Airport Movement Area Knowledge-Assisted Association and Tracking

Abstract

This white paper describes an approach for improving airport movement area aircraft and vehicle tracking using knowledge-based techniques. This design employs a knowledge-based fusion approach that would take into account airport geography, vehicle movement patterns, static prior data, expert rules, and sensor characteristics heuristics.

1. Introduction

The airport movement area, though seemingly benign to the lay public, has a risk level of concern in low visibility and/or high-density situations. Incursions of concern involve airliners, general aviation, airport vehicles, particularly passenger shuttles, and cargo aircraft. Obviously a critical requirement in controlling this environment is knowledge of the kinematics (position, velocity, acceleration) and identification (physical, mission) of the objects of interest.

Various sensor systems have been deployed such as ASDE-3 and ATIDS. Others such as LOOP have been experimented with. It is unlikely that any single sensor will meet all requirements. Just looking historically, the US DoD, which has similar types of problems of target tracking and identification in many domains and has spent billions on sensor research and deployment still employs multi-sensor systems for all its operational missions [1]. Indeed, a recent inventory shows there are 79 unique major systems that associate, correlate, and/or fuse multi-sensor data in DoD [2]. There are many reasons why multi-sensor suites are required, a topic beyond the scope of this paper, see [3], [4], [5], and [6. Reasons include complementary coverage, diverse collection across obervables and target types, and reliability.

Consequently, fusion systems are employed in conjunction with sensor suites, fusion being defined in the broad sense as, "… the process of coming data or information to estimate or predict entity states. "[7]. This paper discusses the current state of fusion systems in the airport movement area, discusses emerging fusion technologies that could be employed to improve performance, and then presents a design for a knowledge-assisted target tracker and identifier.

2. Airport Movement Area Systems

The Airport Movement Area Safety System (AMASS) was originally built to process ASDE-3 radar data as its sole sensor data input. At some airports, additional sensor systems have been added that have been, or are anticipated to be, fused with the ASDE radar data to produce more complete and accurate movement area surveillance. New sensor data inputs for this regime include the ATIDS multi-lateration system and Automatic Dependent Surveillance (ADS)-B.

In its original form, AMASS "fusion" was limited to an α/β ASDE radar tracker. In 1997, the fusion process was extended to include the ATIDS sensor inputs. A Kalman filter for the ATIDS short squitter multi-laterated position estimates was added along with a correlator between the ASDE and ATIDS tracks, and a kinematic fuser. Because the kinematic fuser caused more erratic position estimates than either of the sensors alone, the fuser was disabled for the NASA TAP demonstration in July 1997.

3. Challenge

Sensor data fusion is an established multi-disciplinary field based on statistics, artificial intelligence, and other sciences. Long-range aircraft tracking and satellite tracking are typical applications. Unique challenges in airport movement area surveillance include:

- Multipath effects for beacons, transponders, and radars
- Obstructions creating blind zones for sensors
- Many relatively small vehicles with low observability, unpredictable behavior, and short duration
- Weather in frequency ranges of sensors

4. Design Concepts

4.1 Position dependent process model

The core of almost all target tracking algorithms is a digital filter such as an α/β or Kalman filter that provides a smoothed and predictive estimate based upon time-series and, in the case of fusion systems, multi-sensor data samples. A key feature of these filters is the process model that describes the underlying process being estimated. In most target trackers, the underlying process model is constant parameter although adaptive filters are being implemented. For aircraft tracking the model is usually a constant velocity model. Maneuver detection processing detects model violations and

Copyright © Silver Bullet Solutions, Inc.
www.silverbulletinc.com

selects a resolution technique. This works quite well in most aircraft tracking applications as aircraft are in constant or near-constant velocity over a broad portion of their target lives. This is especially true when velocity accuracy requirements are taken into account, that is, if the requirement is to know generally where an aircraft is heading and the average speed, then slight velocity jinks can be ignored. Maneuvers do, however, have a cost to tracker performance. If the maneuver is slight but persistent (e.g., a change of course), the track will lag the maneuver due to its smoothing with historic data and then "catch up" once the maneuver is realized as not just measurement noise. In order to catch-up, the filter must shed history data which can cause a loss of some built-up "knowledge". Worse still is if the maneuver is not recognized and the original track is lost and a new track initiated. In this case, in effect all history is lost, including accumulated identification and other data that may have been attributed to the track manually or in a one-time opportunity (e.g., when ARTS hands-off to AMASS).

Unfortunately, in the airport surface regime, drastic non-constant velocity motion is frequent. Turning off ramps, accelerations, decelerations, and so forth cause maneuver detections frequently.

A relatively new type of filter aids in this type of situation, called the Interacting Multi-Model (IMM) filter. At each pass on state estimation, multiple models are used, with some decision or combination algorithm used to develop the final state estimate. IMM filters are fairly well-known in the fusion community at this time.

