Bayes Networks for Diverse-State and Large-Scale Fusion

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Abstract -- *Generalized inference provides an elegant formulation for fusing sources that have many diverse states that are nonetheless inter-related, be it in often in weak and complex ways. Indeed, levels 1 through 3 fusion can be characterized as inferring states from evidence; estimation can be viewed as a specific inference discipline. Unfortunately, the elegant inference formulation rapidly becomes intractably complex for any real-world problems due to the permutations of inter-relationships between the interacting state variables. Bayesian networks provide a way of coping with the complexity. Bayesian networks are techniques for making probabilistic inference tractable and have been in broad literature and research for quite some time. This paper describes the application of the Bayes network technique to a real-world large-scale fusion problem. It provides experience with the many adaptations and extensions that are required and illustrates some issues that need further research.*

Keywords: Entity-Relationship Modeling, Semantic Network, Inference Network, Data Fusion

1 Fusion and Inference

To effectively utilize ELINT/ESM parametric data reports the incoming data must be correlated with reports from other SIGINT sensors and must be processed to estimate the platform type identification, kinematics, and other behaviors associated with the emissions. ELINT/ESM parametric reports typically contain emitter frequency, pulse repetition frequency (or interval), pulse width, scan period, scan rate, modulation type, scan characteristics, and so forth. The kinematic components of the reports are typically area-of-probability (AOP) ellipses representing a some agreed-upon confidence area (e.g., 90%) or bearing-only reports, perhaps with some indication of bearing accuracy. These reports present two major challenges. With respect to the parametric data, depending on the completion and accuracy of the parametric information, the parametric density of possible emitters, and the completeness and ambiguity inherent in the EW reference database (e.g., EWIR), a wide variety of ambiguity in the emitter and platform type identifications may be possible because many emitters operate in the same parametric space. With respect to the kinematic data, ambiguity occurs due to the inaccuracy or incompleteness of kinematic data. For example, ELINT reports typically contain only 2-D positional data with no altitude or velocity estimate. In target dense environments, there may be many actual targets within the 95% confidence region about the area of probability ellipse or line of bearing.

Human analysts resolve the ambiguities using a wide assortment of clues and knowledge bases in an inferential reasoning (e.g., deductive, abductive, probabilistic, ...) process that is akin to detective-type reasoning. Many aspects of this process cannot be mimicked by artificial systems at this point in technologic evolution. The human knowledge base is vast, drawing upon years of accumulated information and associations. Also, reasoning methods and their combinations and pattern processes are not fully understood. However, artificial computation can provide enormous aids to, and for some processes, substitution for human SIGINT correlation and fusion. This arises from the ability to consider available knowledge bases thoroughly and perform massive amounts of precise mathematical computations. The proposed research topic herein focuses on this major payoff area with specific focus on Bayesian network techniques for inferential reasoning. QuesTech has built a limited Bayesian Network workstation for ELINT and ESM sources with a knowledge base developed from EWIR, EPL, Kilting, MIIDS IDB, and the ONI characteristics and performance database. The proposed research is to perform minor tailoring of the algorithms, databases, and sensor types to Rome Laboratories requirements, to develop measures of performance and test scenarios, to conduct performance testing, fine-tuning the algorithms, and to analyze the performance results in order to determine the potential benefits of this paradigm for SIGINT correlation and fusion. The following subparagraphs provide a brief overview of Bayesian networks, their potential application to SIGINT fusion and correlation, a brief description of the QuesTech EW Identification workstation, and the proposed MOE analysis.

