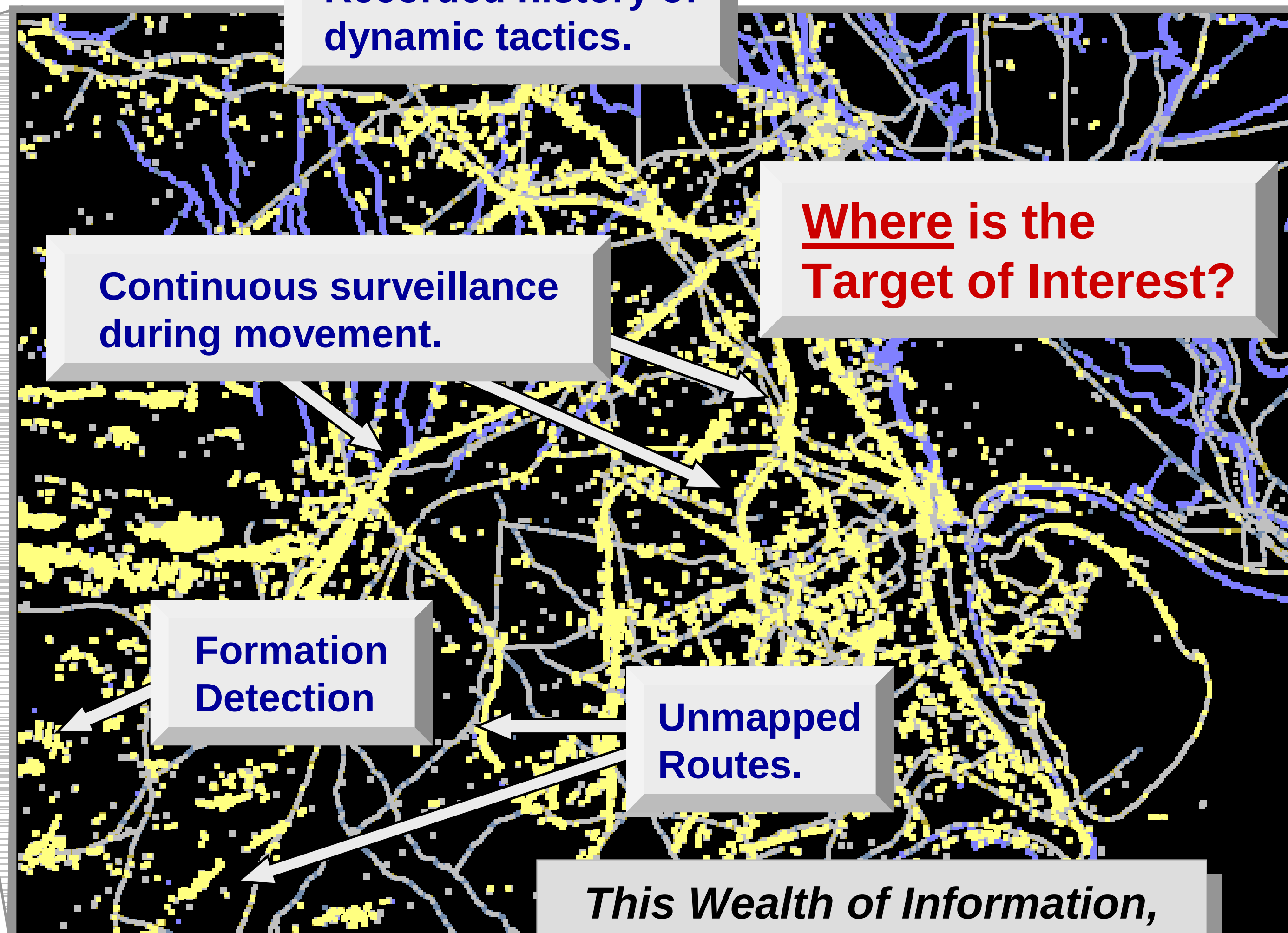
GMTI is Rich, but Overwhelming

U2

Global Hawk

ARL

...



Recorded history of dynamic tactics.

Where is the Target of Interest?

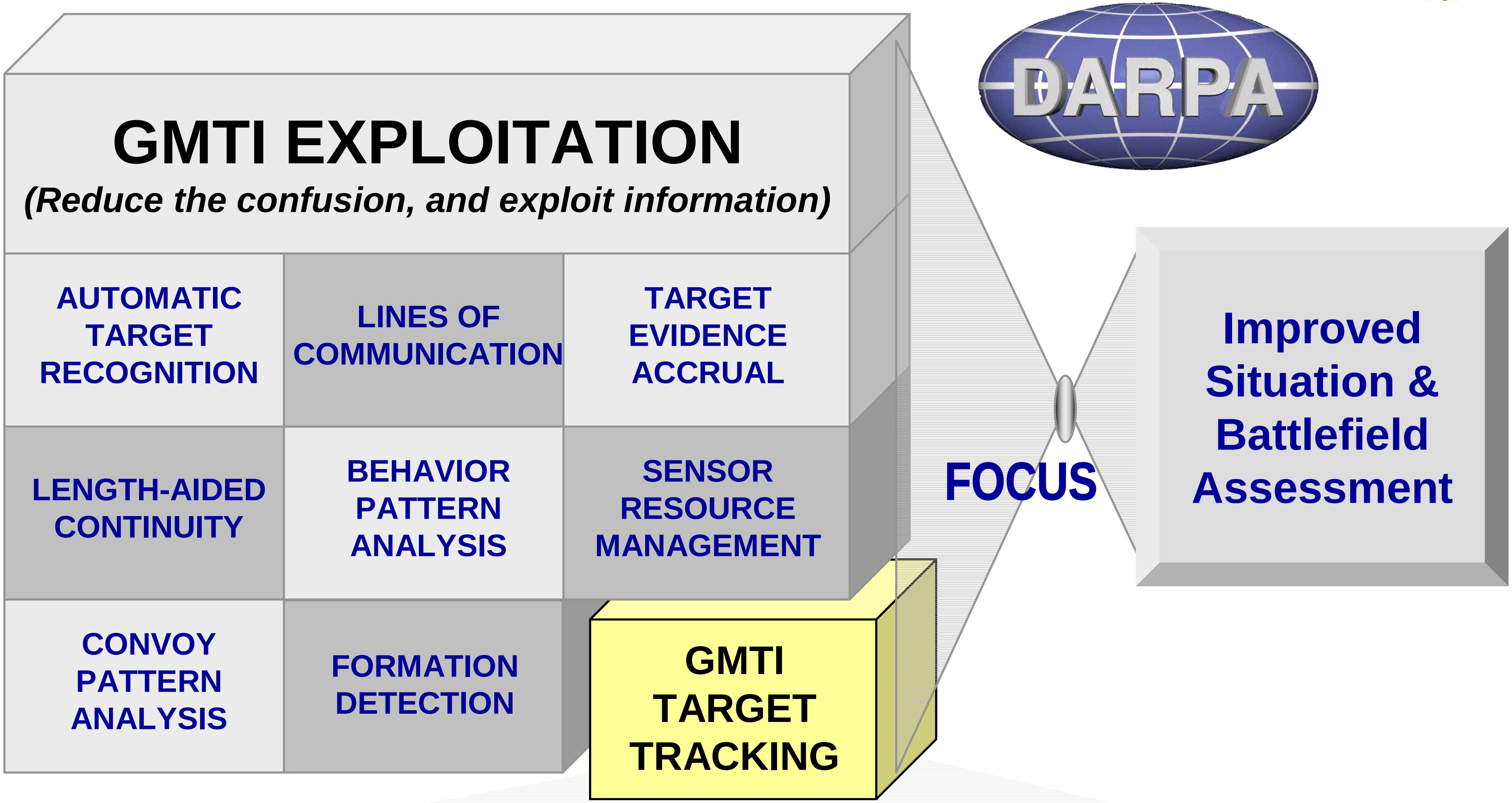
Continuous surveillance during movement.

Formation Detection

Unmapped Routes.

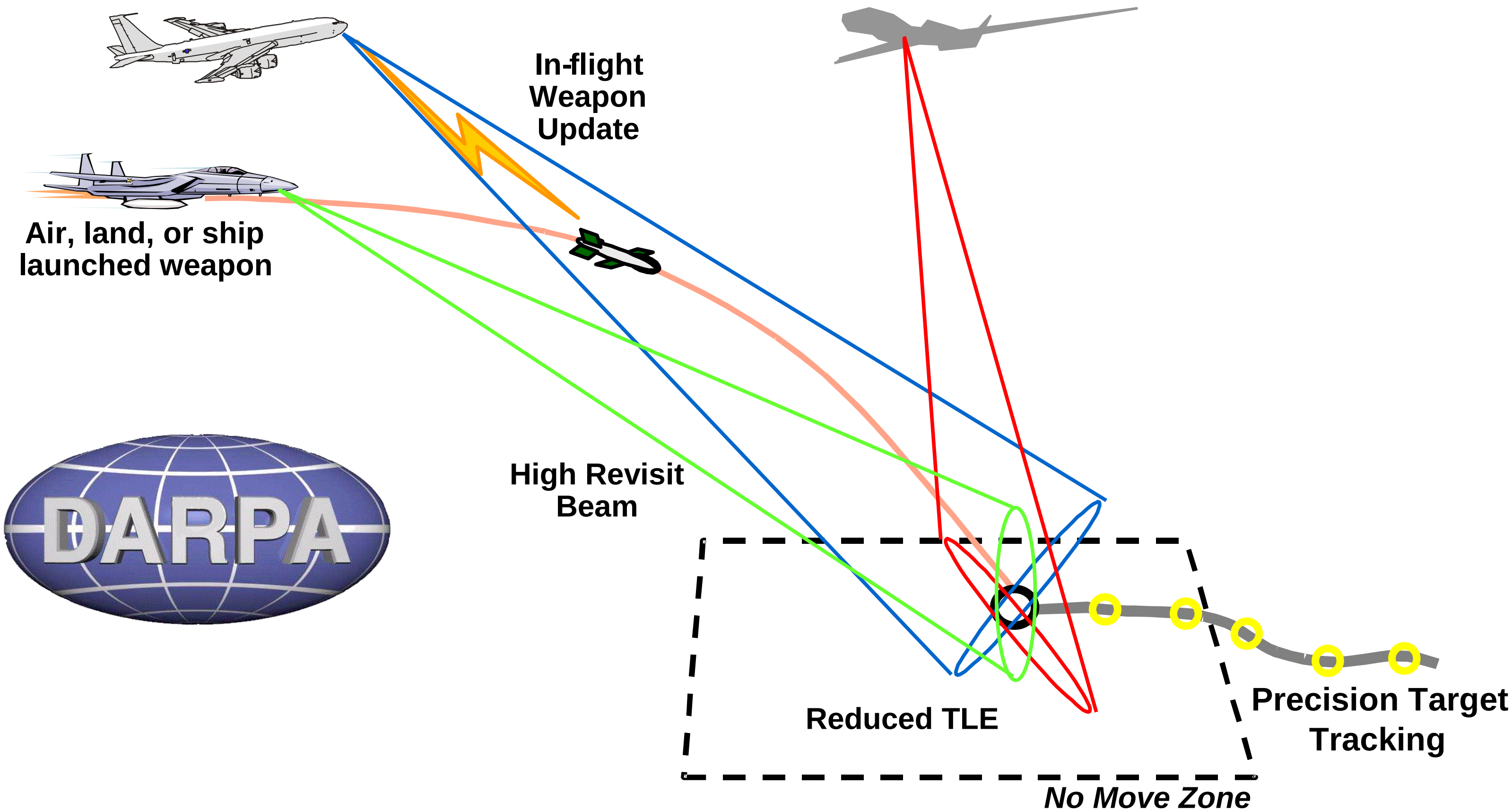
This Wealth of Information, is confusing at first...

Moving Target Exploitation (MTE) Program



Situation Assesment - Cornerstone to exploitation is continuous GMTI Tracking…

Affordable Moving Surface Target Engagement (AMSTE)



But not as continuous as a Precision Fire Control mission, where long term track maintenance & accuracy are crucial.

Parallel Approach to Evaluation

GOAL: Given track nuances, score performance

Define MOPs

Prob. Det. Velocity Error
Position Error Truth/Track Corr.
Continuity Purity

GOAL: Assess difficulty of target & sensing environ.

Quantify Scenarios

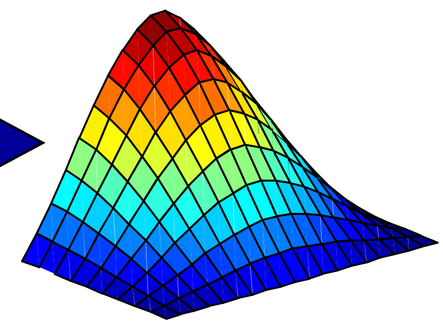
Target Density Target Dynamics
Sensor Resolution Revisit Rate
Absent Returns

GOAL: Develop models, procedures

Develop Testing Infra-Structure

A/C Sim Truth Gen
Sensor Sim Coordinates
Terrain Model Map Fidelity

GOAL:



Performance as Function of Scenario & Sensor

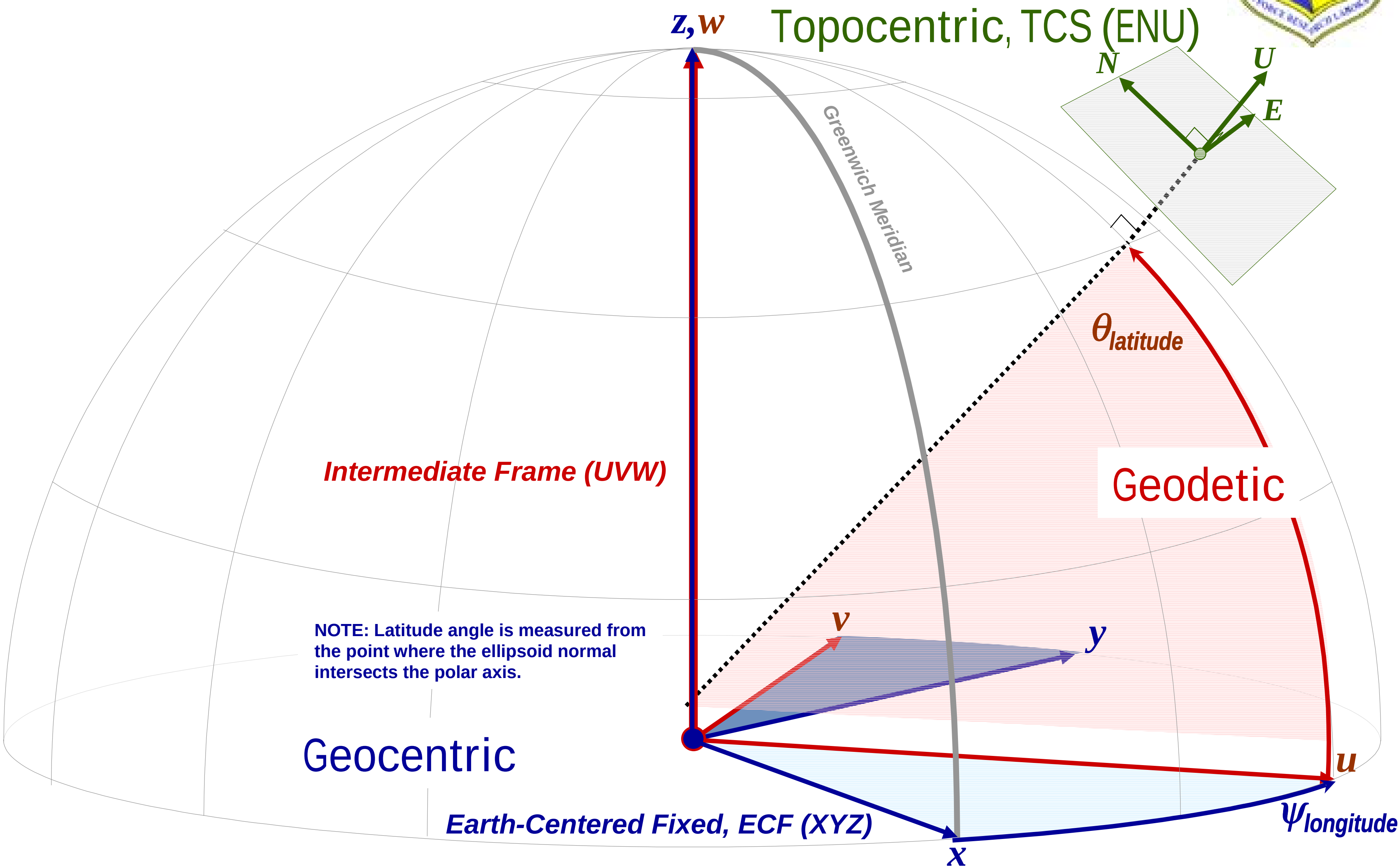
Without all three efforts, evaluation fails.

Testing Infrastructure

- **Defined Data I/O Formats (ICDs)**
  - **Dynamic File I/O: Truth, Detections, Nav., Tracks, MOPs,…**
  - **Streamed I/O: DIS, HLA**
  - **Static Files: DTED, DFAD,…**
- **Coordinates & References**
  - **Geodetic, Geocentric, Topocentric, Radar Measurements.**
  - **WGS-84 Ellipsoid, Geoid, Spheriod.**
- **Tools to Read/Write**
  - **C libraries & Matlab**
- **Data Generators**
  - **A/C & Radar simulators defined & documented**
  - **Truth Generators as well.**

To save time & money AFRL delivers transform libraries; insists on reference frames; chooses maps and resolution level; and provides data format ICDs & C code.

Defined Coordinate Frames

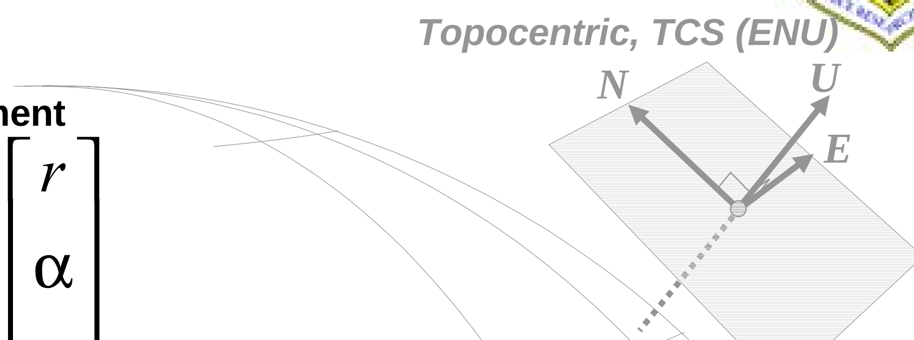


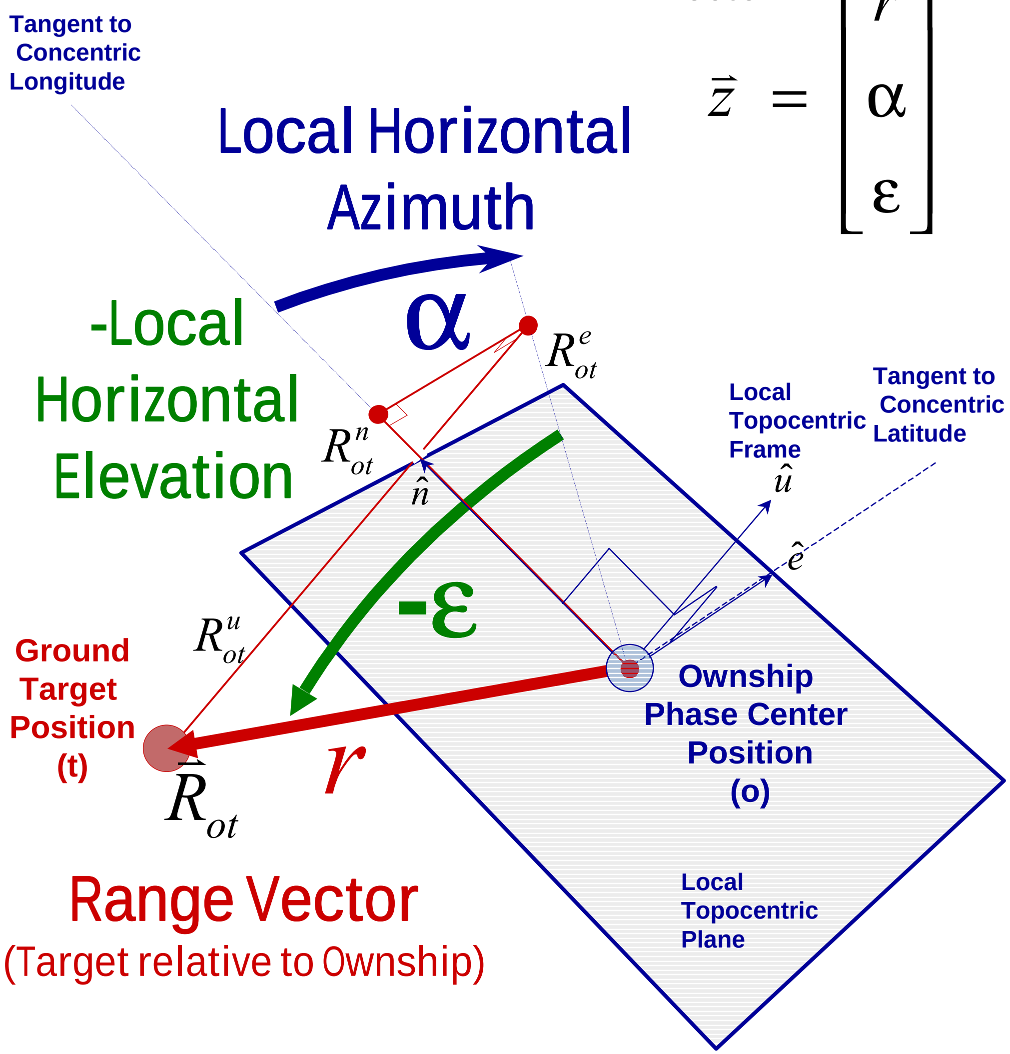
Defined Observation Space

☆ *Most Gimbaled systems report in this horizon-referenced frame.*

UAV Measurement Vector:

$$\vec{z} = \begin{bmatrix} r \\ \alpha \\ \varepsilon \end{bmatrix}$$





UAVSIM Measurements are generated with respect to a translating TCS frame fixed to the Phase Center of the Aperture.