Building into AMASS fusion processing full knowledge of expected behaviors is discussed in the next section herein. A relatively simple improvement would be to initialize and update the ATIDS and fusion tracking filters[1] using position-dependent values for speed and process noise (sometimes called plant noise, an indication of the how closely the process model is expected to be followed.) In the fusion code, a table with the position-dependent values would be added. Then, instead of employing the constants in the trackers, the parameters would be looked-up based upon the current target position estimate.

4.2 Maneuver Detection and Response

The current fusion processor tests for "maneuver". Yet there are distinct maneuver types for aircraft in the runway and taxi areas. Specifically, in the runways there are accelerations and decelerations of known magnitudes. In the taxiways, there are acceleration and decelerations of much smaller magnitude and heading changes. Similarly aircraft tracks have different probabilities of speeds and maneuvers in different areas of the airport. For example, an ATIDS report at the beginning of a landing runway has high probability of speed around 200 mph. An ATIDS report in this area with altitude greater than zero has an even higher probability of flight, not taxi-ing speeds.

The same parameter grid proposed in 4, herein, could be modified to also include probability of maneuver, probability of maneuver type (linear, curvilinear), and probability of maneuver extent (G's, deg/sec, ft/sec^2) and duration.

Also, the current implementation does not use both the AMASS raw and smoothed data but only the smoothed. The raw is more accurate in a maneuver.

4.3 Reduction of Degree of Freedom

When correlating aircraft positions, a degree of freedom can be eliminated since off-center runway/taxiway distances are often due to bias or noise and are irrelevant anyway. Only in very exceptional circumstances, i.e.., accidents, will aircraft move off the runway/taxiway surfaces. Reduction of the degrees of freedom was one of the major mathematical breakthroughs in military fire control (crossrange, downrange). It can greatly reduce complexity and ambiguous hypotheses.

4.4 Sensor Data Registration Grid

The Lincoln Labs report on ATIDS, recorded data, and nature of the ATIDS "sensor", show that the ATIDS bias is not a simple azimuth, lat, long bias. It varies irregularly over the airport. Maintaining a grid of bias over an area would be impractical in mobile applications since sensor platforms enter and exit the surveillance area and the biases are so dynamic they require special algorithms to initiate, track, and monitor. At a fixed site like an airport, the sensor suite is stable and its bias behaviors can be learned over a long period of time. This information can be accumulated in the grid.

4.5 Sensor Data Characterization Models

In Appendix B of the fusion algoritms functional design specification, there is a derivation of the covariance for ATIDS multilateration. Presumably, this how the covariance would be computed for use in the Mahalanobis distance for the fusion algorithm. The covariance is correct, under certain conditions, for the case of a 2D solution (known height), but not for 3D.Both cases have to be handled. Even for the 2D case, a height is assumed, presumably due to the fact that there are only enough measurements available to fix x and y, but not z. Unless the assumed height is correct, another error (not just in the vertical component, but also the horizontal)is introduced, and this error is not modeled in the current

[1] ASDE tracking employs an α/β filter that was developed some time ago that is not amenable to this change. However, it may be useful to implement a Kalman filter for ASDE as an upgrade to the a/b. In this case, ASDE tracker could be included in the position-dependent improvement.

Copyright © Silver Bullet Solutions, Inc.
www.silverbulletinc.com

covariance derivation. The Sensor Characterization found that 2D solution were highly inaccurate but that is not apparent in the modeled covariance.

ASDE covariance estimation should account for tracker effects. These are a function of factors such as the α and β values in use, their "status", number of scans target has been tracked, and hit/miss history.

Currently, many of the ATIDS inputs are unused. For example, Statistical distance squared is filled in November data samples and appears usable. Another is Algorithm, which indicates whether a 2D or 3D solution was achieved. There are many others that indicate the quality of the input. These clues can be used to break ties and influence probabilities.

4.6 A-Priori Non-Realtime Data Usage

Static and non-realtime data can be used to improve detection probability and/or timeliness and target identification if used carefully. This kind of data can be used as background information to break decision ties and influence probabilities. In some fusion systems it is used as an expected situation ground from which sensor information is interpreted or used to update the expected situation, much as human reasoning works [8]. An example of fusion research performed in this area is [9Some sources currently used in the NASA Ames Surface Movement Advisor (SMA) include:

Official Airlines Guide (OAG) database. The OAG database could be used to pre-condition probabilities of detection for aircraft during high-traffic periods and to setup a soft set of likely flights departing in given time periods. The arrival and departure times have to be treated with appropriate error characterizations which are often quite large. Furthermore, probabilities have to be assigned for probability of flight cancellation. Still, the OAG data does provide some information and would very likely be considered as a data point by a human operator.

Flight Information Display System (FIDS). Unlike OAG, FIDS is non-realtime, not static. Like OAG, the FIDS has low accuracy. It does, however, provide predictive pre-conditioning of departures (and arrivals) expectable.