1.1 Bayesian Networks

Bayesian networks are techniques for making probabilistic inference tractable. Traditional expert systems are extensional, with all the information for propagation locally available from local immediate antecedents. This makes them quite tractable from a knowledge base and computational aspects. However, this tractability comes at a significant cost in intelligent reasoning power. Consider the case of a signal “S1” emanating from a target for which the parametrics match reference database min/max intervals for emitter type A and emitter type B on platform types X and Y, respectively. In a traditional expert system, emitter types A and B and platform types X and Y would be activated according to the strength of the sensor information and pre-determined propagation formulas, regardless of information from other sensors. For instance, IFF, SAR/ISAR, or other signal information (“S2”) may be associated with the target that could render platform type Y impossible (or unlikely). The rules S1 > B > Y, which on the surface are analogous to P(Y| B) and P(B| S1), cannot convey P(Y | B) and P(B | S1, S2). The probabilistic, or intensional scheme, however, becomes intractable if one has many dependent clue types since n! joint probabilities need to be specified. Bayesian networks make the probabilistic method tractable through intermediary nodes that convey all the dependent joint probability information while localizing the considered clues as is done in the extensional systems. An example of a possible Bayesian network for a multi-sensor data fusion application is presented in the next paragraph.

1.2 Application of Bayesian Networks to SIGINT Fusion and Correlation

Bayesian networks are applicable to SIGINT fusion and correlation in two primary ways: for signal emitter type and platform type identification and for multi-source correlation. Identification is applicable because it is an inferential process for clues (signals) to conclusions using knowledge about what signals can be caused by platforms and their emitters. Multi-source correlation is applicable because of its high degree of intensionality. That is, more than just spatial information needs to be considered. For example, detection of a signal that is likely to be emitter type A known to be installed on platform type X that also carries emitter type B increases the probability of an correlation when a signal is detected that is likely to be emitter type B. Conversely, the likelihood of the correlation reinforces that probability of the second signal being from emitter type B. Or consider the case when the SIGINT reports are instantaneous or contact reports, not track reports, that must be tracked (e.g., with some Kalman variant) to smooth out noise, estimate other state variables not directly measured (e.g., velocity), and allow time extrapolation (backward or forward) for time-synchronous correlation comparisons. If the measurements are bearing-only, typical for ESM and many SIGINT systems, the platform range can be estimated based on likely emitter and platform types using known emitter power ranges, seeker turn-on ranges, known platform altitude envelopes, horizon limitations, etc. However, the tracker outputs will influence the identification results. This type of circular dependency is difficult, if not impossible, to handle in standard extensional systems. A depiction of a possible application of Bayesian networks to multi-source fusion is shown in Figure 1.

Because identification is a component of an overall fusion process, EWID design and the research innovations must be viewed in the context of fusion. Therefore, as a preface to the EWID design and innovations, the following subparagraphs provide a brief overview of fusion and the role of identification within the overall process.

2 Fusion Techniques and Tools

Developing improved methods for identification estimation is intricately and synergistically related to the employment of data fusion concepts[hal1]. More accurate and complete knowledge of what something is contributes to making decisions about what things go together and how, in fact, how things may behave and, possibly, where they might be expected to go. The converse is also true: knowledge of what things go together, how they are behaving, and where they are often aids identification estimates performed by humans (i.e., exploitation of kinematics and behavior for identification). Despite the mission importance and the integral potential for fusion, currently fielded data fusion systems oriented to identification have not employed formal estimation techniques nor explored the combined use of estimation and AI. IFF systems are typical of fielded identification systems. There are a number of data fusion <u>prototype</u> systems that attempt to perform identification estimation beyond IFF. About 30 systems involve semi-automated situation assessment. However, the systems which address the EW identification problems are typically merely pattern recognition systems which utilize neural networks or other pattern classifiers [hal2].

One may speculate one reason for the is the shortfall in fielded identification systems is the large amount of sometimes subconscious data and complex inference used by humans in making identification decisions relative to current limitations in machine capabilities for this type of reasoning. Identification estimation done by humans is not strictly formulatic but, instead, resembles investigative "detective" work. Humans perform "approximate reasoning". That is, they have the ability to reason with uncertain data, vague concepts, and to determine patterns in noisy/incomplete environments. There are various approaches used to emulate such reasoning including probabilistic reasoning (e.g., Bayes, Dempster-Shafer, Generalized Evidential Processing Theory), fuzzy logic, automated pattern recognition via neural networks, etc. No single techniques "solves the problem," but several may be used in combination to address a specific problem. Therefore, in our EWID research, we have not felt compelled to adhere to specific techniques, but to use whatever technique might improve the identification estimate. This "data fusion toolbox" approach, depicted in Figure 1[1], is necessary to mimic the patterns of human identification reasoning, in some sense, then, a phenomenological approach.