Azimuth and Elevation are ordered Euler angles. Azimuth is measured in the negative, right-hand, Euler sense about the TCS frame's tertiary axis (u). The Azimuth angle is in the Local Topocentric plane, CW relative to North.

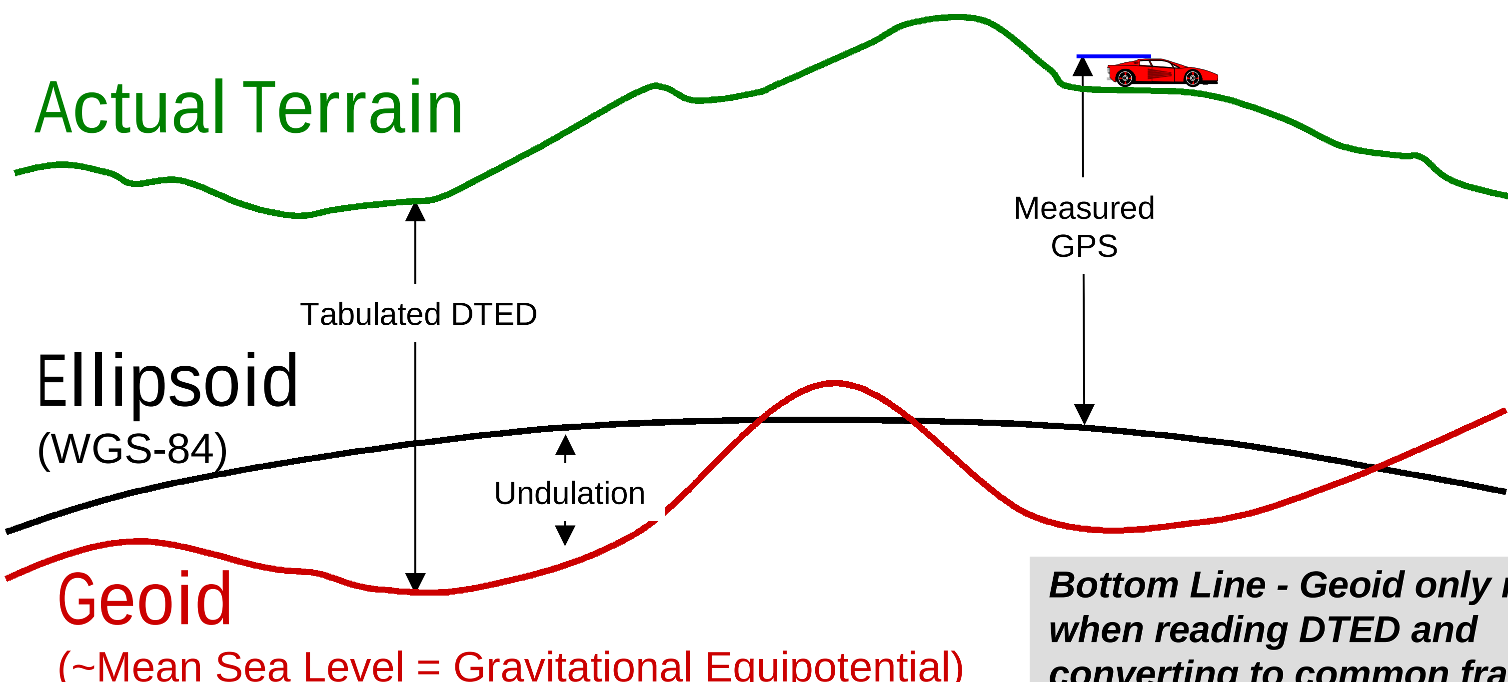
Having rotated the TCS frame through the azimuth angle, the elevation angle is measured in the positive, right-hand, Euler sense about the rotated TCS's secondary axis (e' - not shown). Elevation is measured perpendicular to the local topocentric plane, positive upward, above the horizon.

Range is the magnitude of the relative vector from the Aperture's Phase Center

ERRORs are assumed independent, Gaussian, and white.

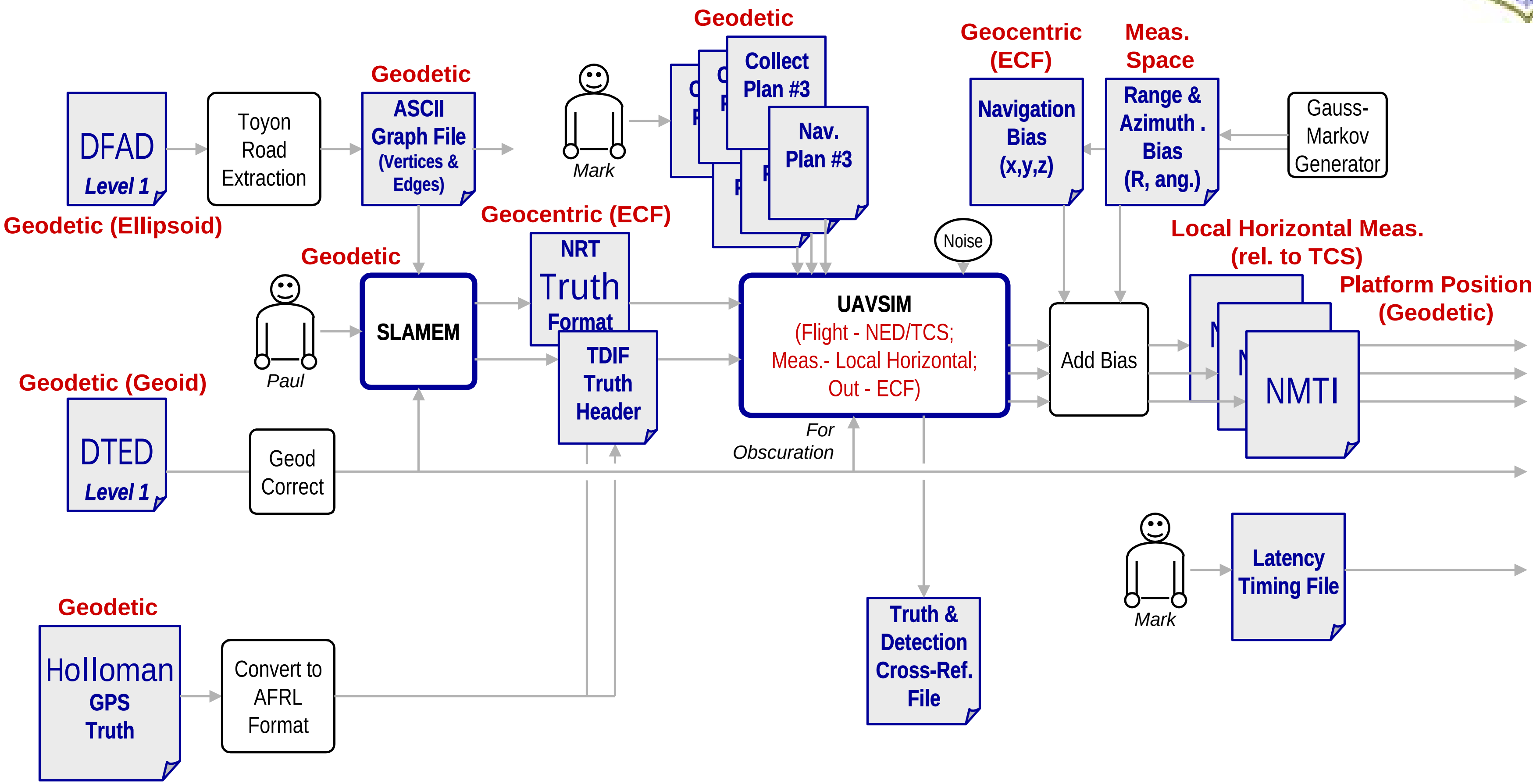
Defined Elevation References

- Truth data is GPS (relative to WGS-84 ellipsoid)
- DTED is relative to Geoid (equipotential gravity surface, or approximately mean sea level)
- The sensor simulation performs terrain obscuration using DTED + Geoid undulation data.
- The nMTI geodetic target position is marked invalid. If valid, the elevation is relative to the ellipsoid.



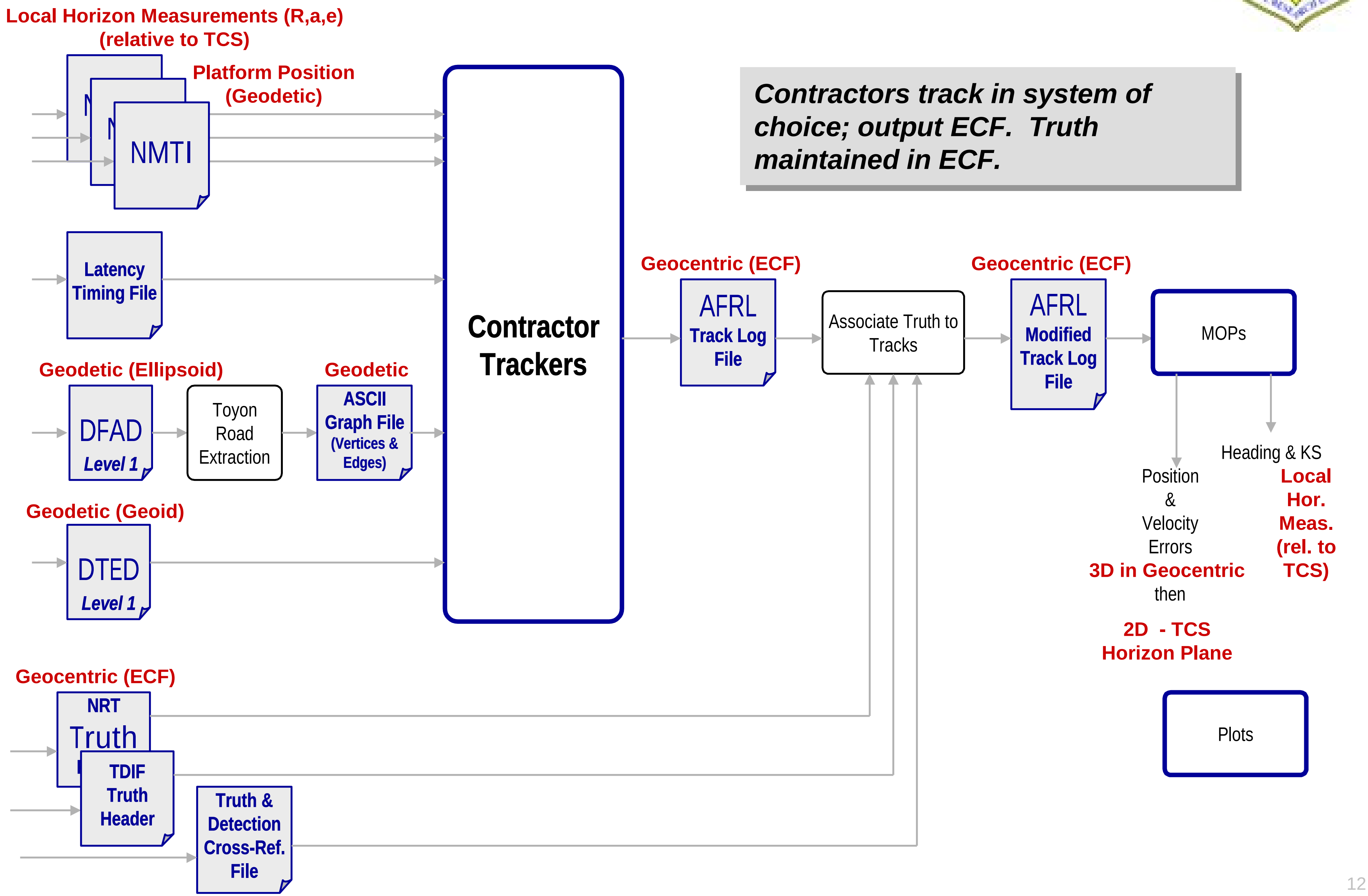
Bottom Line - Geoid only required when reading DTED and converting to common frame.

e.g. AMSTE Detection Generation

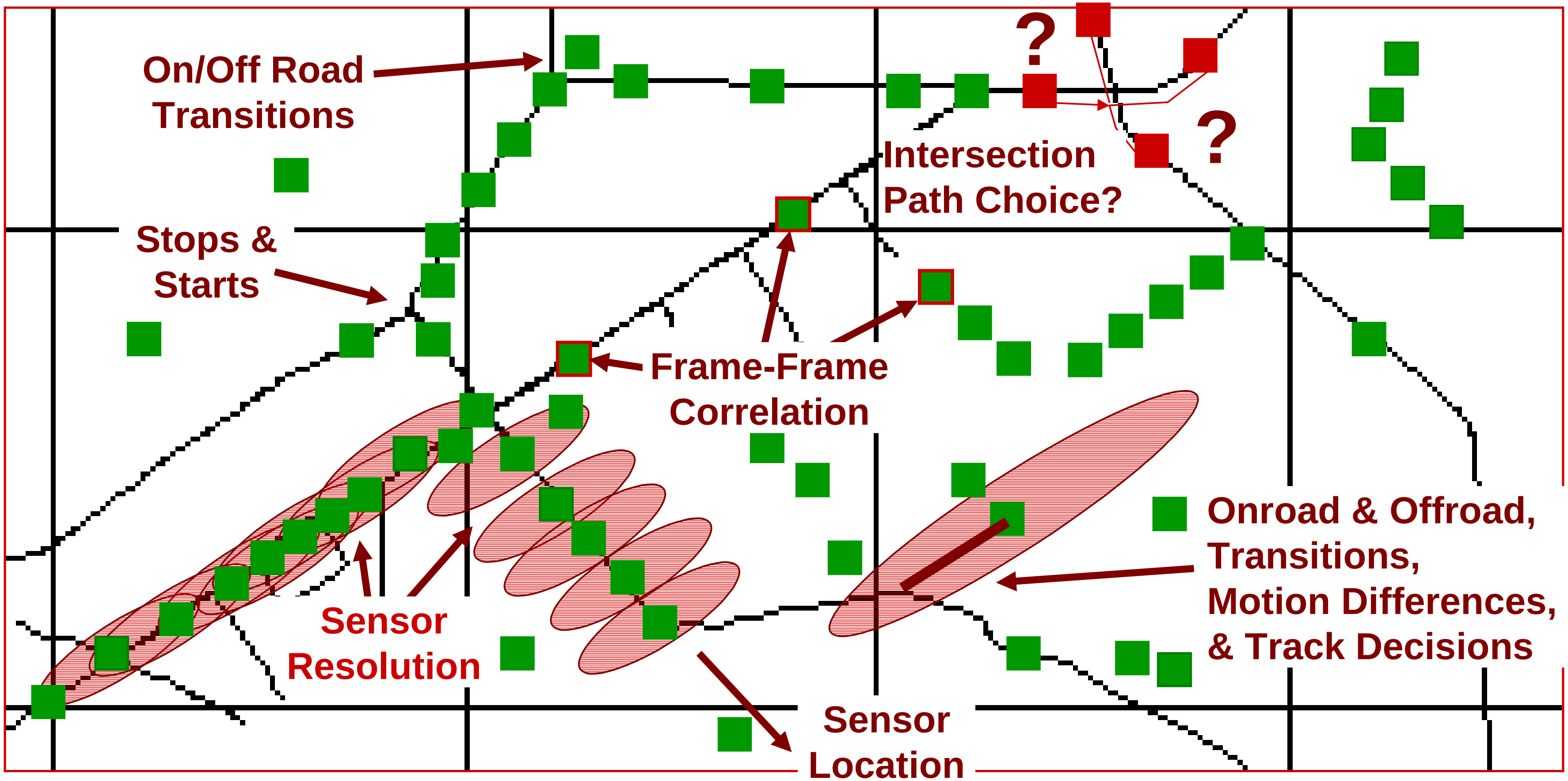


UAVSIM accepts truth in ECF and produces measurements of range and azimuth in Local Horizon-Stabilized (TCS). All contractors used the same transformations. AFRL provided both a Matlab and a C library for ALL transformations.

e.g. AMSTE Tracking and MOP Generation



GMTI Tracking Realities



Tracking in Dense & Mobile Target Environments is challenging.

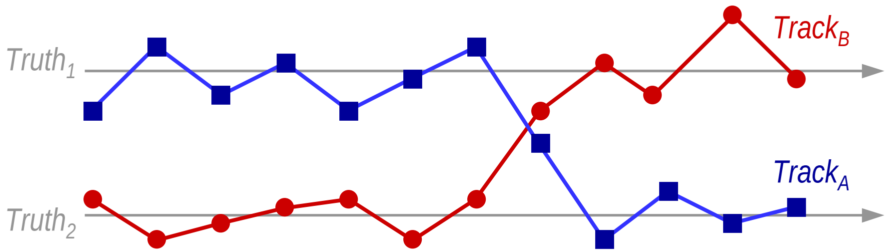
Tracking Difficulties

- ♦ **Unpredictable kinematics (unlike airborne)**
  - Acceleration/Decelerations
  - Turn dynamics and choices
  - Non-stationary (at least 2 models)
- ♦ **Sensor limitations**
  - Intermittent Detectability and False Alarms
  - Sample rate
  - Incomplete measurement space
  - Resolution
  - ID ambiguity
- ♦ **Volume of Data**
  - Traffic Density
  - Area of Interest Size
  - False Alarms do contribute

Solutions Exist

•Road Networks Help.
•Transition Regions Identification.
•Feature development (length - HRR, RCS, CEPSTRUM, etc.)
•Dual-models; linear, constrained kinematics; non-linear, maneuverable kinematics.
•Group tracking

Track Process Complexities

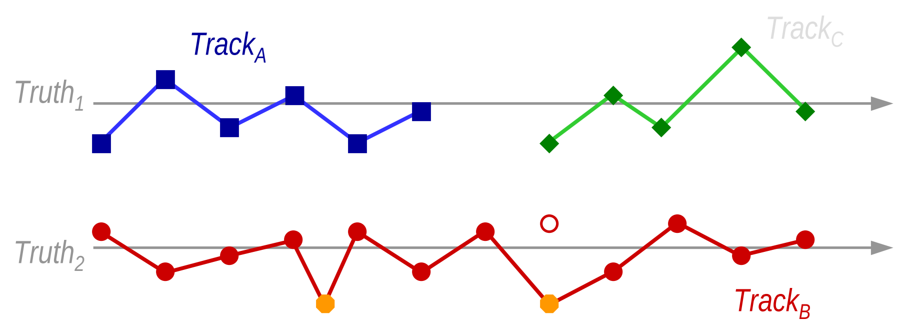


Track Accuracy??
Situation Fidelity??