Pushback Signals. These are fairly accurate although they suffer from latency. However, they can provide another datapoint for departures.

4.7 Robust Statistics

Robust statistics is a relatively new branch of statistics that takes advantage of new computing power to base estimates and hypothesis decisions on an exhaustive tabulation of all outcomes rather than using parametric techniques. The advantage of robust techniques is that it is not necessary to make distribution assumptions, which often cannot be verified or guaranteed for all sample sets to which the algorithm is to be applied. In cases where the distribution assumption is wrong, estimates and decisions can be skewed. More significantly for the airport movement area application, the distribution assumptions can be very sensitive to outliers. Robust statistical techniques do not have this sensitivity. For an introduction to robust statistical techniques see [10] or [11]. Because the multipath and multilateration ambiguities create what amount to outliers, robust statistical techniques hold promise to reduce sensitivity in the fusion algorithms without degrading gain and dynamic response. A design to use robust statistical procedures, however, is beyond the scope of the present paper.

5. Design

An alternative design, taking advantage of some of the unique features of the surface fusion problem is described in this section. The design uses knowledge base techniques for intelligent fusion that are implementable as simple table lookups. The layout of these tables (knowledge bases) is depicted in the figures. This design at this point is intended to show the approach. Details that have not been covered would be covered by a full design that would also include descriptions of each of the functions and the data flows. The symbol / acronym glossary for the design diagrams is as follows:

Design Glossary

MAN	a maneuver has been declared
RAWPOS	ASDE-3 raw position estimate (not tracked through α / β tracker)
SMOOTH STATE	ASDE tracked position and velocity estimate (through α / β tracker)
FTF	Fusion Track File
NC	Number of Candidates
SUP	an ASDE report suppression has been declared
NT	New Track
UT	Update Track
RAWPOS H_i	Score using unfiltered (not tracked) input for hypothesis that track $pair_i$ is the same target
RAWPOS H_0	Score using unfiltered (not tracked) input for hypothesis that the input report is a new track
Score H_i	Same as RAWPOS H_i but using filtered (tracked) input
Score H_0	Same as RAWPOS H_0 but using filtered (tracked) input
CAND	Track-to-track candidate
$x^c y^c$	Input xy, bias corrected
MSB	Most Significant Bits
seg_s	$Segment_s$

Copyright © Silver Bullet Solutions, Inc.
www.silverbulletinc.com

θ_t	Segment angle for (x, y) to (Rhat, Rhot) conversions
$Rhat_s$, $Rhot_s$	Crossrange, downrange in segment s
σ_s^{Rhat}, σ_s^{Rhot}	Std dev crossrange and downrange in segment s
P_{un}^{Rhat}	Probability, unnormalized, of crossrange
$P(s_i \text{->} s_j)$	Probability of transition from $segment_i$ to $segment_j$
P_s	Probability target is actually in $segment_s$
P^{Rhot}	Probability of divergent downrange coordinate measurements from same target
P(Mahalanobis)	Probability conversion of Mahalanobis distance
Δx, Δy	Bias correction pad

For each of the design diagrams presented, color coding of the algorithmic function is used to show the correspondence to the fusion concepts described in 4. The color-code legend is in Figure 2.

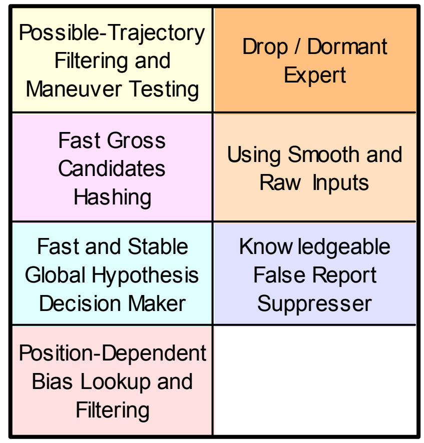


Figure 2. Design Color-Code to New Fusion Concepts

5.1 ASDE Input Process

The overall ASDE track input processing is shown in Figure 5-1. Many of the functions labeled in the process boxes are described in more detail in subsequent paragraphs, herein. This overall process is mostly conventional, with some enhancements in the form of dual raw and smoothed processing. This overcomes some of the problems in maneuvering and in using the pre-existing AMASS α/β filter.