[1] Variation on taxonomy of algorithms developed in [kess].

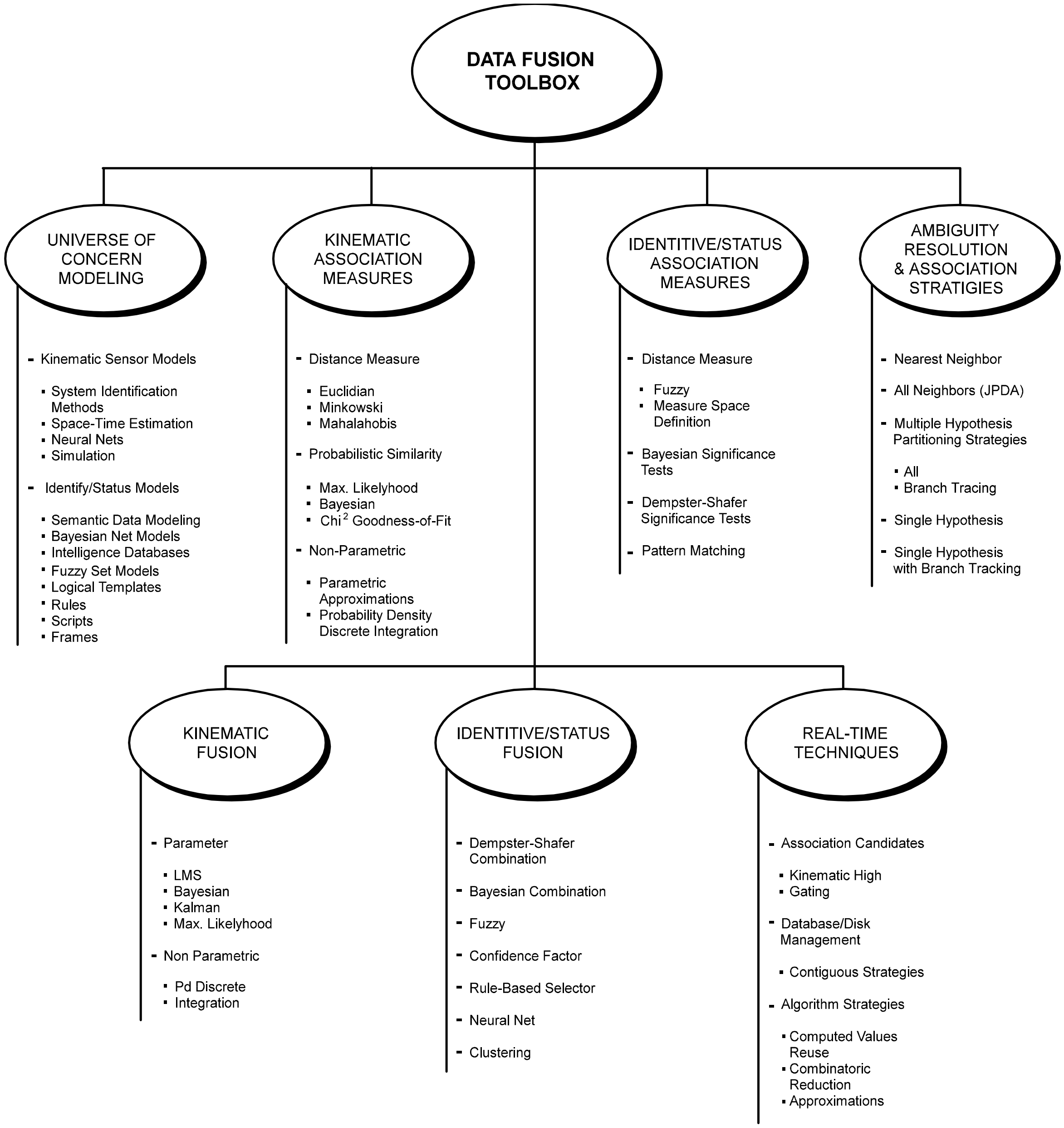


Figure 1. Data Fusion Toolbox

2.1 Fusion Architectures Overview

As with most new disciplines, lack of standardized terminologies and paradigms hampers communication and community teamwork. Initiating efforts to resolve this problem, the Joint Directors of Laboratories (JDL) Data Fusion Group (DFG) have defined four levels of data fusion, very briefly described herein. The reader is referred to [walt] for more involved discussion.

Level 1 fusion - This process combines location, parametrics, and identity information from multiple sensors and sources to achieve refined estimates of the identity and location of individual objects (e.g., emitters, platforms, weapons, or geographically constrained military units).

Level 2 fusion - Dynamic development of a description of current relations (i.e., situation refinement) among objects and events in the context of their environment. This process assesses functional, causal, temporal and environmental relationships to determine the "meaning" of the battlefield situation.

Level 3 fusion - Threatre refinement projects the current situation into the future to draw inferences about enemy threats, intent, lethality, friendly and enemy vulnerabilities, and opportunities for operations.

Level 4 fusion - This metaprocess monitors the overall data fusion processing to provide information about real-time control and long-term performance improvement. Level 4 processing determines the source-specific data requirements needed to improve the multi-level fusion process. In addition this process allocates and directs resources to achieve mission goals.

Systems of today are primarily at level 1 where the problem is relatively "closed form" and rigorous mathematical derivations have been effective. The higher levels, however, are more subjective and require the combined application of numeric and symbolic methods to effect automated method for approximate reasoning.