Track Switching

Fragmented Tracks

Tracking Helps, But…



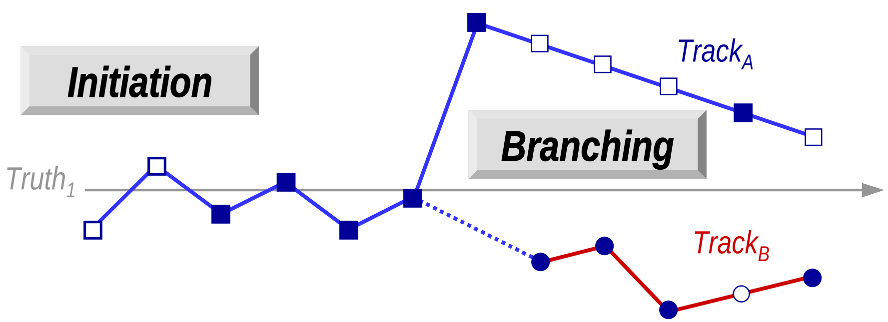
Coasting

False Alarms

Missed Detects

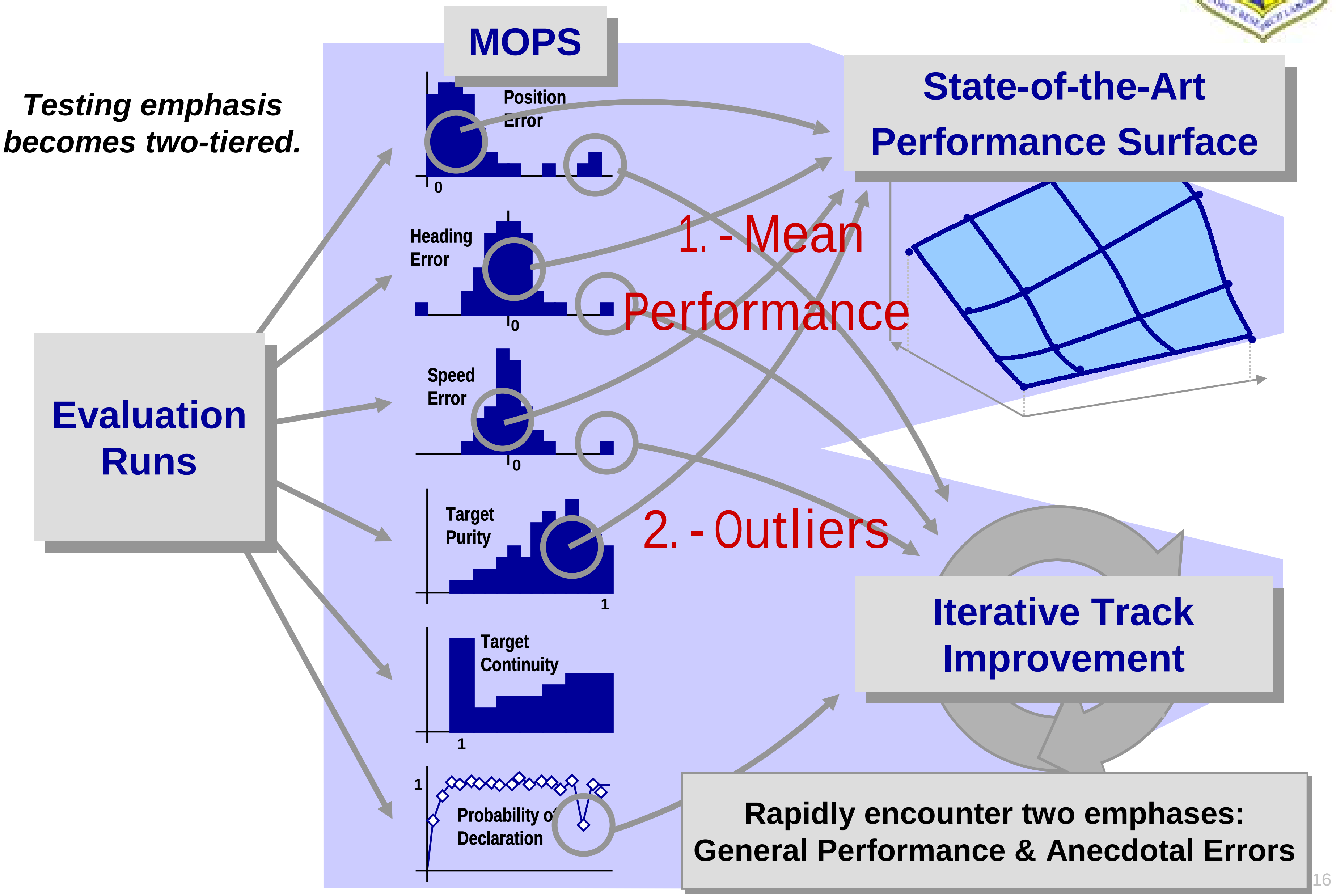
Initiation

Branching

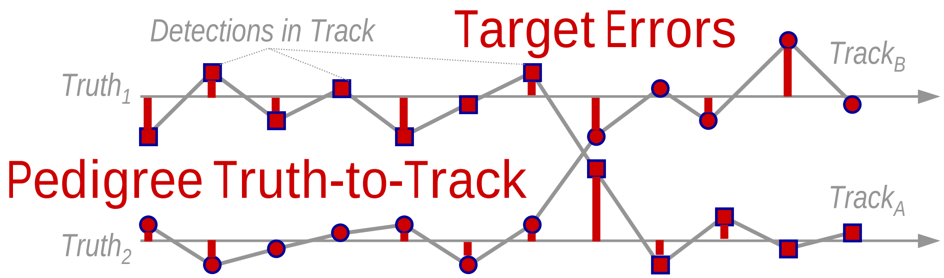


Track Evaluation <u>must</u> consider the Artifacts of Track Processing

MOP Evaluation Process

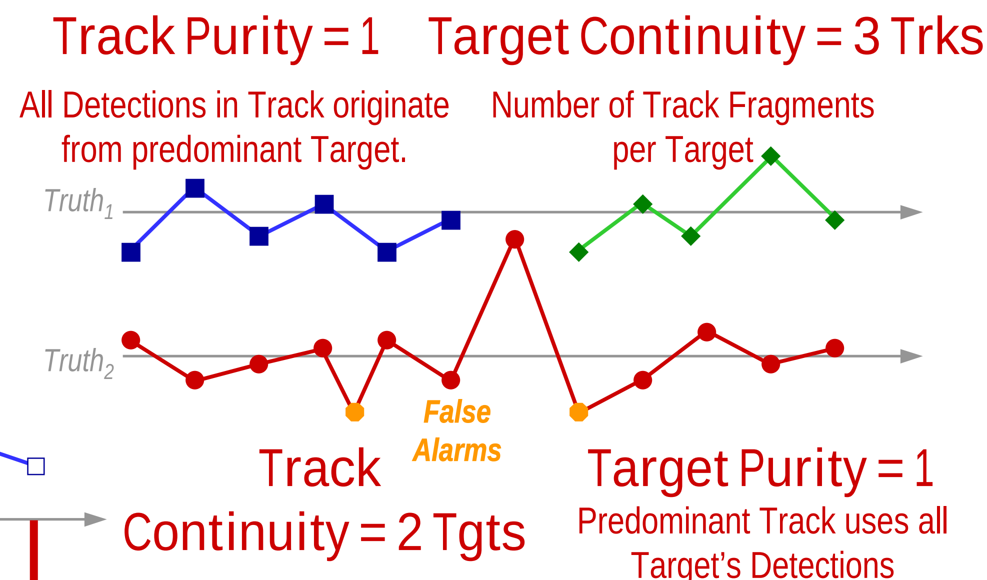


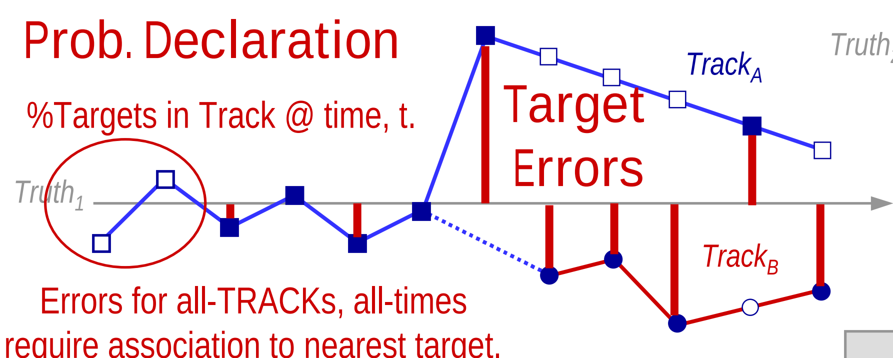
AFRL MOP Definition



ERRORS:
Est. Target POSITION – 2D & 3D
Est. Target SPEED
Est. Target HEADING

MAINTENANCE FIDELITY:
Target & Track Purity
Target & Track Continuity
Prob. of Declaration





General Agreement on Eight MOPS.

Measures of Performance - Brief Description

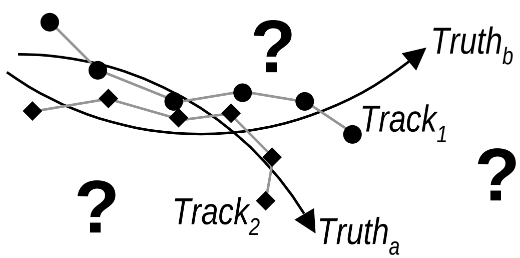
Infer Intent ?	♦ ***Position Accuracy*** - RSS tracking positional error. ♦ ***Speed Accuracy*** – Track's speed error. ♦ ***Heading Accuracy*** – Track's heading error. ♦ ***Group Purity*** – #Good Hits / (Possibles Plus Contaminants). ♦ ***Targeting Statistic*** – Combination of accuracy and classification (see following). ♦ ***Target Classification*** – #Correctly classified / # Total Tracks.
Assess Situation ?	♦ ***Target Continuity*** – Number of track segments for a given target. Number of ingredients. ♦ ***Target Purity*** – (#Good track hits / #Total hits) per target. ♦ ***Track Continuity*** – Number of target segments for a given track. Number of ingredients. ♦ ***Track Purity*** – (#Good track hits / #Total hits) per target. ♦ ***Track Redundancy*** – #Redundant Tracks out of # of Total Tracks as a function of time.
Sensing Capability?	♦ ***Probability of Declaration*** – Number declared / number visible targets. ♦ ***Probability of False Declaration*** – # False Tracks declared / # Total Tracks. ♦ ***Normalized Initiation Time*** – Time to declare. Normalized by revisit interval.
Deploy ?	♦ ***Normalized Throughput*** – Process Time / Baseline Process Time. ♦ ***Average Latency*** – Average time for output to reflect influence of new detection.

General Agreement on just Eight MOPS.

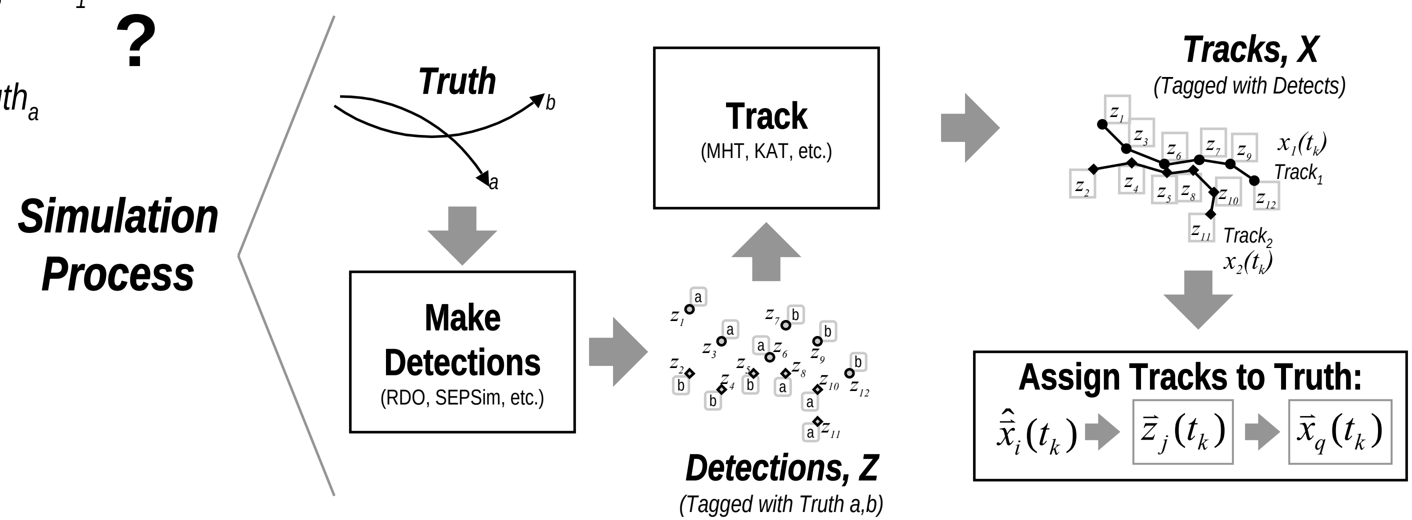
MOP - Accuracy - Truth Assignment

ASSIGNMENT of TRUTH to TRACK Problem:

- ***At time, t_k, what truth value and track are paired?***



Employ TAGGING Approach Within Simulation



- ***Follow tags; select Truth, q, at time t_k.***
- ***If track coasts, retain last truth assignment.***

At any given time, a track will be compared to the truth trajectory that generated its most recently assigned detection.

Growth

- ***Add assignment of track to truth instantaneously at each frame. Gated with 3σ.***

MOP - Position Accuracy - Single Tracks

- ***Given truth and track assignment,***

$$\hat{\vec{x}}_i(t_k) \Longleftrightarrow \vec{x}_q(t_k)$$

where,

$$\hat{\vec{x}}_i(t_k) = \begin{bmatrix} \hat{x}_i(t_k) \\ \hat{y}_i(t_k) \\ \hat{z}_i(t_k) \end{bmatrix}$$

- $\hat{x}_i(t_k)$ — i-Track's EAST Pos. Estimate
- $\hat{y}_i(t_k)$ — i-Track's NORTH Pos. Estimate
- $\hat{z}_i(t_k)$ — i-Track's UP Pos. Estimate

$$\vec{x}_q(t_k) = \begin{bmatrix} x_q(t_k) \\ y_q(t_k) \\ z_q(t_k) \end{bmatrix}$$

- $x_q(t_k)$ — q-Truth EAST Pos.
- $y_q(t_k)$ — q-Truth NORTH Pos.
- $z_q(t_k)$ — q-Truth UP Pos.

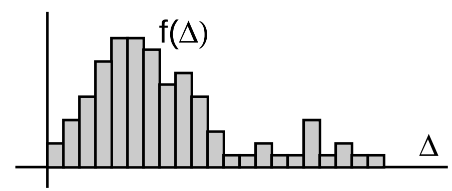
- ***NOTE: Error will be 3D.***

POSITION ERROR:

$$\vec{\varepsilon}_q(t_k) = \hat{\vec{x}}_i(t_k) - \vec{x}_q(t_k)$$

$$\Delta_q(t_k) = \sqrt{\vec{\varepsilon}_q^{\,T}(t_k) \cdot \vec{\varepsilon}_q(t_k)}$$

- ***HISTOGRAM, Δ, for all t_k and all targets, q***
- ***Investigate individual outliers or anomalous modes with additional plots. Perhaps Monte Carlo.***



$$\sigma_q(t_k) = \sqrt{\frac{\sum_{k=0}^{N} \Delta_q^2(t_k)}{N}}$$

Planning to add some Variance or Moment Measure.

Position Error is the RSS of the three-dimensional, track-truth difference.

MOP - Velocity Accuracy - Single Tracks

•*Given truth and track assignment,*

$$\hat{\vec{x}}_i(t_k) \leftrightarrow \vec{x}_q(t_k)$$

with velocity estimates,

$$\hat{\dot{\vec{x}}}_i(t_k) = \begin{bmatrix} \hat{\dot{x}}_i(t_k) \\ \hat{\dot{y}}_i(t_k) \\ \hat{\dot{z}}_i(t_k) \end{bmatrix}$$

- $\hat{\dot{x}}_i(t_k)$: i-Track's EAST Vel. Estimate
- $\hat{\dot{y}}_i(t_k)$: i-Track's NORTH Vel. Estimate
- $\hat{\dot{z}}_i(t_k)$: i-Track's UP Vel. Estimate

$$\dot{\vec{x}}_q(t_k) = \begin{bmatrix} \dot{x}_q(t_k) \\ \dot{y}_q(t_k) \\ \dot{z}_q(t_k) \end{bmatrix}$$

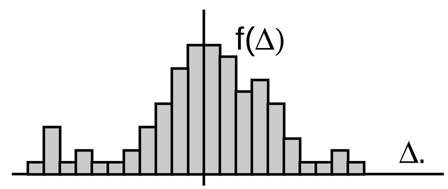
- $\dot{x}_q(t_k)$: q-Truth EAST Vel.
- $\dot{y}_q(t_k)$: q-Truth NORTH Vel.
- $\dot{z}_q(t_k)$: q-Truth UP Vel.

SPEED ERROR:

$$s_q(t_k) = \sqrt{\dot{\vec{x}}_q^T(t_k)\cdot\dot{\vec{x}}_q(t_k)} \;;\; \hat{s}_i(t_k) = \sqrt{\hat{\dot{\vec{x}}}_i^T(t_k)\cdot\hat{\dot{\vec{x}}}_i(t_k)}$$

$$\Delta_q(t_k) = \hat{s}_i(t_k) - s_q(t_k)$$

•*HISTOGRAM, Δ, for all t_k and all targets, q.*

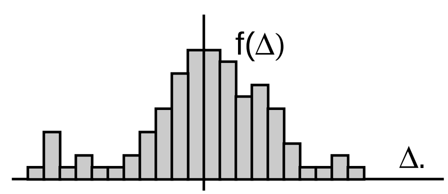


HEADING ERROR:

$$\psi_q(t_k) = \text{atan}\left[\frac{\dot{y}_q(t_k)}{\dot{x}_q(t_k)}\right] \;;\; \hat{\psi}_i(t_k) = \text{atan}\left[\frac{\hat{\dot{y}}_i(t_k)}{\hat{\dot{x}}_i(t_k)}\right]$$

$$\Delta_q(t_k) = \hat{\psi}_i(t_k) - \psi_q(t_k)$$

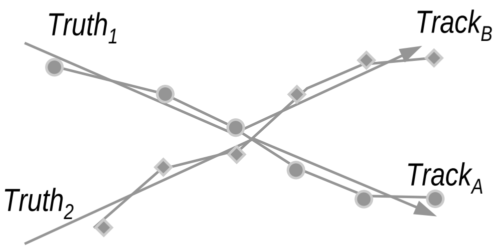
•*HISTOGRAM, Δ, for all t_k and all targets,q.*



MOP - Target Continuity - Individual Tracks

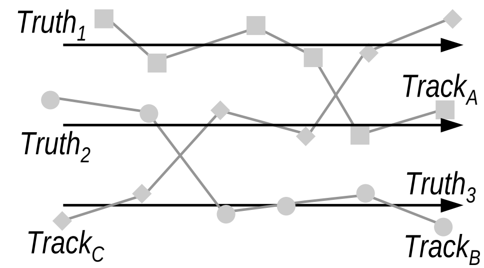
- ***Total number of tracks consuming detections from a given target. One is ideal.***

Crossing Switch



$$C_1 = 2$$
$$C_2 = 2$$

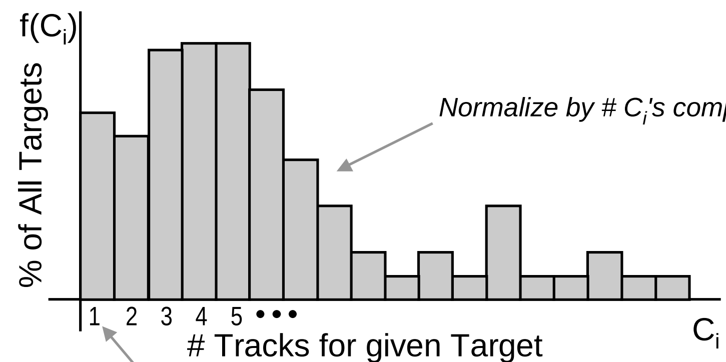
Miscellaneous Switches



$$C_1 = 2$$
$$C_2 = 3$$
$$C_3 = 2$$

Histogram Normalized Counts

$$C_i = \#Track\ IDs \,|\, Target_i$$



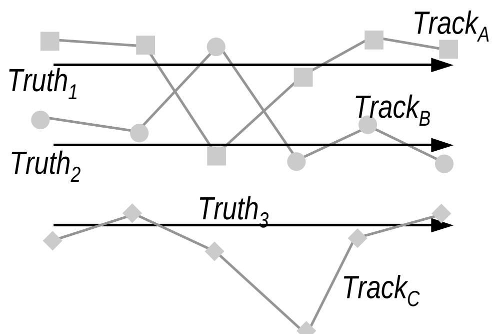
- ***Best Case = 100% Bin #1***

Global measure of the track mix used to estimate a target's trajectory. (Number of Ingredients.) Traditional Continuity measure. Fails to account for duration of contamination.

MOP - Target Purity - Individual Tracks

- *Measures number of target observations not lost to competing tracks.*

Spurious Associations - Original Continuity

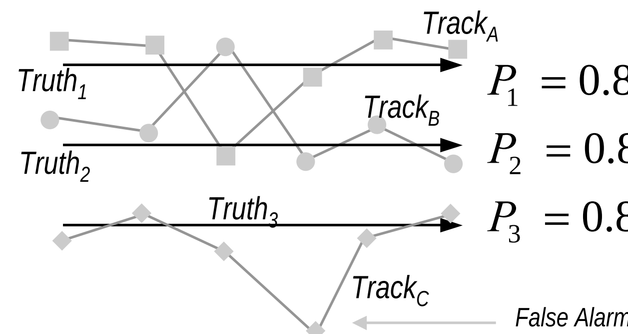


$C_1 = 2$

$C_2 = 2$

$C_3 = 2$

Spurious Associations - Purity



$P_1 = 0.833$

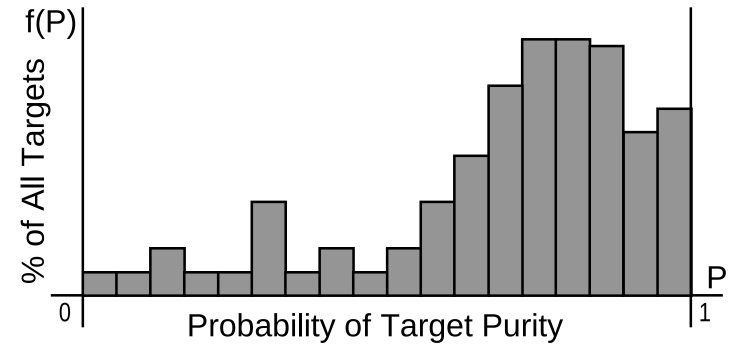
$P_2 = 0.833$

$P_3 = 0.833$

- ***Find predominant track with most Target$_i$ observations.***
- ***How many observations did the predominant track retain?***

Histogram Normalized Probability

$$P\left[\vec{\zeta}_{x_j}(t_k) = \vec{z}_{\hat{x}_i}(t_k) \in \left\{\vec{z}_{\hat{x}_i}(t_0)\ldots\vec{z}_{\hat{x}_i}(t_M)\right\} \mid Z_{x_j}\right] = \frac{N_{Z_{\hat{x}_i}}}{N_{\zeta_{x_j}}}$$



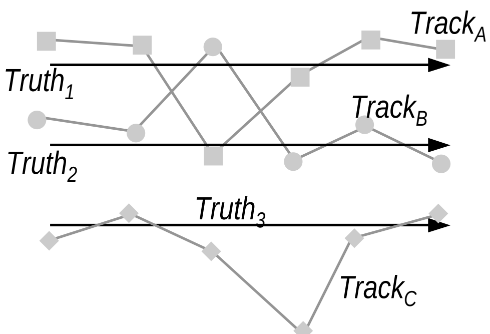
$$\text{P\{Tgt}_j\text{ Tracked Purely | Tgt}_j\text{\}} = \frac{(\text{ \#Target}_j\text{ Hits in Longest Track of Target}_j\text{ })}{(\text{ \#Target}_j\text{ Hits })}$$

Measure's how "purely" tracker reports a given target. Contaminants as a function of time.

MOP - Target Continuity & Purity - Examples

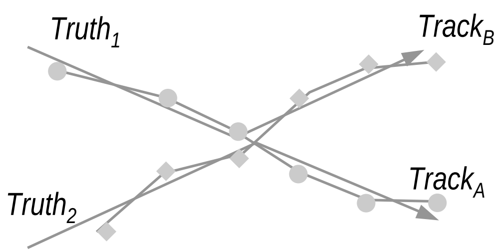
Original Continuity

Spurious Association



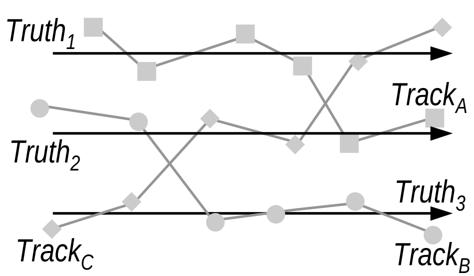
$$C_1 = 2$$
$$C_2 = 2$$
$$C_3 = 2$$

Crossing Switch



$$C_1 = 2$$
$$C_2 = 2$$

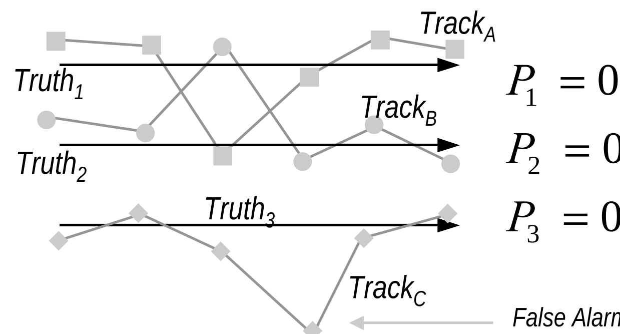
Miscellaneous Switches



$$C_1 = 2$$
$$C_2 = 3$$
$$C_3 = 2$$

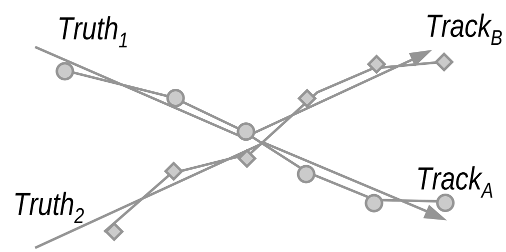
Purity

Spurious Associations



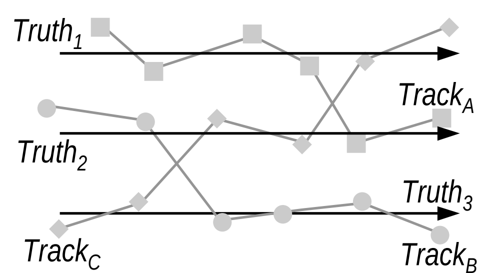
$$P_1 = 0.833$$
$$P_2 = 0.833$$
$$P_3 = 0.833$$

Crossing Switch



$$P_1 = 0.500$$
$$P_2 = 0.500$$

Miscellaneous Switches

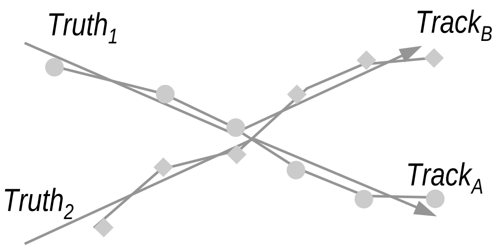


$$P_1 = 0.667$$
$$P_2 = 0.333$$
$$P_3 = 0.667$$

MOP - Track Continuity - Individual Track

•Distribution of the number of targets contributing detections to each track.