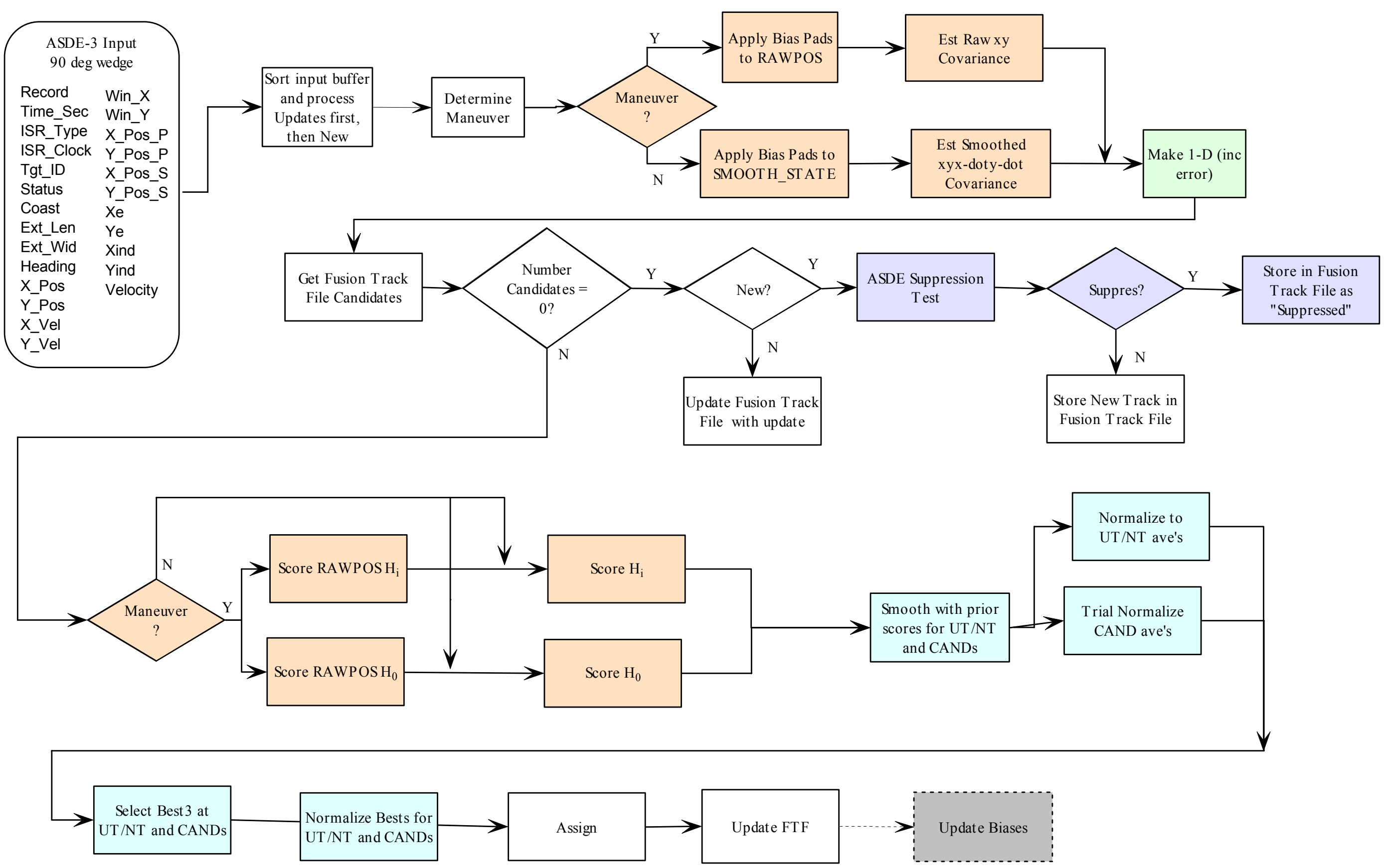


Figure 5-1. Overall ASDE Input Process -- *Showing fusion features 4.2, 4.3, 4.4, and 4.5*

Copyright © Silver Bullet Solutions, Inc.
www.silverbulletinc.com

5.2 Reduce Degree of Freedom

This routine eliminates a degree of freedom in the problem space by converting the 2-D inputs to 1-D, as shown in Figure 5-2. The assumption is that movement of interest occurs in the runways and taxiways. In addition to reducing a degree of freedom, target motion prediction is improved. Targets do not move in random directions. Rather, they have constrained directional movement. Converting to runway/taxiway segments also allows maintenance, update, and usage of probability of false target, probability of detection, and probable speed in segment knowledge.

This technique is common in the field of mechanics (see, for example, [12]) and is applied almost universally in artillery and guided missile fire control solutions for cross-range and down-range coordinate computations, for example [13].

5.3 Track Correlation Functions

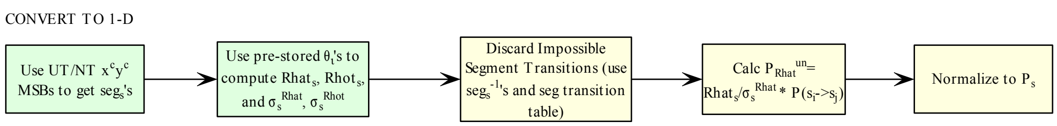
These functions perform tests to determine which tracks pertain to the same target.

5.3.1 Score Candidates

Scoring is via the very simple Mahanobolis distance along the segment, converted to a probability, and then multiplied by the probability that the target is in the segment.