At Level 1, two prevalent opposing characteristics of fusion architectures are sensor vs. data fusion and centralized vs. distributed [bar1, blac]. Universally accepted distinctions between sensor and data fusion do not exist. However, general opinion is that sensor fusion: 1) is close to the raw sensor data processing, 2) is real-time, 3) is short range, 4) is cross-disciplinary, and 5) involves sensor cueing. Data fusion, on the other hand, is: 1) multiple similar and dissimilar sensor, 2) theater-wide, and 3) database and INTEL aided. Coherent architectures integrating both sensor and data fusion features are not prevalent, due somewhat to the existence of two technical communities.

In distributed (or federated) architectures, each sensor processes its inputs to form target state estimates which are then processed by a multi- sensor fusion processor. In a centralized architecture, the raw sensor data from each sensor is processed by a central processor. Centralized data fusion has theoretically better performance than distributed fusion because there is not information loss from the sensor to the fused product. There are rather limited numbers of comparative studies. Nevertheless, there are empirical results which confirm the improved performance of centralized processes and the notion of improved performance as fusion occurs ever close to the sensors. In distributed fusion, data are compressed (i.e., sensor data are represented by a state or identification vector) resulting in less information (viz, the statistics of the raw data are either unavailable or only approximated via a covariance matrix) at the fusion process. However, it may not be possible to perform centralized fusion due to communications bandwidth limitations (between the sensor sand central processor) or noncommensurate sensors (i.e., sensor data may be required to be transformed into state parameters to admit fusion). Also, centralized architectures have not been prevalent because implementation often requires getting access to near-sensor signal processing operations, a step that is often infeasible due to either political or technical constraints.