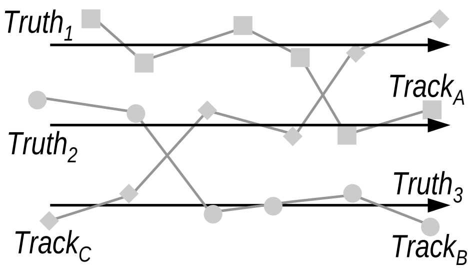
Crossing Switch



$C_A = 2$

$C_B = 2$

Miscellaneous Switches



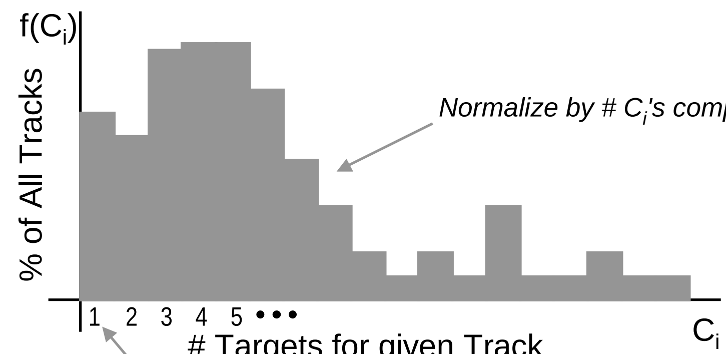
$C_A = 2$

$C_B = 2$

$C_C = 3$

Histogram Normalized Counts

$$C_j = \#Target\ IDs \mid Track_j$$



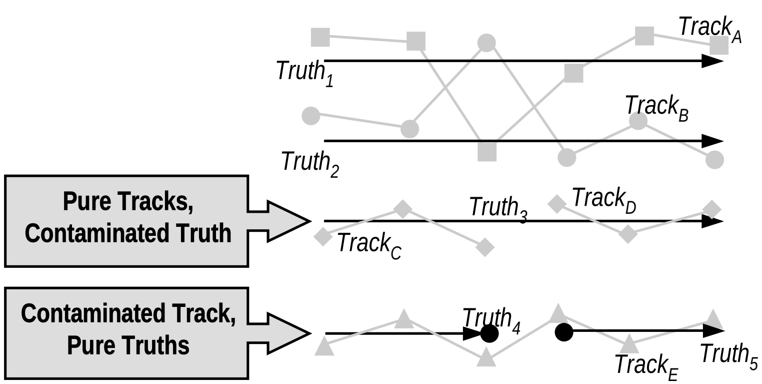
•Best Case = 100% Bin #1

Global measure of the target mix that generated detections associated to a given track. (Number of Track Ingredients.) Traditional Purity measure. Fails to account for duration of contamination.

MOP - Track Purity - Individual Tracks

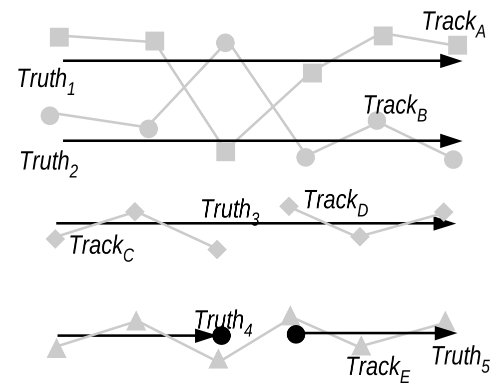
- *Given a track, the number of observations from the predominant target.*

Spurious Associations - Original Purity/Continuity



$$C_A = 2$$
$$C_B = 2$$
$$C_C = 1$$
$$C_D = 1$$
$$C_E = 2$$

Spurious Associations - Purity

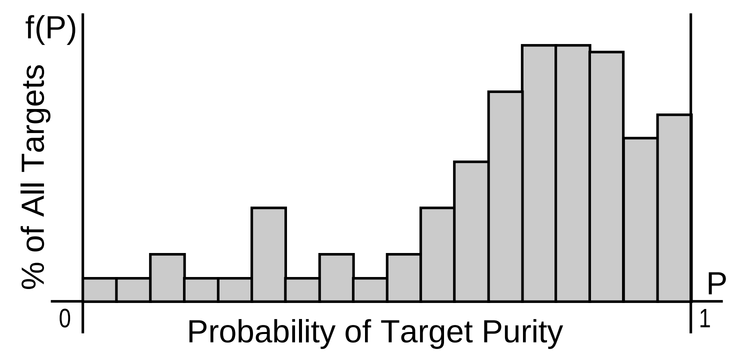


$$P_A = 0.83$$
$$P_B = 0.83$$
$$P_C = 1.00$$
$$P_D = 1.00$$
$$P_E = 0.50$$

- *Find predominant target that contributed the most observations to $Track_i$.*
- *How many observations did the predominant target contribute?*

Histogram Normalized Probability

$$P\left[\vec{z}_{\hat{x}_i}(t_k) = \vec{\zeta}_{x_j}(t_k) \in \left\{\vec{\zeta}_{x_j}(t_0) \ldots \vec{\zeta}_{x_j}(t_m)\right\} \middle| Z_{\hat{x}_i}\right] = \frac{N_{\zeta_{x_j}}}{N_{Z_{\hat{x}_i}}}$$



$$P\{\text{Trk}_i \text{ Exclusive to One Target} \mid \text{Trk}_i\} = \frac{(\#\text{Hits from Longest Target Contributor to Track}_i)}{(\#\text{Hits Contributed to Track}_i)}$$

Measure's whether a given track's detections came exclusively from one target.

MOPs - Deployment

Normalized Throughput:

- ***Time for tracker to process scenario on Sparc Ultra compared to time for perfect correlator to process scenario on same machine.***

$$\overline{T} = \frac{T_{Test\ Algorithm}}{T_{Perfect\ Correlator}}$$

- **I/O?**
- **Display?**

Average Latency:

- ***Number of revisits for tracker to respond to step changes in speed and direction.***

$$N_L = \frac{t_{trk\ change} - t_{detect}}{\tau_{revisit}}$$

Difficult to define fairly. Difficult to measure accurately.

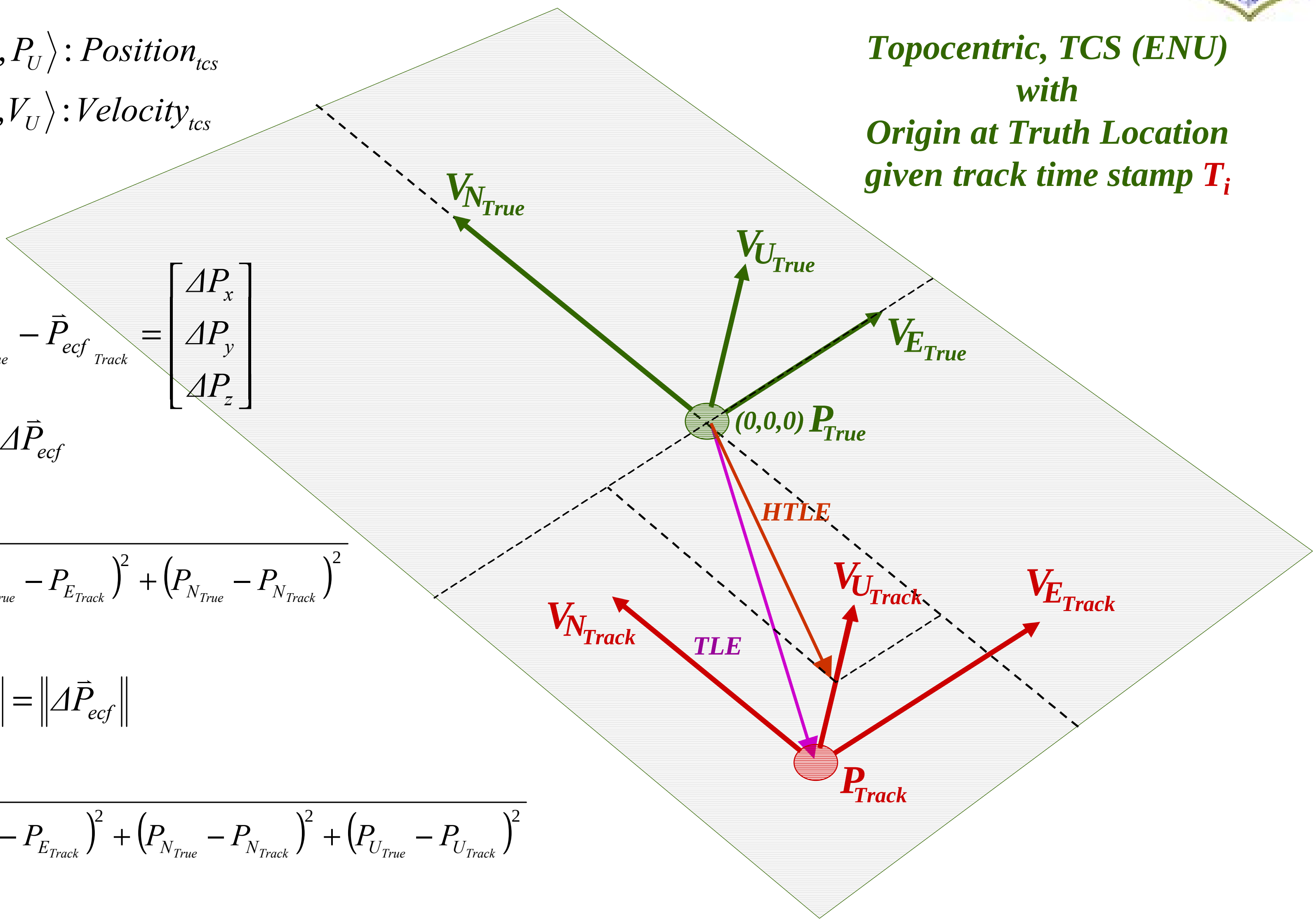
Target Location Errors

2d Horizontal (HTLE) and 3d (TLE)

$$\vec{P}_{tcs} = \langle P_E, P_N, P_U \rangle : Position_{tcs}$$

$$\vec{V}_{tcs} = \langle V_E, V_N, V_U \rangle : Velocity_{tcs}$$

Topocentric, TCS (ENU)
with
Origin at Truth Location
given track time stamp T_i



$$\Delta\vec{P}_{ecf} = \vec{P}_{ecf_{True}} - \vec{P}_{ecf_{Track}} = \begin{bmatrix} \Delta P_x \\ \Delta P_y \\ \Delta P_z \end{bmatrix}$$

$$\Delta\vec{P}_{tcs} = C_{ecf}^{tcs} \cdot \Delta\vec{P}_{ecf}$$

$$HTLE = \sqrt{\left(P_{E_{True}} - P_{E_{Track}}\right)^2 + \left(P_{N_{True}} - P_{N_{Track}}\right)^2}$$

$$TLE = \left\|\Delta\vec{P}_{tcs}\right\| = \left\|\Delta\vec{P}_{ecf}\right\|$$

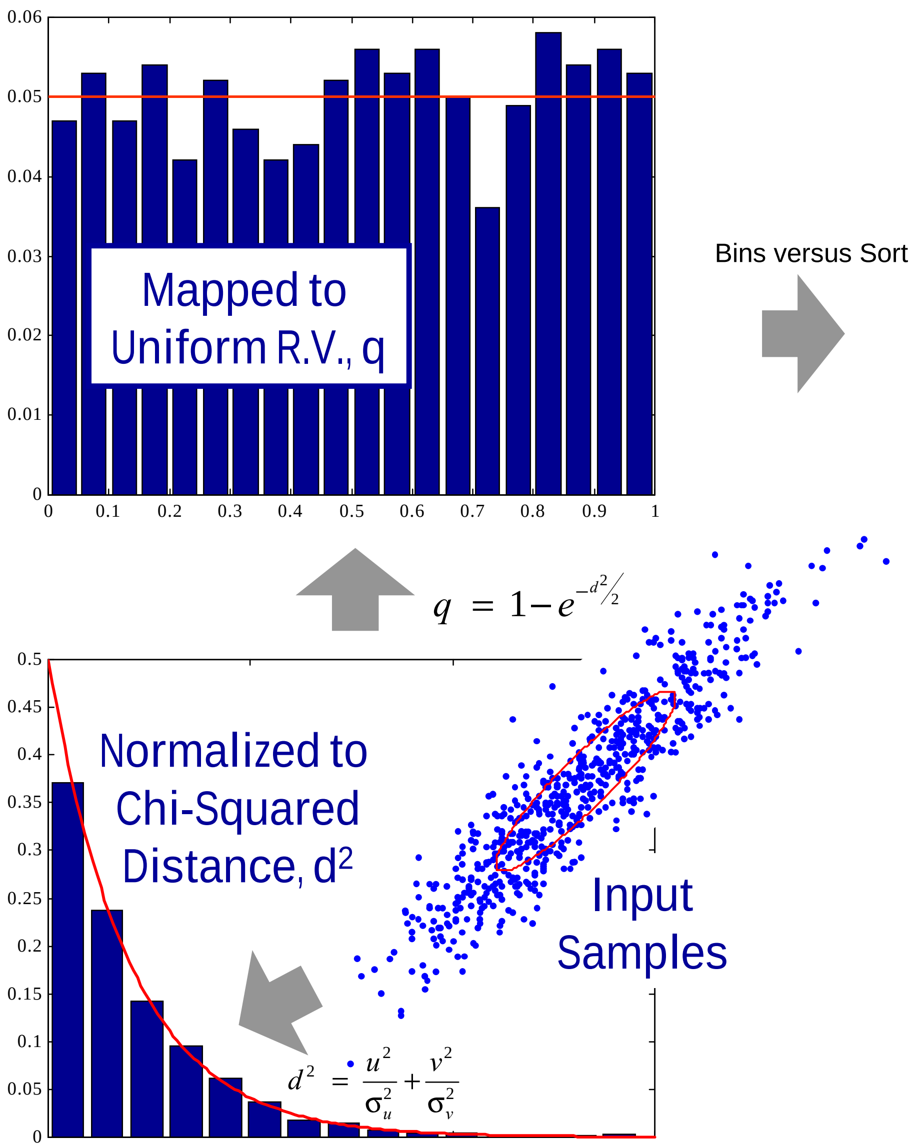
$$TLE = \sqrt{\left(P_{E_{True}} - P_{E_{Track}}\right)^2 + \left(P_{N_{True}} - P_{N_{Track}}\right)^2 + \left(P_{U_{True}} - P_{U_{Track}}\right)^2}$$

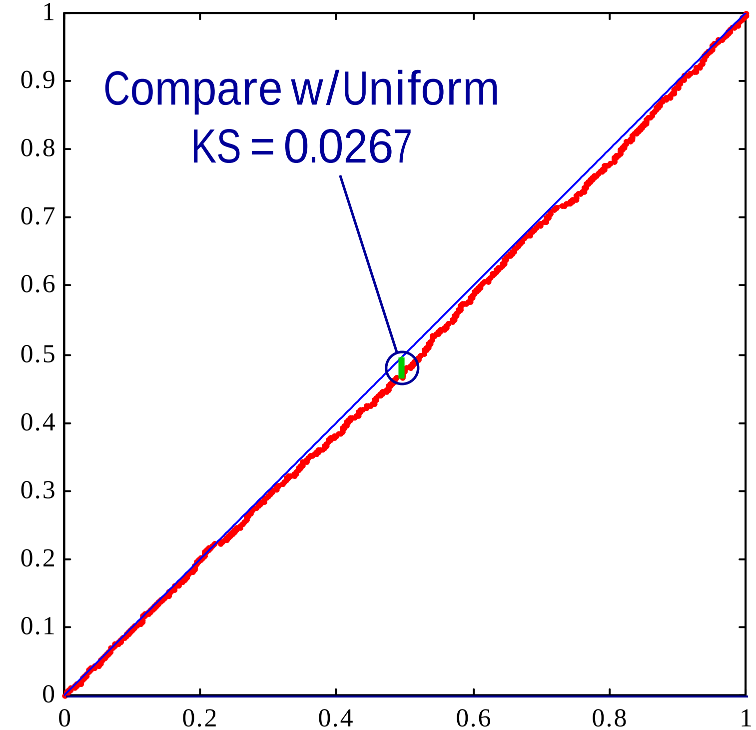
Kolmogorov-Smirnoff Procedure

- ♦ Input (x,y) track estimate & covariance.
- ♦ De-correlate and Normalize.
- ♦ Calculate distances. (They have Chi-Square distribution.)
- ♦ Map into Uniform distribution.
- ♦ Sort.
- ♦ Plot as uniform distribution.
- ♦ Compare against ideal distribution.
- ♦ Difference is KS Statistic.

KS measures sample distribution's deviation from ideal Gaussian distribution - size, shape, orientation, modality.

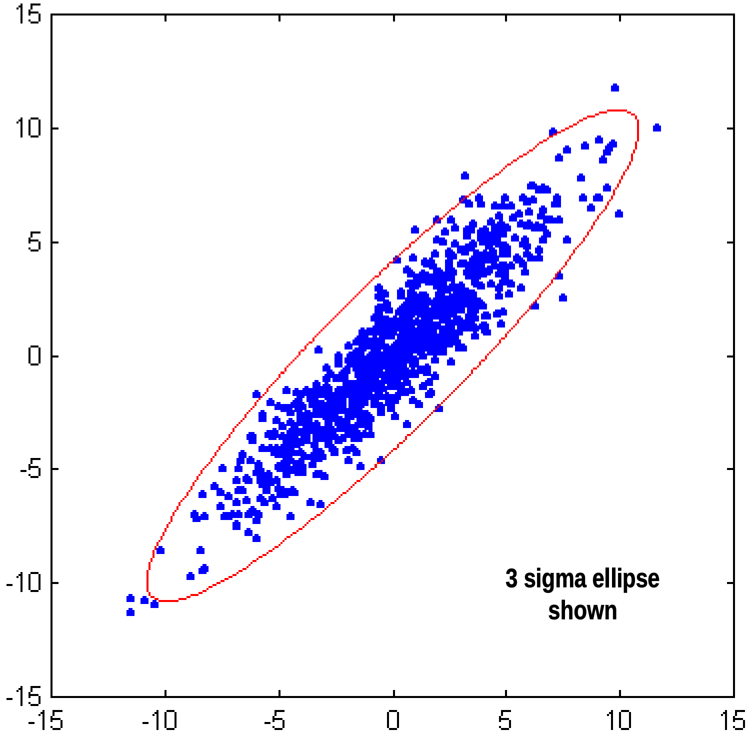
Matched Example - 1000 pts

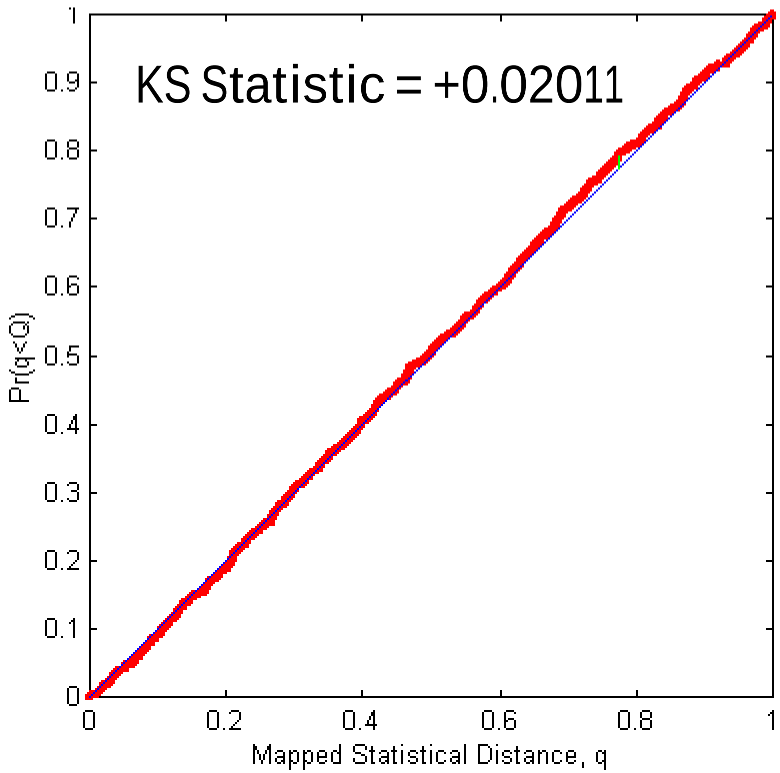




More samples produce very accurate metrics.