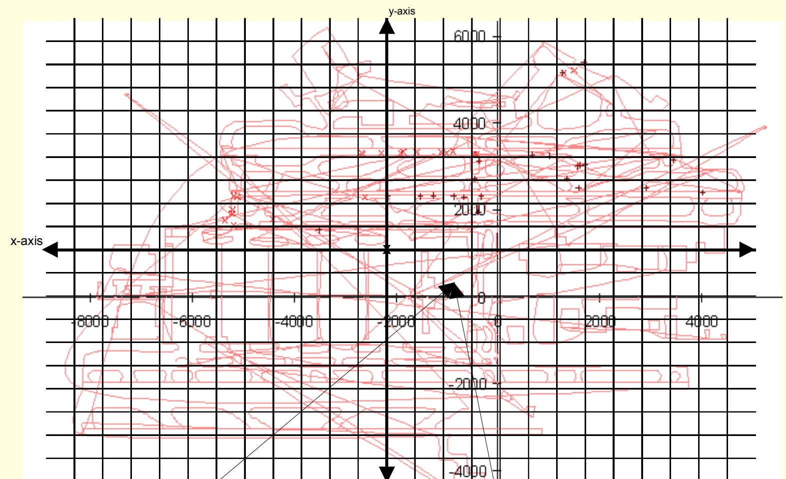
5.3.2 Extrapolate

The extrapolation function extrapolates the most likely trajectory along the Rhot "axis" using the surface movement map and its associated probability of accelerations (maneuvers). This provides a much greater increase in intelligence over conventional linear extrapolation. Until confirmation, a track may actually have several possible segment branches, each representing the probability that the vehicle turned into a surface segment. These are maintained



Runway/Taxiway Segment Table

s	Segment number
θ	Angle from North for this segment
Rhat	Cross-range distance from airport SCC for Theta
Rhot	Down-range
Cos(θ)	Precomputed for quick Rhat/Rhot conversions
Sin(θ)	Precomputed for quick Rhat/Rhot conversions
Spd	Most likely aircraft speed in this segment
σ_{Spd}	+/- of most likely aircraft speed



Segment, Track, Bias, P_{ft}, and P_d Hash Table

Δx	x-bias
Δy	y-bias
$P_{ft}^{3,cw}$	P(false target | ASDE, clear weather)
$P_{ft}^{3,bw}$	P(false target | ASDE, bad weather)
$P_d^{3,cw}$	P(detect | ASDE, clear weather)
$P_d^{3,bw}$	P(detect | ASDE, bad weather)
$P_d^{T,cw}$	P(detect | ATIDS, clear weather)
$P_d^{T,bw}$	P(detect | ATIDS, bad weather)
seg_1	1st segment in this cell
seg_2	2nd segment in this cell*
⋮	
seg_m	mth segment in this cell*
trk_1	1st track in this cell
trk_2	2nd track in this cell*
⋮	
trk_k	kth track in this cell*

SPEEDUP

* = could be via linked-list

Note: all ASDE Pd's are for one sec. integration
Note: all ATIDS Pd's are for one sec. interval

Figure 5-2. Making the Problem 1-Dimensional Along Possible Trajectories

Copyright © Silver Bullet Solutions, Inc.
www.silverbulletinc.com

until convincingly contradicted by sensor inputs.

5.3.3 Update Biases

By maintaining biases for each xy cell in the runway/taxiway area, the need to relate the R/T source of bias to the MWS-reported xy's is bypassed. This simple accumulation, with process (plant) noise in the filter to account for bias drift, will improve over time since the drift is assumed to be small.

5.3.4 Determine Maneuver

Maneuver in this design merely means the sensor input does not fall within any extrapolation segment. Since the segments account for true maneuvers, many maneuver declarations may actually indicate spurious sensor inputs that will be discarded via the sensor report suppression test (paragraph 5.3.5).

5.3.5 Sensor Report Suppresion Test

The suppression tests are table-driven conditions upon which an ASDE (or ATIDS) input would be considered an outlier having no recoverable data input. As a table-driven function, the conditions would be setup statically at program generation time and modifiable via ground controller's selection of criteria and actions.

5.3.6 Smooth Scores

Inter-track similarity assessments should not be allowed to vacillate erratically from sensor update to sensor update or across short time intervals. This function provides that stability for multiple assessment periods. However, it does allow for rapid reaction to new events and for recurring trends. It does this with the analog of a "maneuver detector" (new events) and a "speed" (recurring trend). It is