Matched Covariance

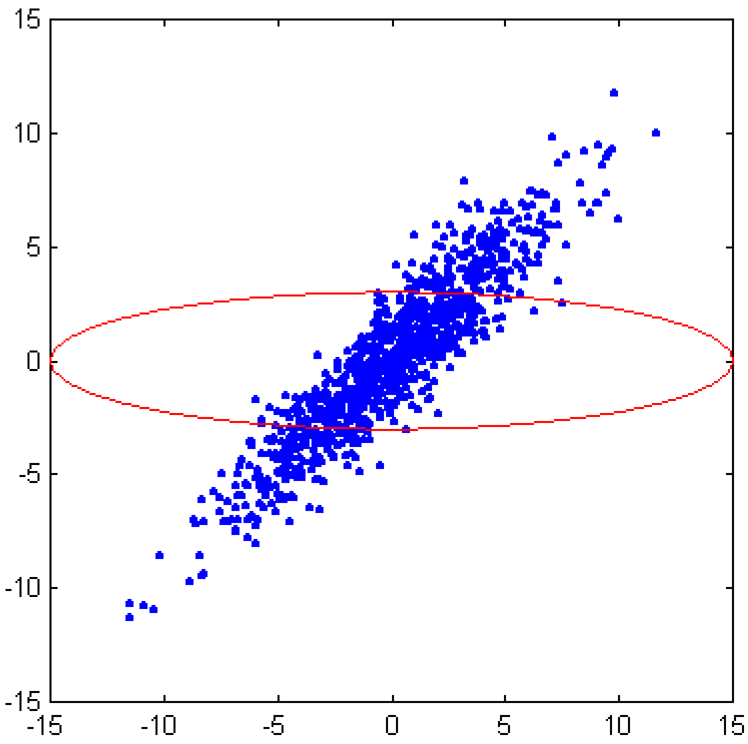


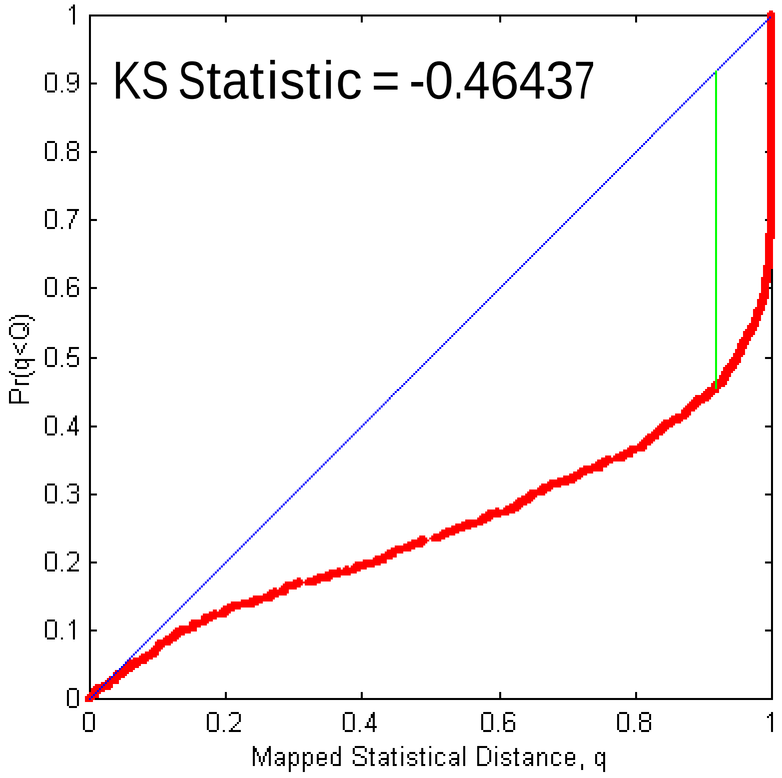


Good Match gives a low KS number.

rotAng=-pi/4; npts=1000; sigx=5; sigy=1;

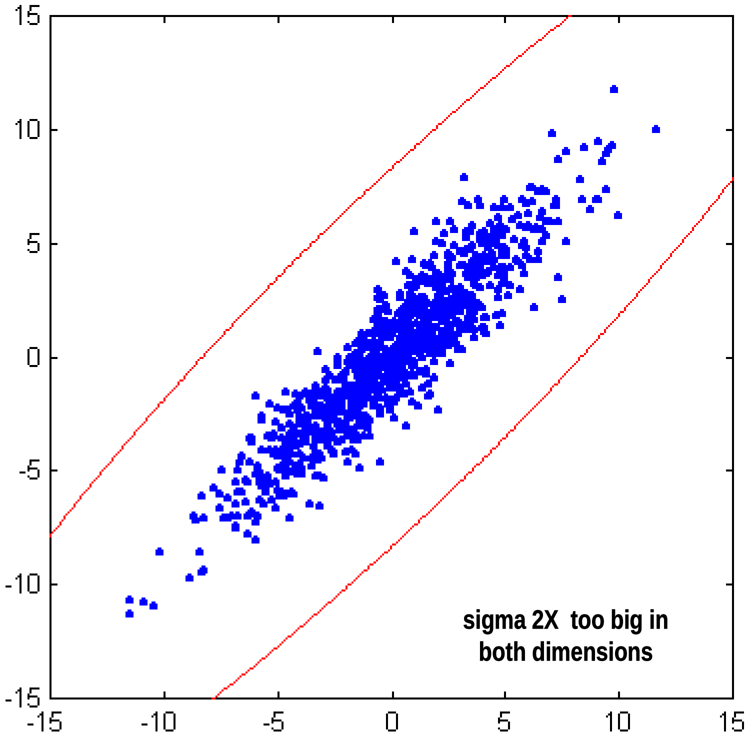
Mismatched Rotation

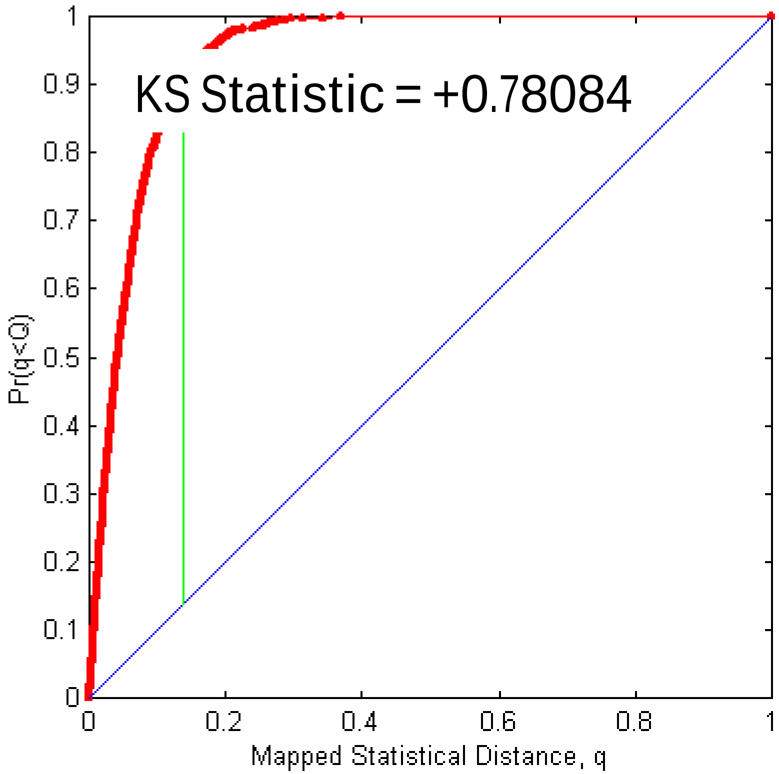




When too little ellipse area intersects sample region, KS statistic falls below distribution curve.

Oversized Covariance

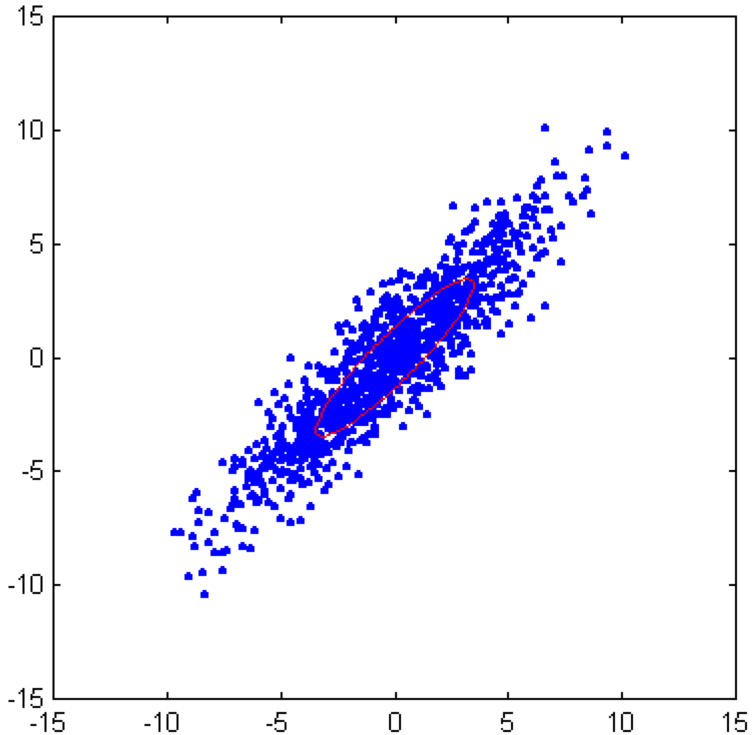


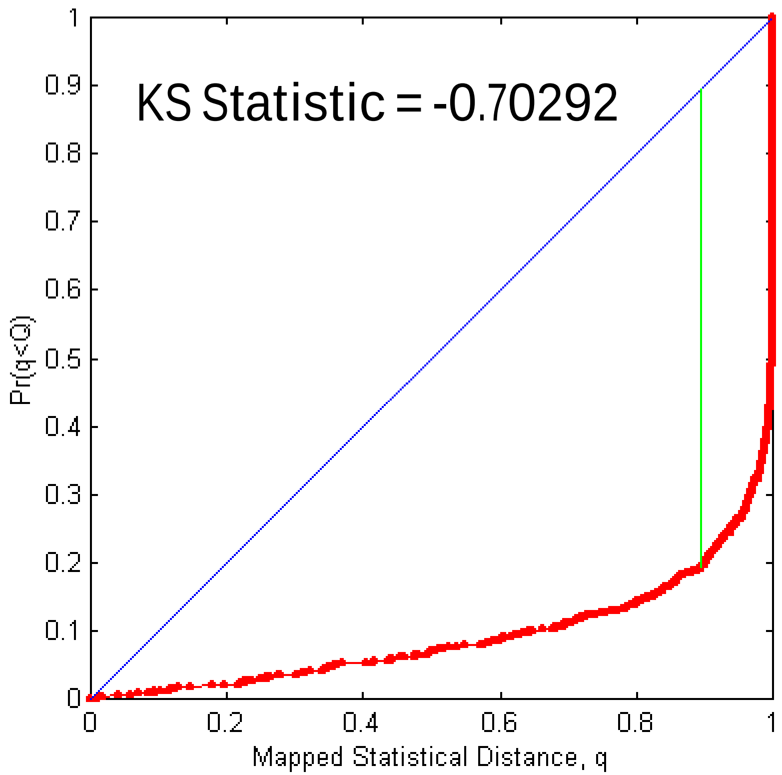


Points fit in an area 1/4 of the size. 75% is wasted space

Too much ellipse area intersects sample region, KS fall above distribution curve.

Undersized Covariance

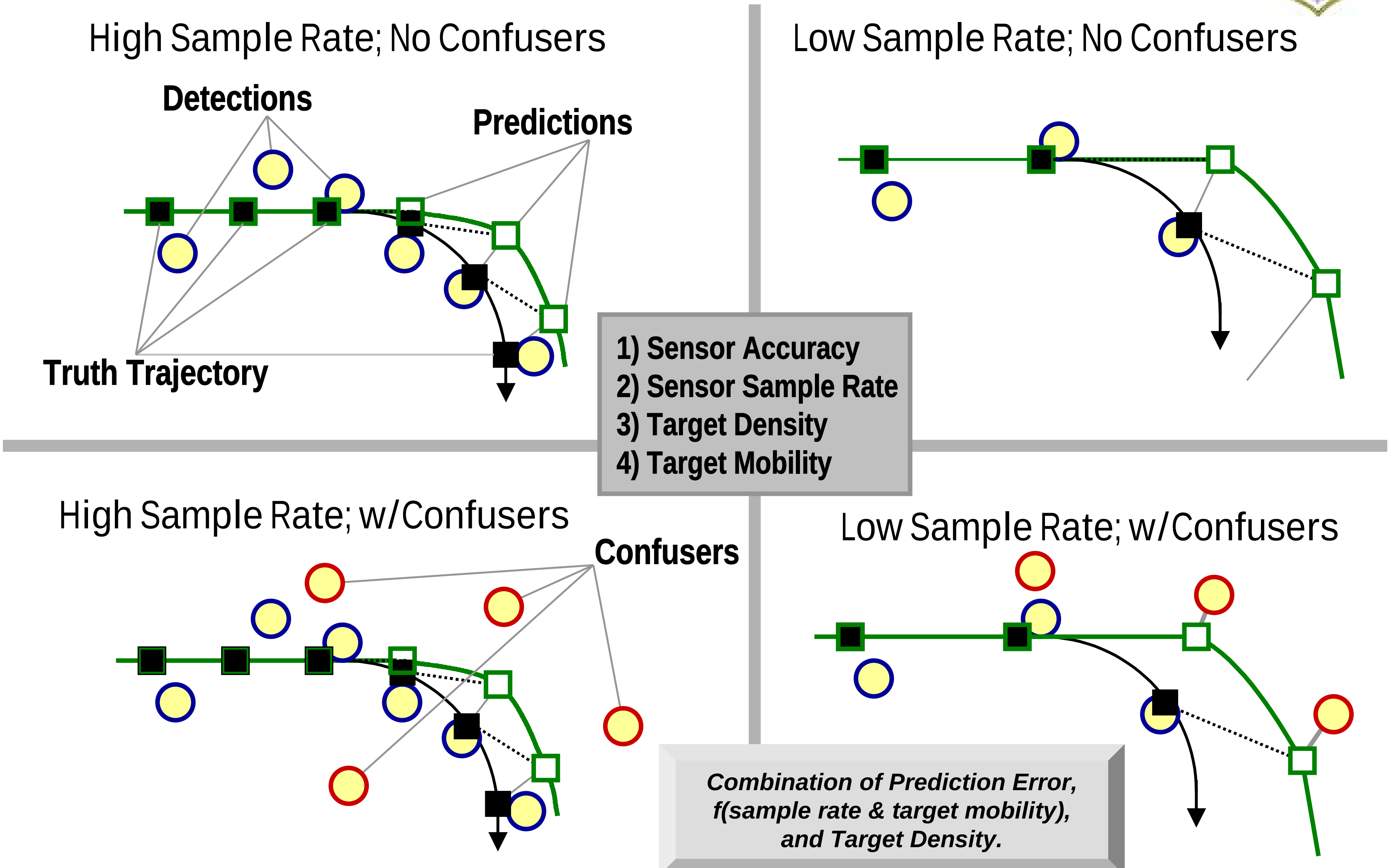




sigma 0.32X should leave 1/4 of the points within.

KS values reflect percentage of points not matching uniform distribution.

Critical Tracking Issues – Accuracy & Assoc.

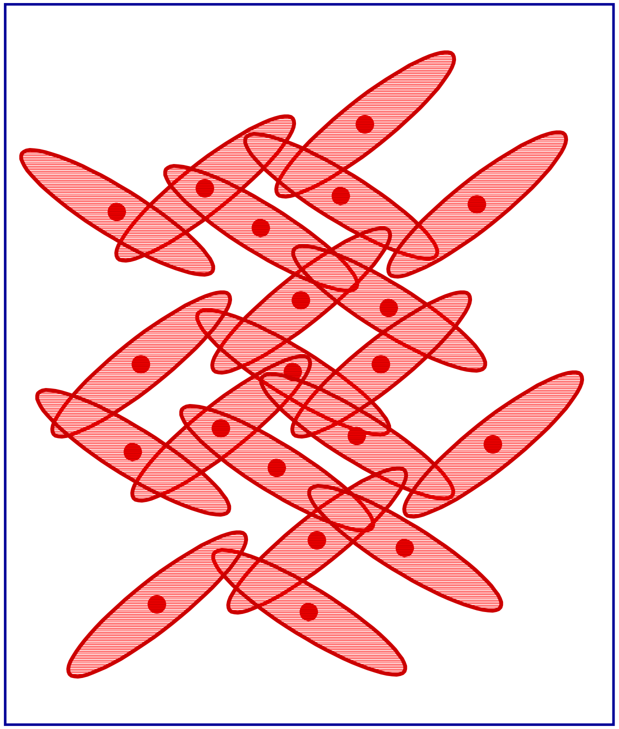


1) Sensor Accuracy
2) Sensor Sample Rate
3) Target Density
4) Target Mobility

Combination of Prediction Error, f(sample rate & target mobility), and Target Density.

Density & Accuracy are Related

Sparse?

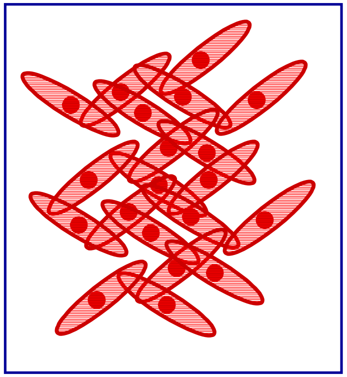


Moderately Accurate Sensor

Which is more difficult

?

Dense?



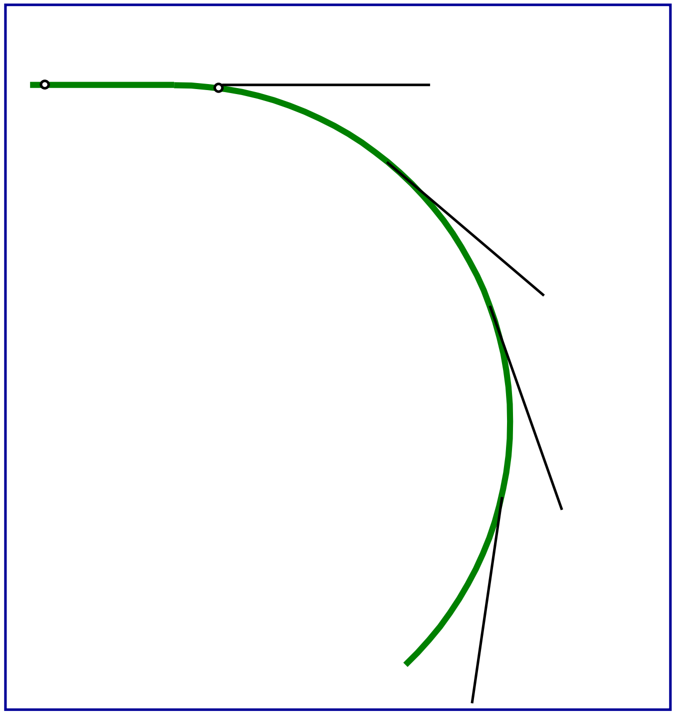
Very Accurate Sensor

- *Tracker performs equally well.*

Spatial DENSITY and Sensor ACCURACY COMBINE to influence TRACK performance.

Mobility & Sample Rate are Related

Benign?

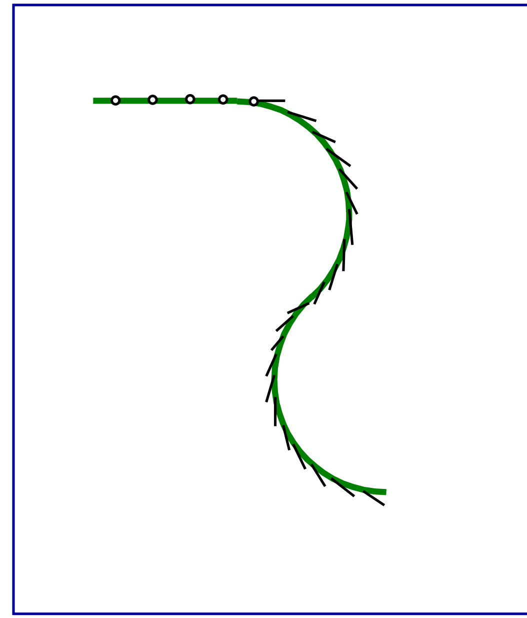


Low Sample Rate

Which is more difficult

?

Mobile?

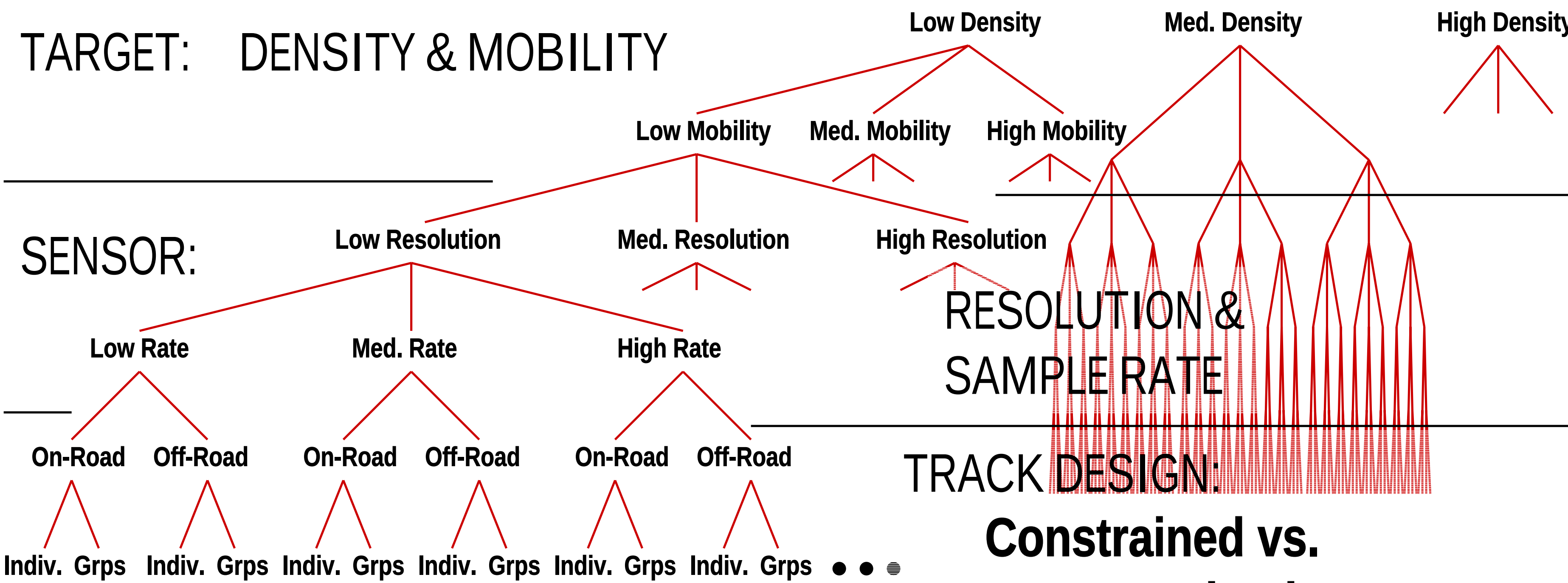


High Sample Rate

- ***Tracker may perform better here.***

Target Mobility and Sensor Sample Rate COMBINE to influence TRACK performance.

Test Space is Huge



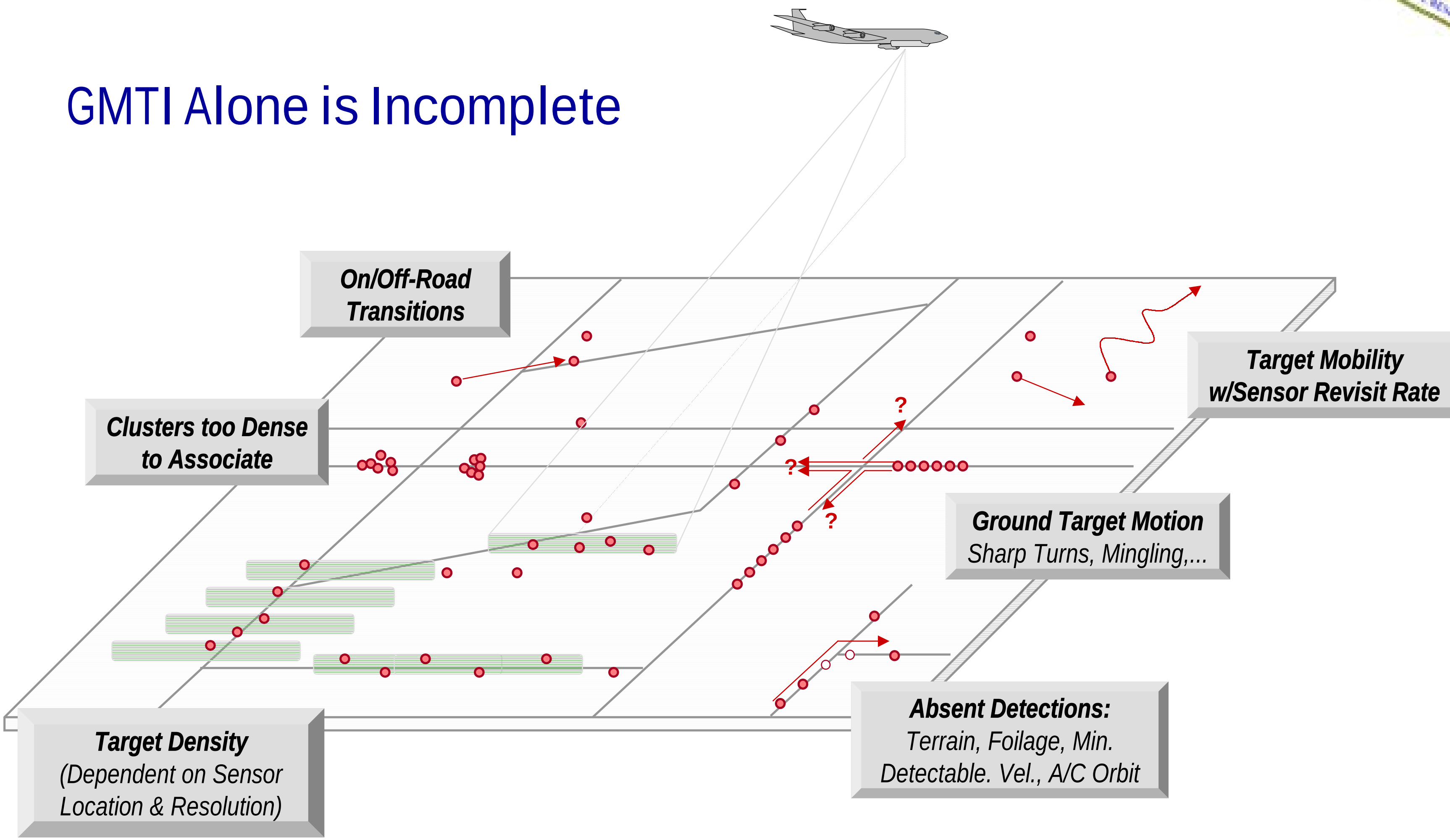
Constrained vs. Unconstrained, Groups vs. Individuals

Two Reasons for Scenario Qualification:

1) ***Desire to understand Scenario's "Level of Difficulty".***
2) ***Breadth of Test Space demands a Reduction.***

GMTI & Target = Track Challenges

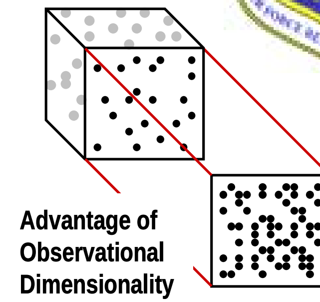
GMTI Alone is Incomplete



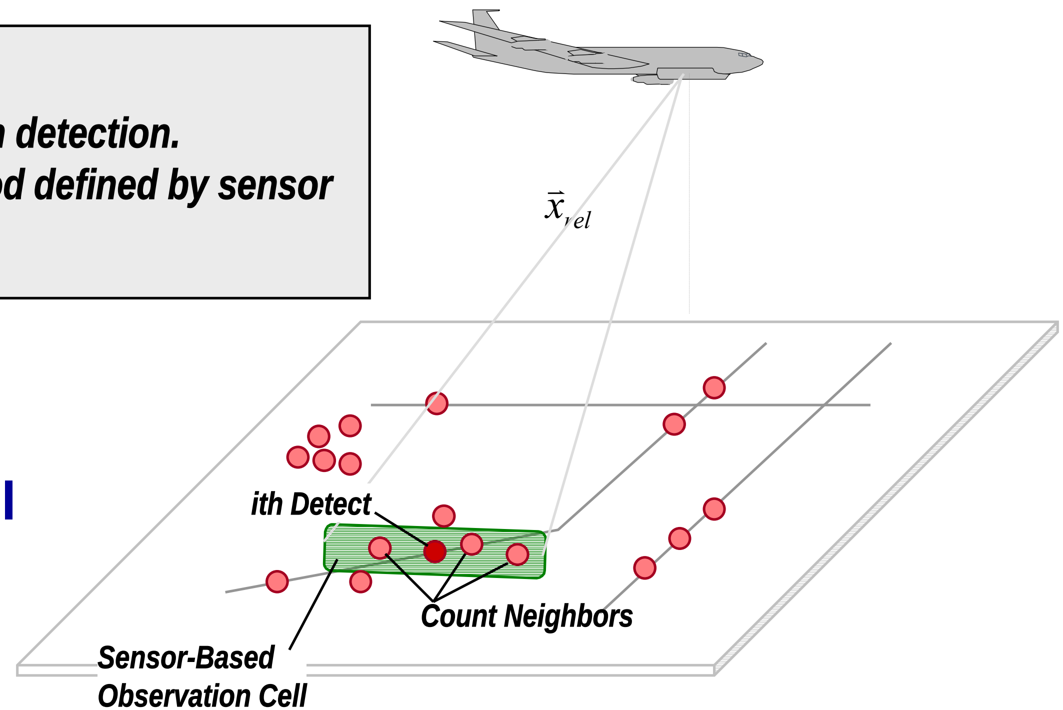
Track Evaluation <u>must</u> consider the Challenges inherent in native GMTI and underlying Target Behavior.

Normalized Target Density - Definition

NTD is Function of Observation Components AND A/C LOS
(Range, Azimuth & Range Rate)



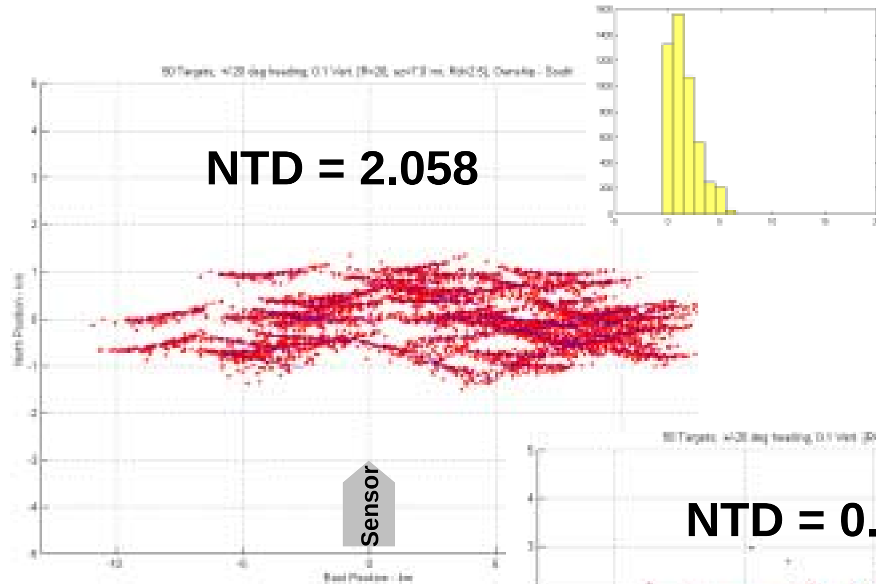
Calculation Algorithm
- *For given collection, extract each detection.*
- *Count detections in neighborhood defined by sensor observation cell.*

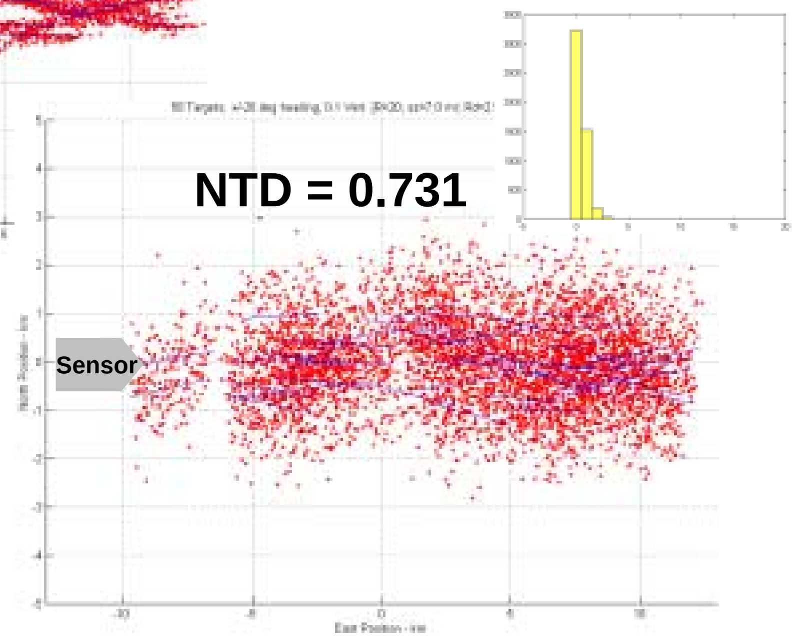


#Neighbors
K*Observation Cell

Density couples interdependency of accuracy volume & target proximity

Difficulty Depends on Geometry

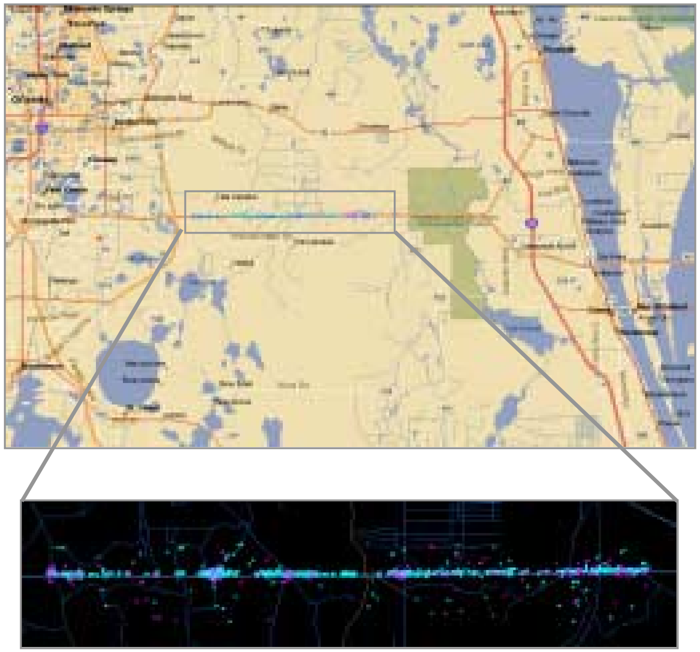


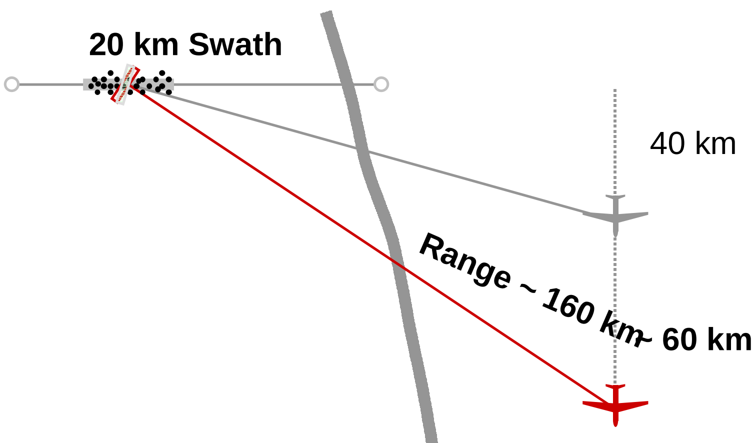


Difficulty depends on sensor location.

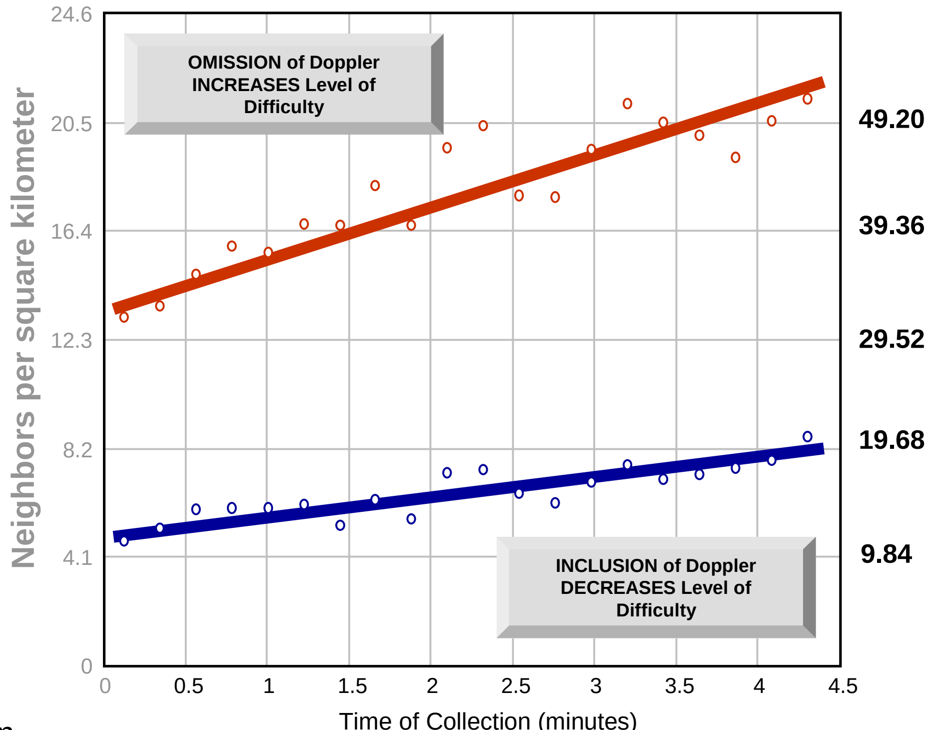
NTD measures this.

For Reference, Florida Beeline Traffic exhibits Neighborhood Densities of 9 to 19.





4 minutes at 1400 on the Beeline - May 1996



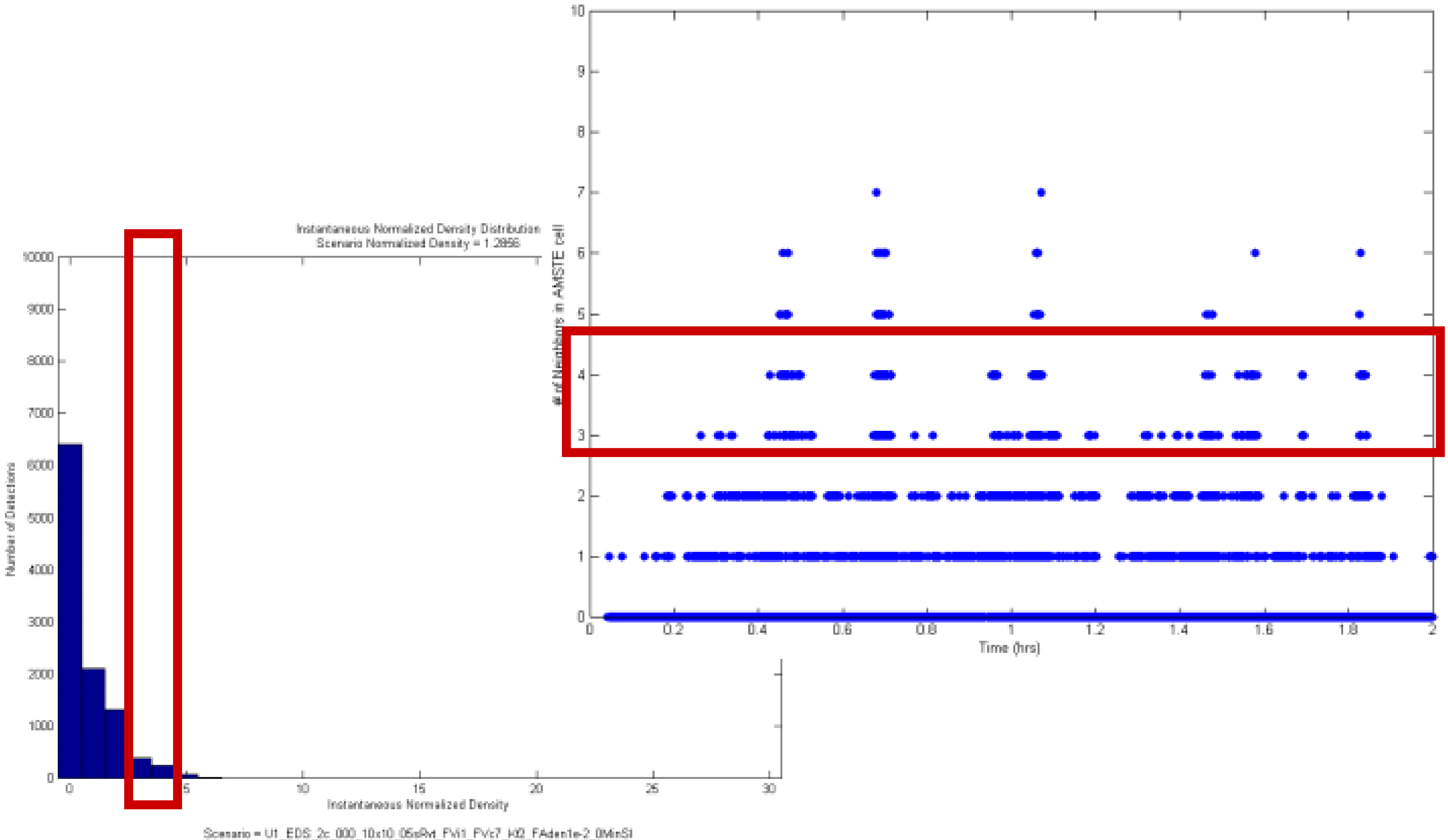
Neighbors per 5-sigma MTE Observation Cell

Compare Beeline Data with x-axis of Performance Curves

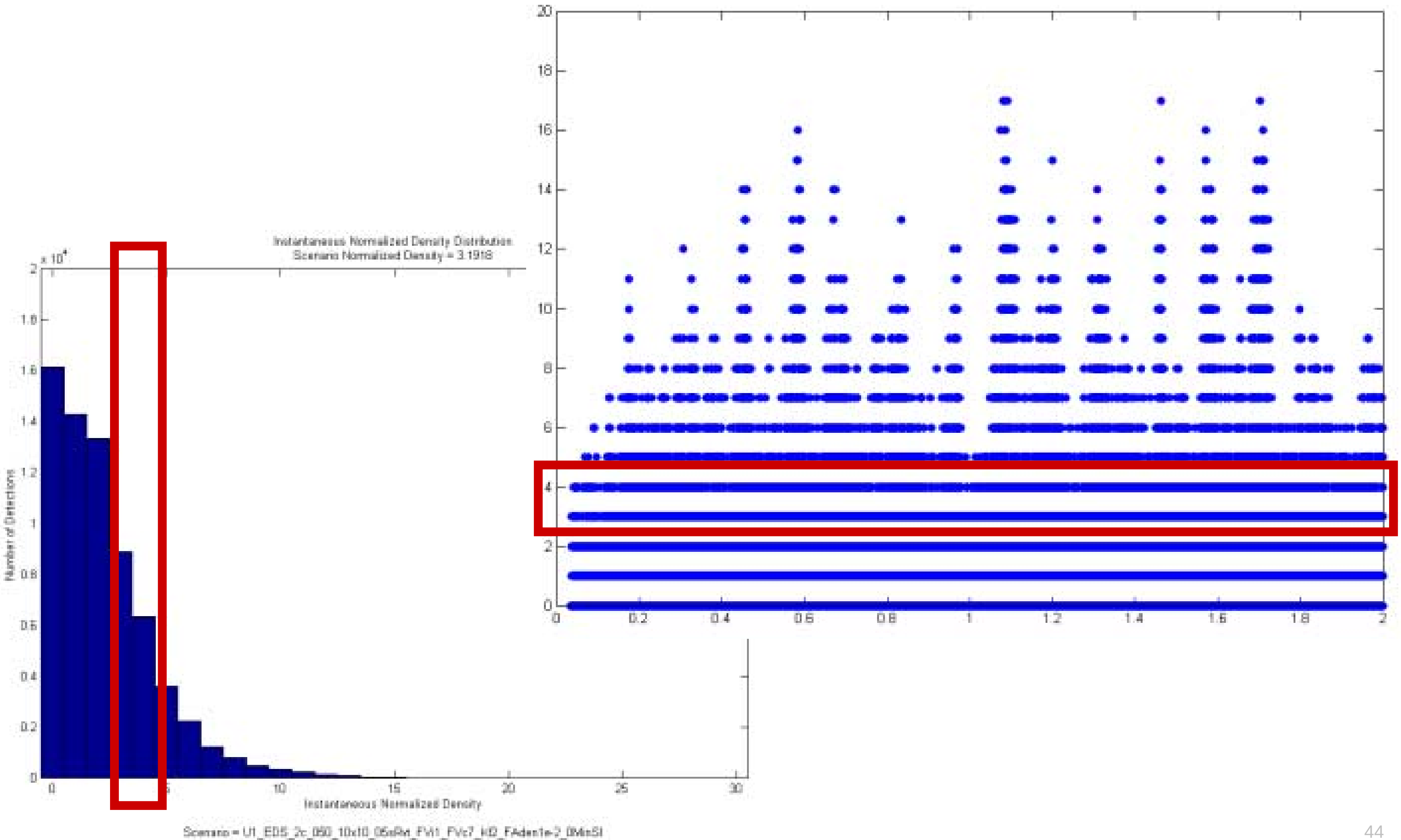
Density depends on sensor resolution, aircraft flight path, and target location. It directly impacts the difficulty of the tracking problem.