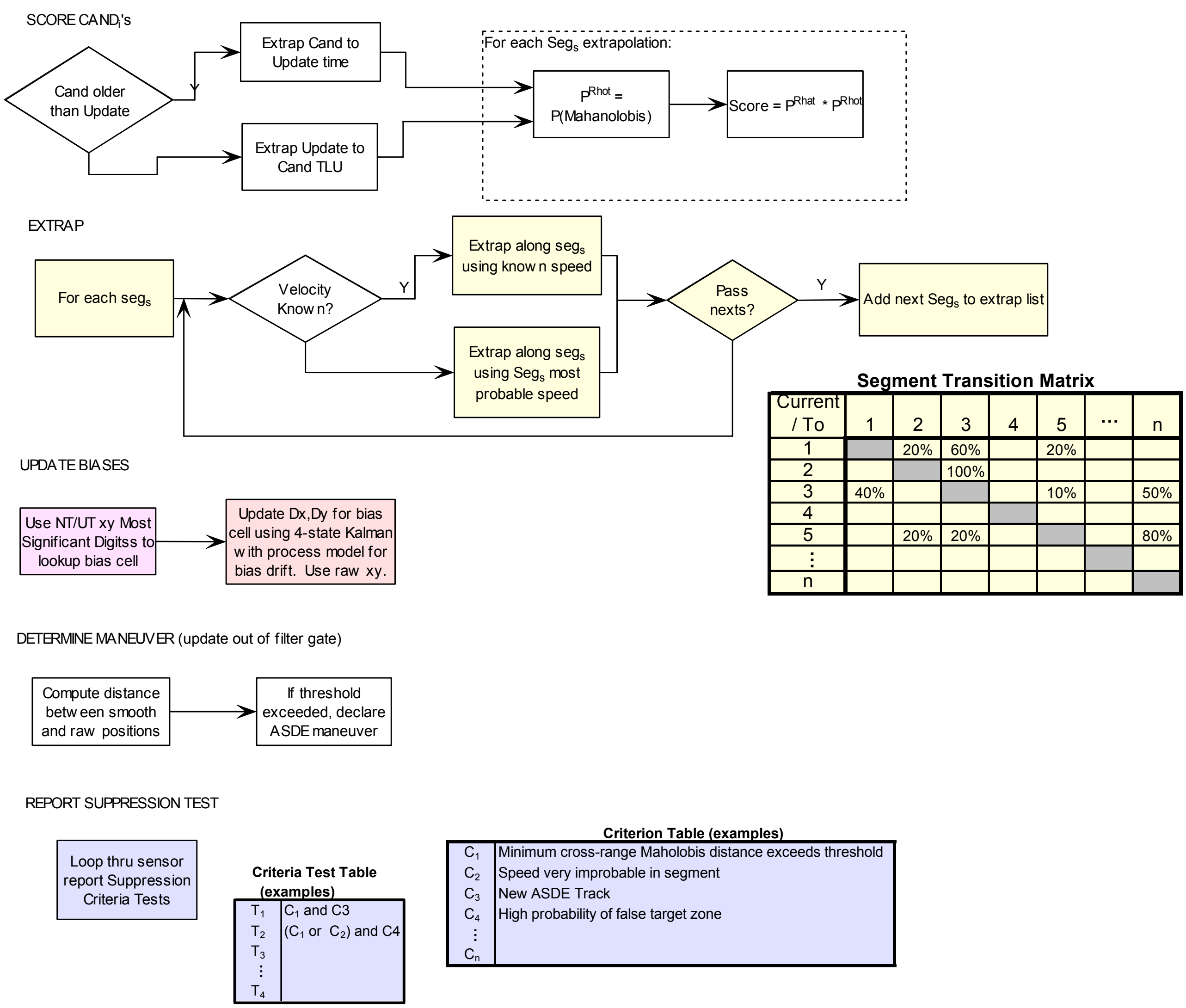


Figure 5-3. Track Correlation Functions

Copyright © Silver Bullet Solutions, Inc.
www.silverbulletinc.com

accomplished with a simple 1-dimensional 2-state Kalman with a maneuver reset.

5.3.7 Select and Assign

Various good algorithms exist for selection of candidates, assignment, or global hypothesis calculation and selection. Decision stability competes with rapid reactions, as in the prior function. These are not detailed here as further analysis of assignment versus global hypothesis formulation is needed.

5.4 ATIDS Input

This is the analog of the ASDE overall input process described in paragraph 0. Again, the overall process is largely conventional. Again, many of the functions are described in more detail in other paragraphs and diagrams. The color coding on the sensor data inputs indicates which data fields have been observed as filled versus unused in data recorded to date.

5.5 Periodic

The periodic process is necessary to monitor for tracks which have lost sensor support. Decisions are made as to whether to drop the track, meaning it is believed to no longer exist in the surface movement area, put the track in an undisplayed mode, meaning the track probably no longer exists in the movement area, or extrapolate the track, meaning the track probably does still exist but sensor inputs have been temporarily lost. The extrapolation, as in the earlier presented functions, uses the one-dimensional coordinates so that the most likely trajectory is estimated.