*An observation cell equals approximately 2.4 km^2

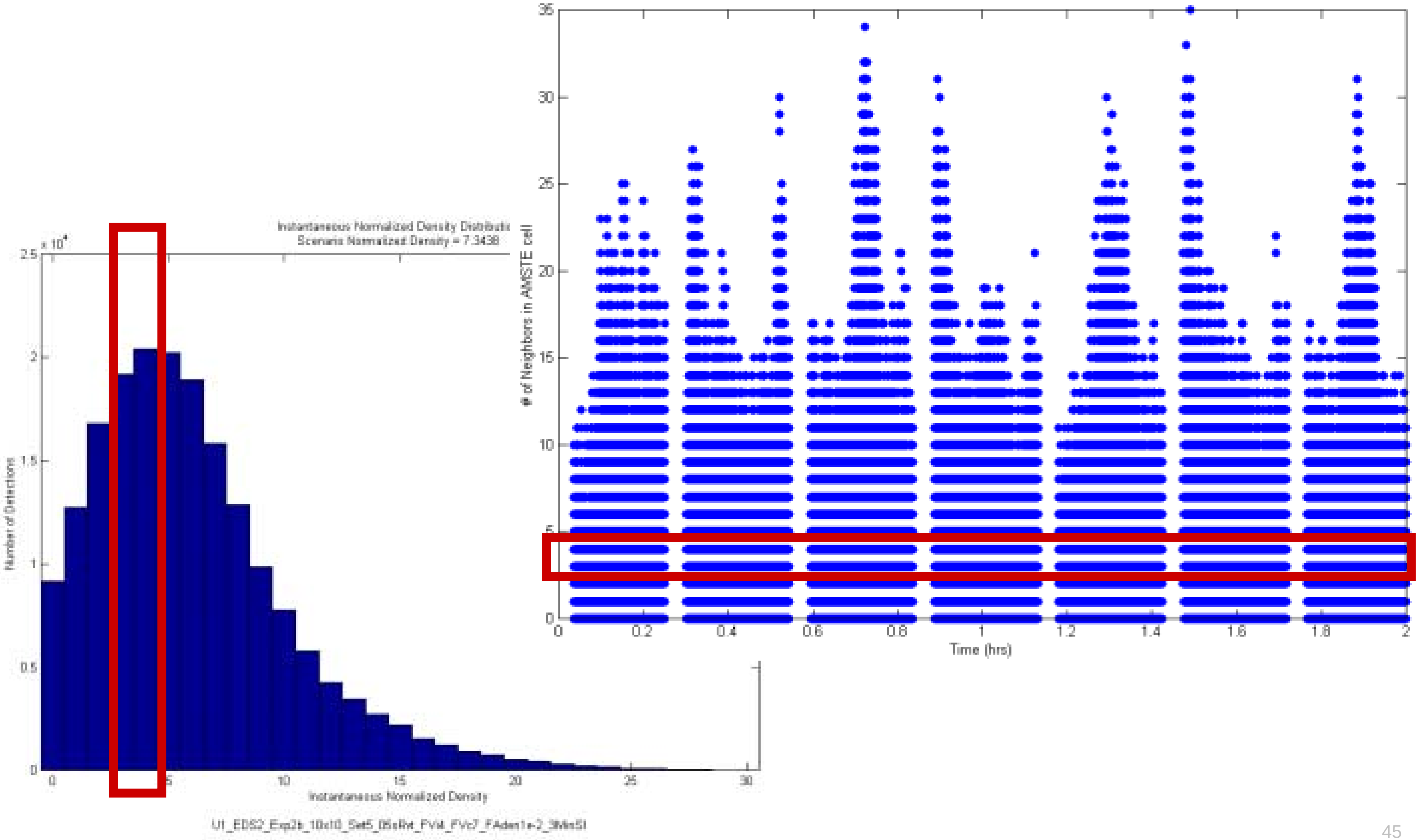
Kosovo Scenario – 0 Confusers



Kosovo Scenario – 50 Confusers



Kosovo Scenario – 200 Confusers

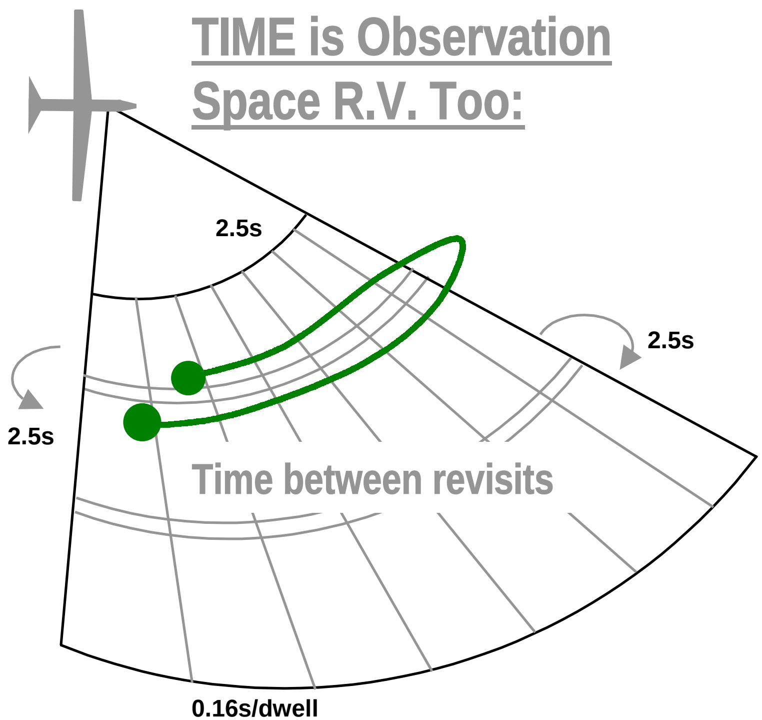


Extend to NTD to Multisensor

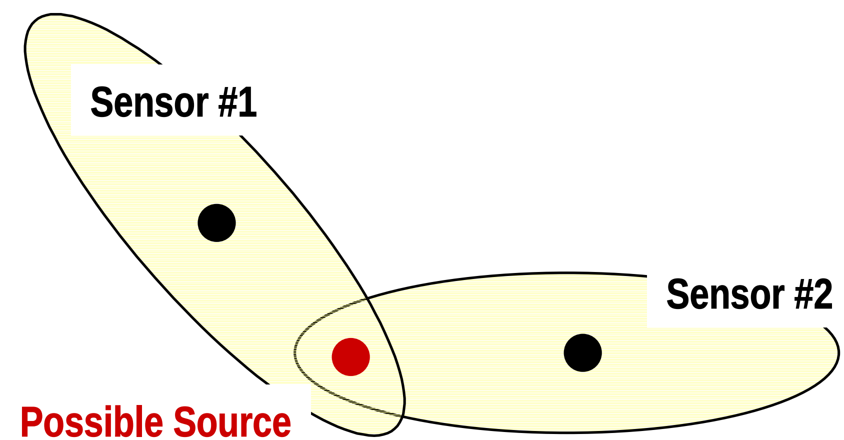
$$\bar{\rho}_i = \frac{\#Targets}{K \cdot Obs.\,Cell(R, \dot{R}, \alpha, \ldots, \Delta t)} \approx \#Detections \in \{Error\ space, Cov(Z_i)\}$$

- ***Observation Space Includes Time (Observation Interval)***
- ***Gate is now touching error ellipses.***

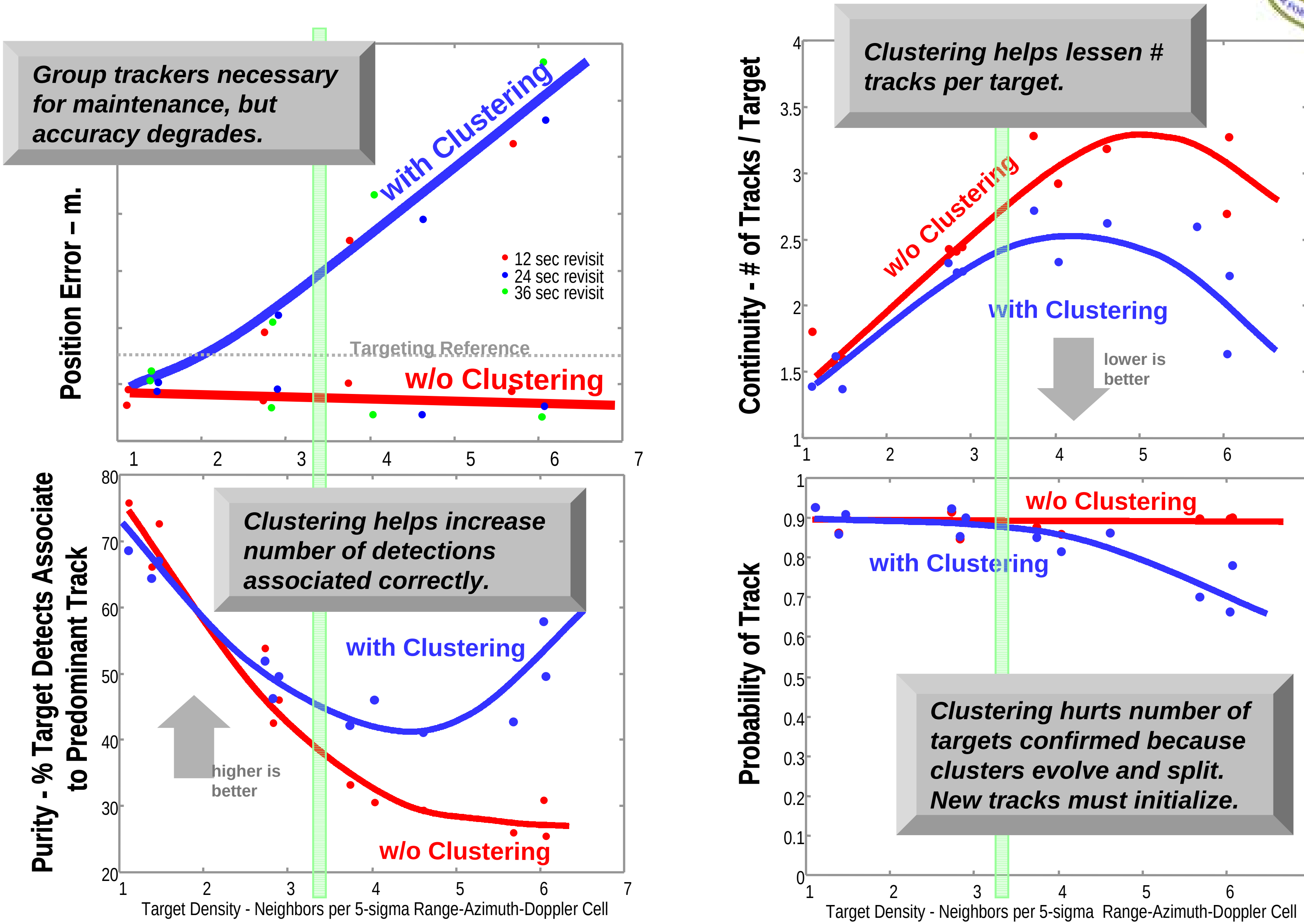
TIME is Observation Space R.V. Too:



Gate on Touching Error Ellipses.

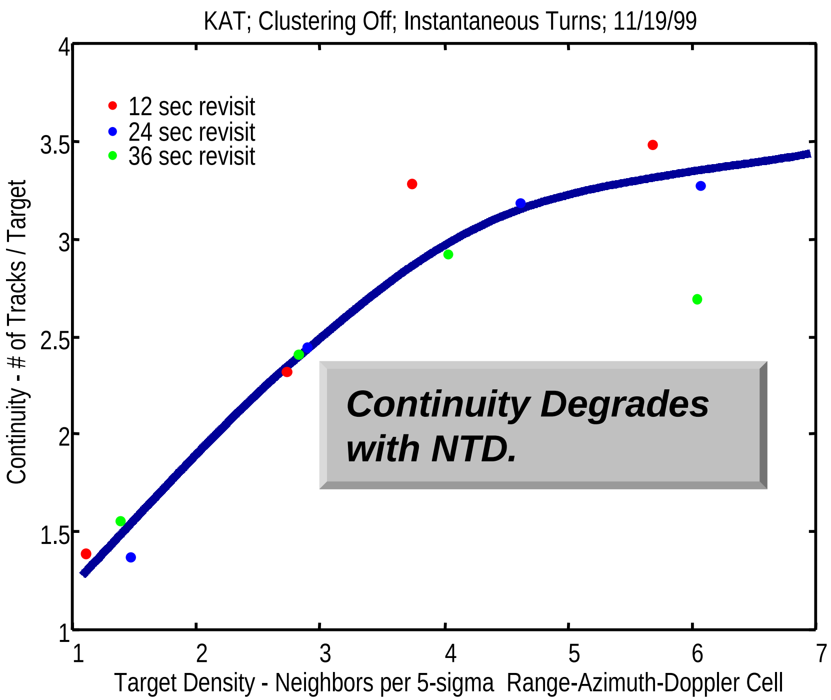


MTE: Track Clustering Required in Traffic

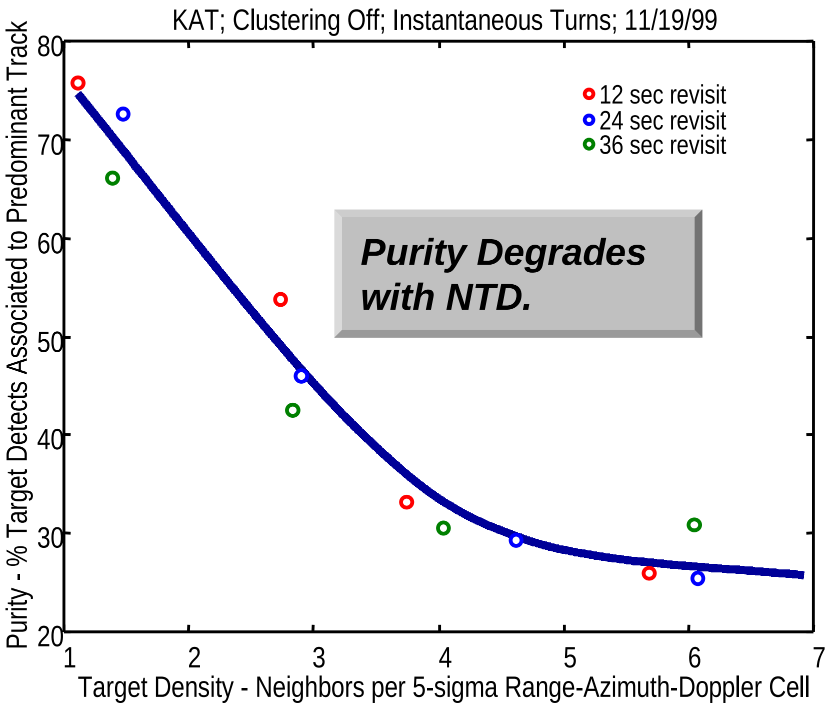


***KAT Tracker; MHT is comparable*

MTE: Continuity & Purity vs. Revisit Rate



Continuity Degrades with NTD.



Purity Degrades with NTD.

Continuity and Purity relatively insensitive to revisit rate for short runs.

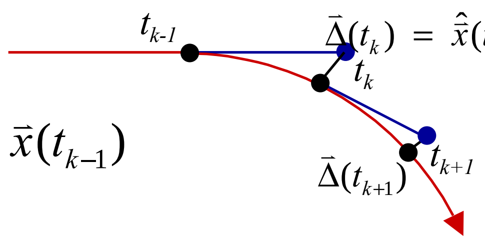
Normalized Target Mobility - Unconstrained

EXPECTED SAMPLE INTERVAL:

$$\bar{\tau}_s = \frac{1}{N_t}\sum_{j=1}^{N_t}\left[\sum_{i=1}^{N_j}\frac{\left(\tau_i^j\right)^2}{T_j}\right] \Leftarrow \bar{\tau}_s = \frac{1}{N_t}\sum_{j=1}^{N_t}\left(\sum_{i=1}^{N_j}P_i^j\cdot\tau_i^j\right);\; P_i^j = \frac{\tau_i^j}{T_j}$$

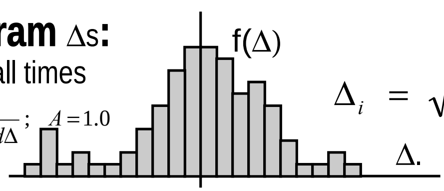
Move in τ_s increments:
(constant velocity vector)

$$\hat{\vec{x}}(t_k) = \Phi(t_{k-1}, t_{k-1}+\bar{\tau}_s)\cdot\vec{x}(t_{k-1})$$



Histogram Δs:
all tgts; all times

$$f(\Delta) = \frac{f_{cnt}}{\sum f_{cnt}\cdot d\Delta};\quad A = 1.0$$



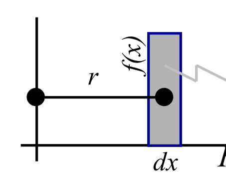
$$\Delta_i = \sqrt{\vec{\Delta}_i^T(t_{k+1})\cdot W\cdot\vec{\Delta}_i(t_{k+1})} \leftarrow$$

Prediction Error

NORMALIZED TARGET MOBILITY (RMS):

$$R_\Delta = \sqrt{\frac{1}{N}\sum_{i=1}^{N=\#bins}\Delta_i^2\cdot f(\Delta_i)\cdot d\Delta_i}\quad \frac{meters}{sample\ \ interval}$$

P_i^j	Probability of target being visible in ith-interval, given sensor is sampling an observation for the jth-track.
τ_i^j	ith-sample interval in the jth-track. Distance between hits. Include visibility.
N_j	Number of sample intervals in the jth-track.
T_j	Time duration for jth-track, including misses, even at endpoints.
N_t	Number of tracks in scenario.
$\hat{\vec{x}}(t_k)$	Propagated state vector.
$\vec{x}(t_k)$	True Target state vector.
$\Phi()$	State Transition Matrix (Constant Velocity.)
$\vec{\Delta}(t_k)$	Maneuver difference.



$$I = \int r^2 dm$$

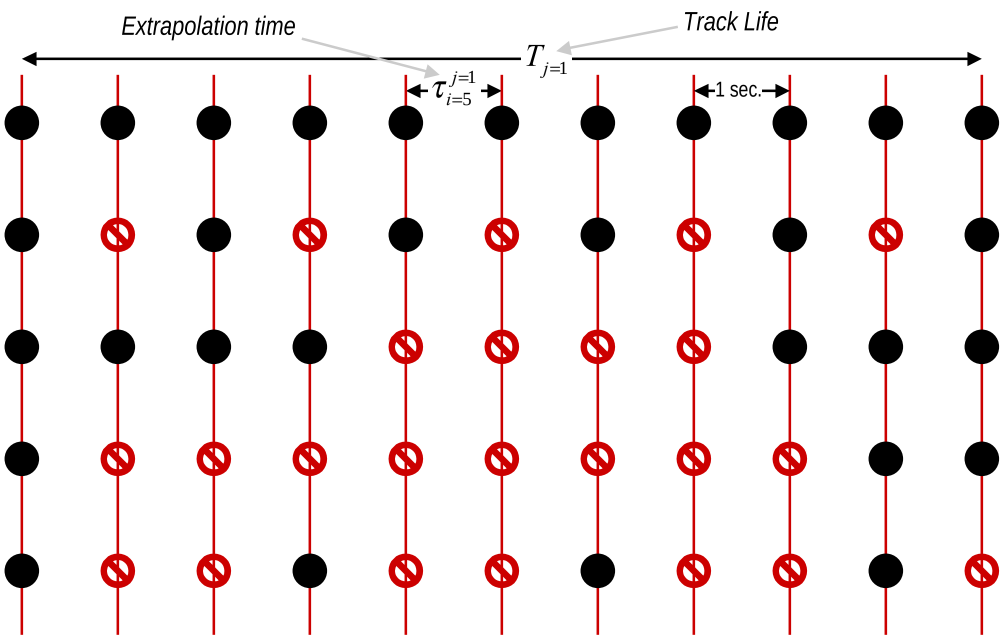
$$R = \int x^2\cdot f(x)\cdot dx$$

Normalized Target Mobility measures scenario complexity given sensor's sample rate.

Norm. Tgt. Mobility - Expected Sample Time

$$\bar{\tau}_s = \frac{1}{N_t}\sum_{j=1}^{N_t}\left(\sum_{i=1}^{N_j} P_i^j \cdot \tau_i^j\right) \quad P_i^j = \frac{\tau_i^j}{T_j}$$

***More difficult cases have gaps in MTI data stream.**



$$\tau_s^1 = \sum_{i=1}^{10} \frac{1}{10}\cdot 1 = 1.0$$

$$\tau_s^2 = \sum_{i=1}^{5} \frac{2}{10}\cdot 2 = 2.0$$

$$\tau_s^3 = \sum_{i=1}^{5}\left(\frac{1}{10}\cdot 1\right) + \sum_{i=1}^{1}\left(\frac{5}{10}\cdot 5\right) = 3.0$$

$$\tau_s^4 = \left(\frac{1}{10}\cdot 1\right) + \left(\frac{9}{10}\cdot 9\right) = 8.2$$

$$\tau_s^5 = \sum_{i=1}^{3}\left(\frac{3}{9}\cdot 3\right) = 3.0$$

3.44

Ignore Coasts at end of track

Based on probability that target is in a particular region of track extrapolation. Gives a little longer average interval than an unweighted mean.

Normalized Target Mobility - Constrained

EXPECTED SAMPLE INTERVAL:

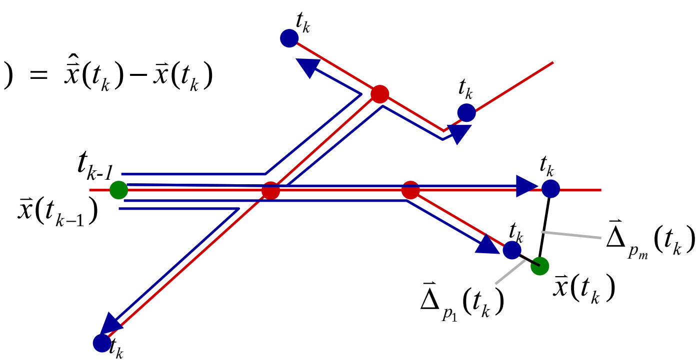
$$\bar{\tau}_s = \frac{1}{N_t}\sum_{j=1}^{N_t}\left[\sum_{i=1}^{N_j}\frac{\left(\tau_i^j\right)^2}{T_j}\right]$$

Move in τ_s increments along road network:

$$\hat{\vec{x}}(t_k) = \Phi(t_{k-1}, t_{k-1} + \bar{\tau}_s)\cdot\vec{x}(t_{k-1})$$

(constant speed)

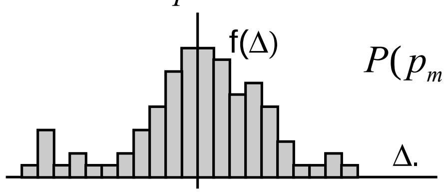
$$\vec{\Delta}(t_k) = \hat{\vec{x}}(t_k) - \vec{x}(t_k)$$



(Paths are constant length)

Histogram Δs; account for equally likely paths:

$$f(\Delta_i) = \sum_{Npaths} f(\Delta_i | p_m)\cdot P(p_m)$$



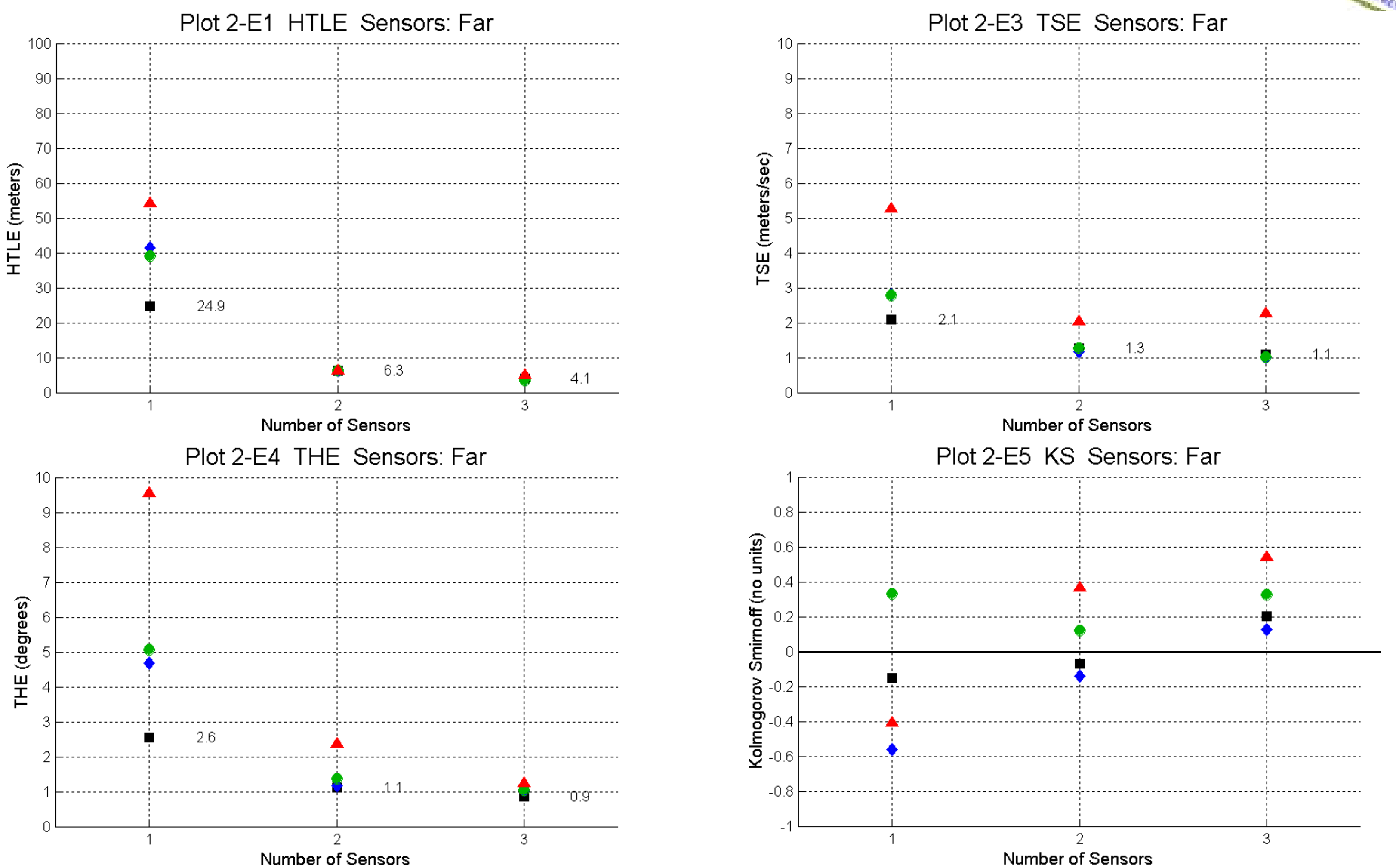
$$P(p_m) = \frac{1}{M}$$

NORMALIZED TARGET MOBILITY:

$$R_\Delta = \sqrt{\frac{1}{N}\sum_{i=1}^{N=\#bins}\Delta_i^2\cdot f(\Delta_i)\cdot d\Delta_i} \quad \frac{meters}{sample\ \ interval}$$

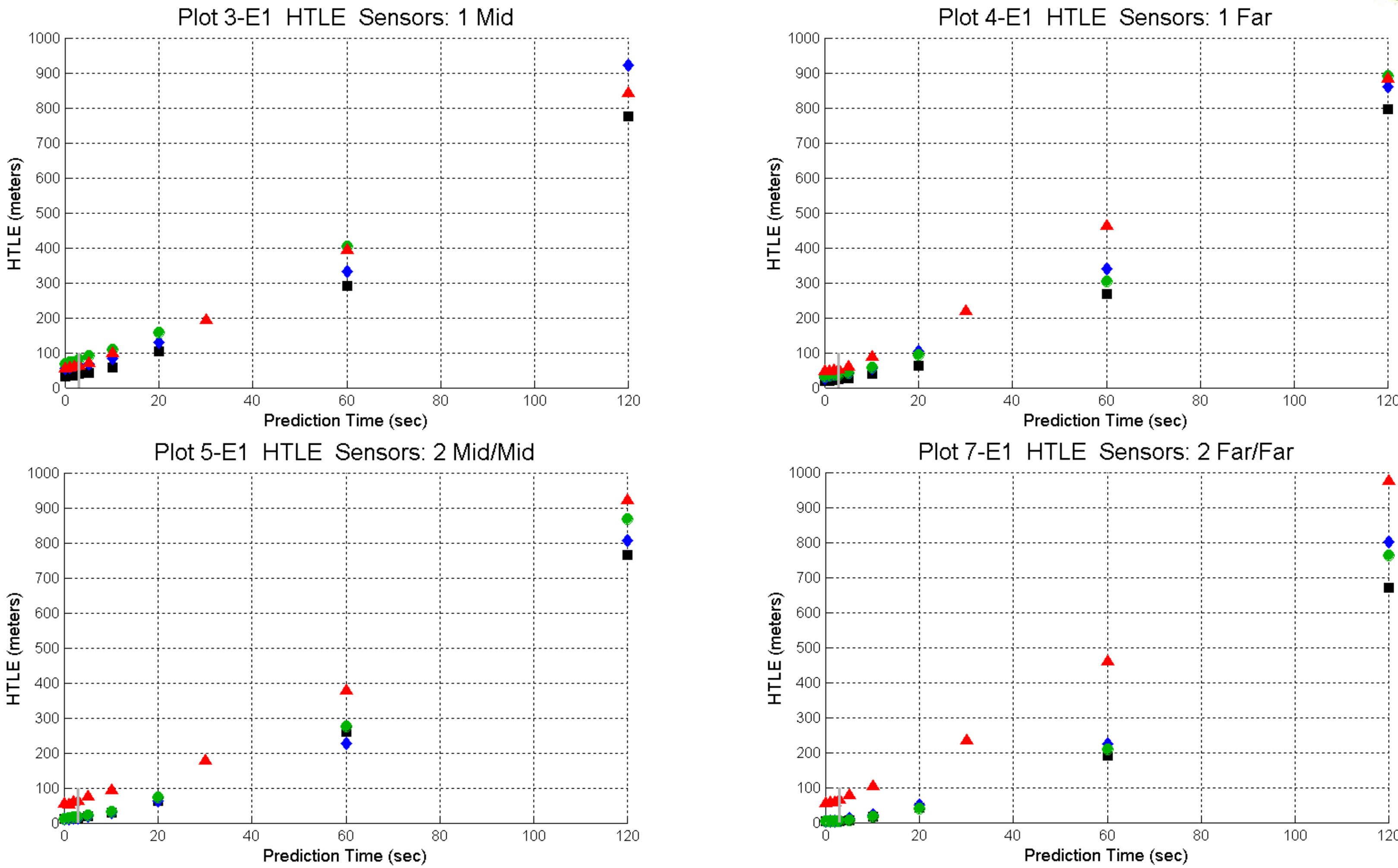
Similar to constrained case, but must account for road nodes & branches.

Track Precision Experiments
Number of Far-Term Sensors



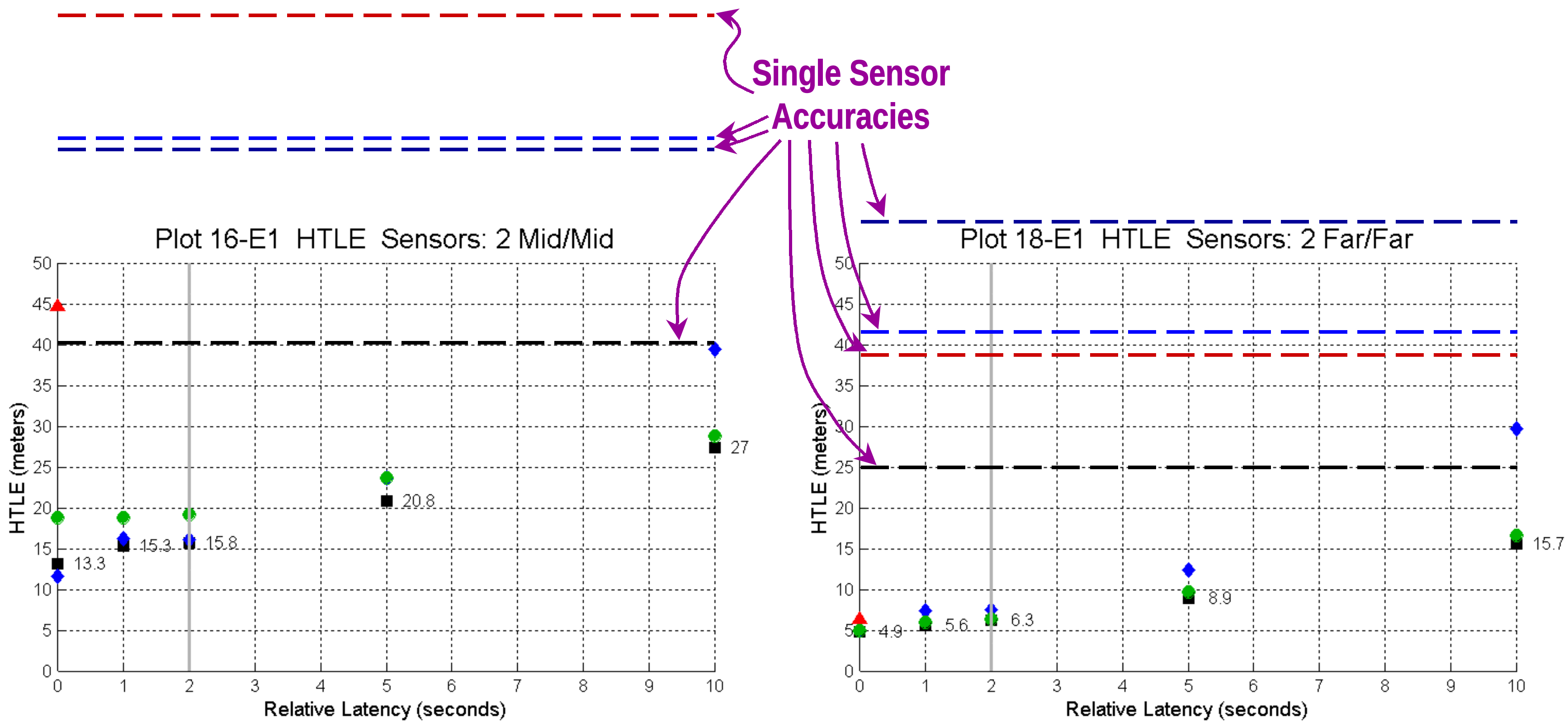
- Target precision errors can be made to be approximately 5 meters using multilateration of far-term sensors

Track Precision Experiments
Prediction Time (1)



- **A robust, low-cost weapon data link is most critical technology element for achieving target precision, regardless of architecture**

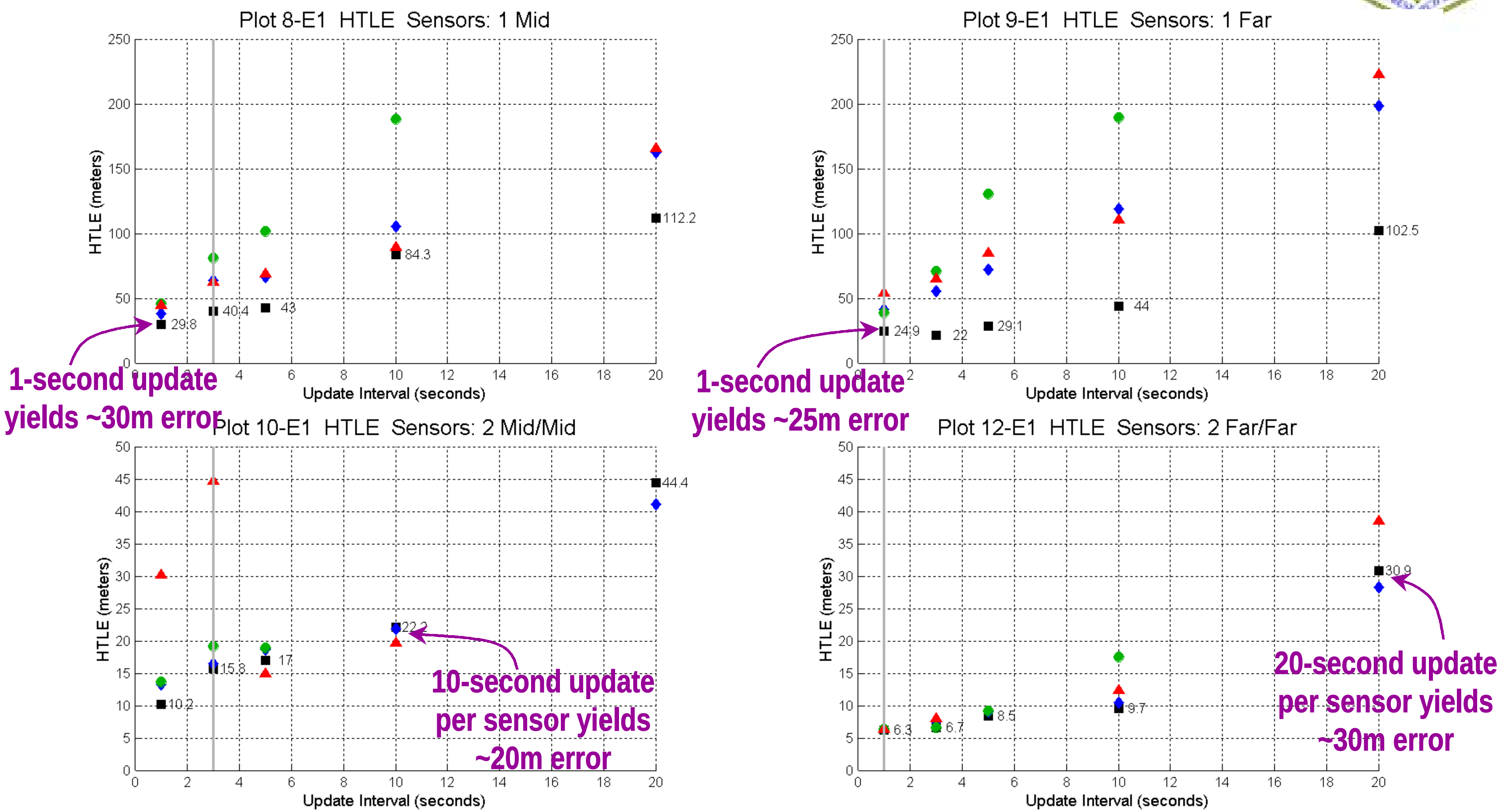
Track Precision Experiments
Relative Latency Interval



- It is important for precision tracker algorithms to be able to process out-of-sequence (late) measurements
  - Otherwise, single-sensor accuracies would result

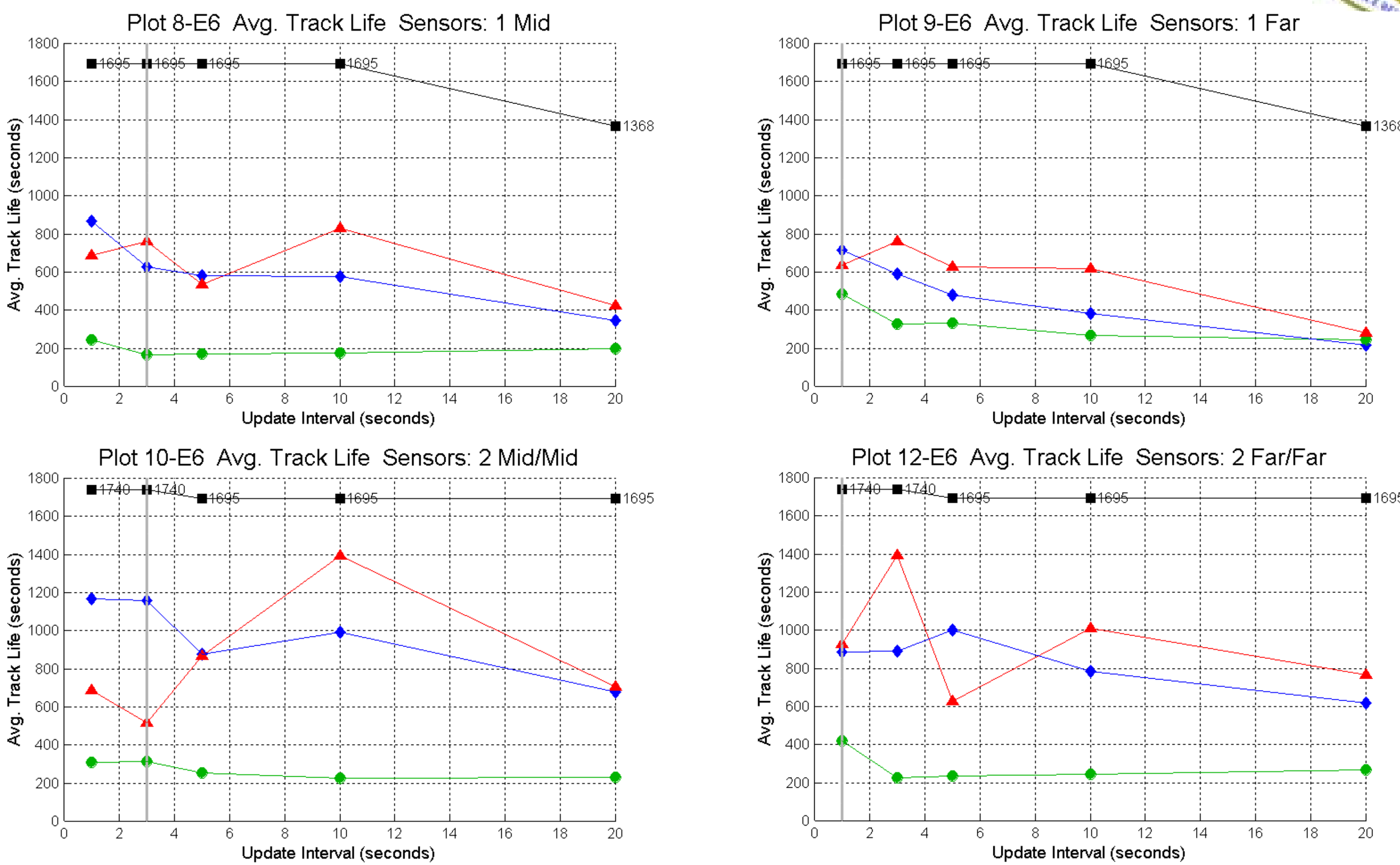
Track Precision Experiments

Update Interval



- **Considerable sensor resource savings are obtained though multi-lateration**
  - **Reasonable 2-sensor performance for relatively long update intervals**

Track Precision Experiments
Average Track Lifetime (1)



- One tracker contractor was able to maintain long track lifetimes
  - Should not have been too difficult, given large vehicle separations

Conclusions

- ♦ MOP Definition is important, but…
- ♦ Clear ICDs and data definitions allow tracker to tracker comparisons.
- ♦ Scenario Difficulty must be factored.
  - Normalized Density
  - Mobility Measure
- ♦ GMTI Tracking is still Evolving
  - MHT and IMM popular, but model types and levels ill-defined.
  - Dense scenarios still difficult.
  - Group tracking needs to mature.
  - Road networks and terrain usage is inconsistent.
- ♦ Evaluation requires iteration with the developers.