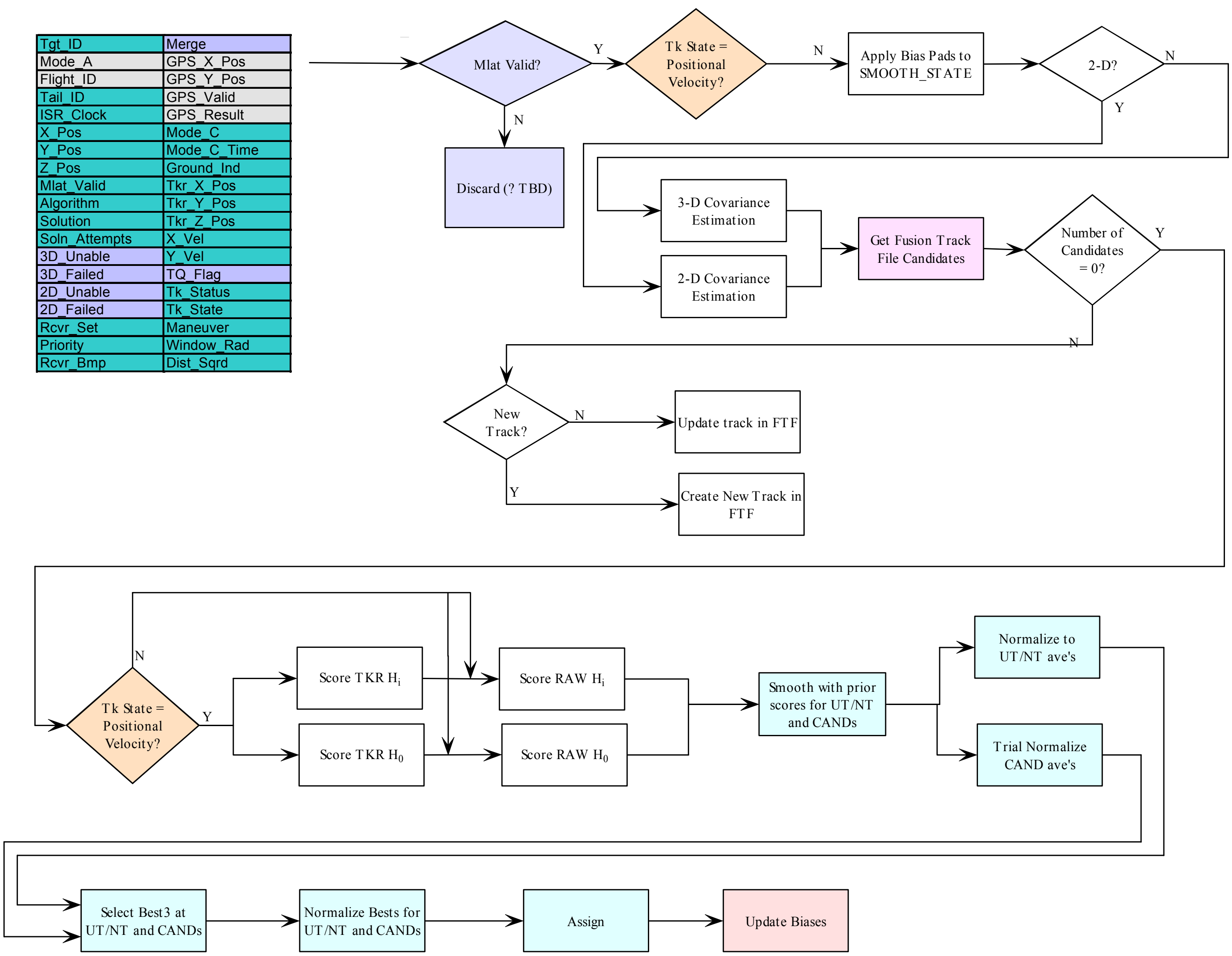


Figure 4. Overall ATIDS Input Processing

Copyright © Silver Bullet Solutions, Inc.
www.silverbulletinc.com

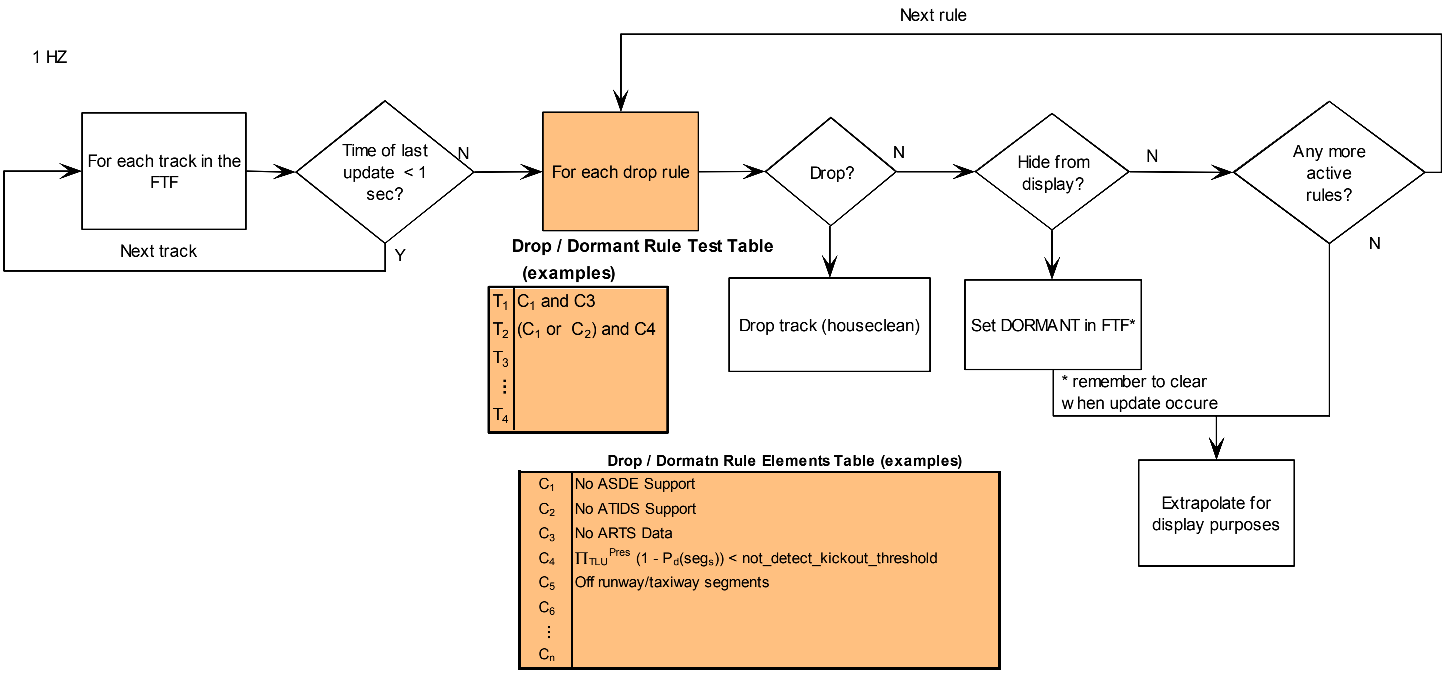


Figure 5. Periodic Processing

6. Summary

Enhanced utilization of multiple sensors in surveilling the surface regime is possible by improving the fusion processing in AMASS. Some AMASS fusion processing improvements are very simple and can be achieved in the near term while others, employing knowledge-assisted fusion, are achievable over a longer term, specifically:

- Fusion of multi-sensor data
- Intelligent tracking filter initialization and process model parameters
- Intelligent maneuvering
- Hypothesis reduction through degree of freedom reduction
- Sensor data characterization modeling
- Intelligent sensor registration
- A-priori knowledge utilization

7. References

[1] Global Information Grid (GIG) Architecture, Version 1.0, US Assistant Secretary of Defense for Command, Control, Communications, and Intelligence (C3I), 2000

[2] Nichols, M., "A Survey of Multisensor Data Fusion Systems", in Handbook of Multisensor Data Fusion, ed. By Hall, D. and Llinas, J., CRC Press, New York, NY, 2001

[3] Waltz, E., Llinas, J., Multisensor Data Fusion, Artech House, Inc., Norwood, MA, 1990

[4] Hall, D., Llinas, J., "Multisensor Data Fusion", in Handbook of Multisensor Data Fusion, ed. By Hall, D. and Llinas, J., CRC Press, New York, NY, 2001

[5] Office of the Assistant Secretary of Defense for Command, Control, Communications, and Intelligence (C3I), Decision Support Center, *Multi-INT Fusion Evaluation Study, Final Report,* 2001.

[6] Hall, D., Llinas, J.., "Multisensor Data Fusionl", in *Handbook of Mutisensor Data Fusion*, ed. By Hall, D. and Llinas, J., CRC Press, New York, 2001

[7] Steinberg, A., Bowman, C., "Revisions to the JDL Data Fusion Model", in *Handbook of Mutisensor Data Fusion*, ed. By Hall, D. and Llinas, J., CRC Press, New York, 2001

Copyright © Silver Bullet Solutions, Inc.
www.silverbulletinc.com

[8] Stein, B., Meredith, M., The Merging of the Senses, MIT, Cambridge, MA, 1994.

[9] McDaniel, D., Electronic Warfare Identification (EWID), Final Report, Space and Naval Warfare Systems Command, San Diego, CA, 1994.

[10] Efront, B., "Computers and The Theory of Statistics: Thinking the Unthinkable", in SIAM Review, Vol 21, No. 4, 10/79

[11] Huber, P, Robust Statistical Procedures, Society for Industrial and Applied Mathematics (SIAM), Philadelphia, PA, 1977

[12] Symon, K., *Mechanics*, Addison-Wesley, 1971.

[13] Naval Sea Systems Command, Program Performance Specification for Weapons Direction System Mark-14, 1985.

Copyright © Silver Bullet Solutions, Inc.
www.silverbulletinc.com