There may also be hybrid strategies for fusion architecture that take appropriate elements from the various architectures. For instance, an architecture could be two-layer with the sensor layer providing discipline expertise in the processing of the raw sensor data to a partial target state followed by a sequential observation multi-sensor multi-disciplinary fusion process that would utilize databases and INTEL. Rationale for such an architecture is that processing of, for example, raw image data is fundamentally different from processing of raw ELINT/ESM data. Also, correlation of multi-sensor ELINT/ESM is best accomplished using discipline-specific observation features (e.g., frequency, pulse repetition interval, pulse width) as well as knowledge of the final target fusion estimate. An important element of such an architecture that overcomes some of the disadvantages of current non-centralized architectures would be feedback from the final layer to the sensor layers to cue detections and to provide final target states to all processes so that all processes know the system's best estimate. Also the communication paths might allow discipline-specific processes to communicate their unfinished or partial data with each other, thus allowing quick responses and occasional bypassing of assumptions such as the assumption of constant velocity, common in many statistical trackers. This concept is illustrated in Figure 2. In some sense, the concept depicted in this figure is analogous to a blackboard architecture in AI, since individual sensor-specific domain knowledge is applied, followed by global knowledge.

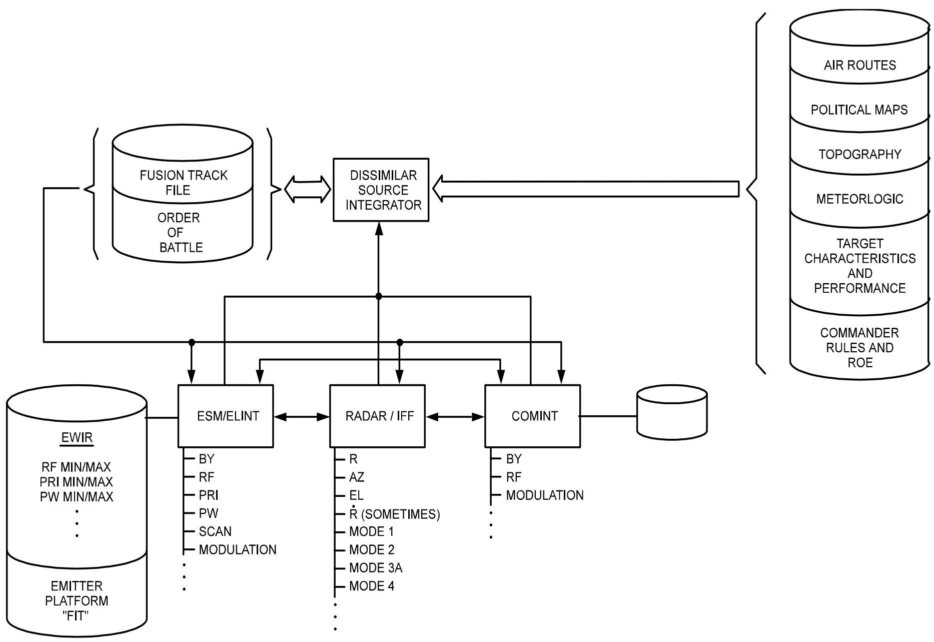


Figure 2. Layered Sensor/Data Fusion Architecture for Level 1 FusionRole of Identification in the Overall Fusion System

An improved EW identification function is a component of an overall fusion system. Identification estimation, the subject of this SBIR effort, can greatly aid the overall fusion process. Each discipline (e.g., COMINT, IMINT) applies its domain-specific expertise (e.g., demodulation and nodal analysis, pattern recognition and model construction). They then fully communicate their conclusions, not as a single answer, but with the certainty estimated for each identification element. These identification estimates can then be used with the kinematic estimates and other inferential knowledge, rules, etc. to make final multi-discipline identification and fusion decisions.

3 Design of an ESM/ELINT Inference System

3.1 Overview

First, input EW classical parameters (RF, PRI, etc.) reports are normalized to a common "superset" format, the Sensor Track (ST) format. In this process, a model of the sensor characteristics is used to estimate variance parameters not provided by interfacing systems. Next the EW parameters are used with an innovative candidates determination technique that determines candidates without searching the database. This scheme allows near instantaneous mode candidate determination. The candidates are further pruned according to compatibilitly of discrete parameters.

The next 6 steps accomplishe the recursive Bayesian net, a powerful probabilistic reasoning method we researched for accomplishing machine intelligence. If the report is not indicated by the sensor system or an association process as corresponding to a previously reported track, a-priori values must be computed. In experiments prior to this SBIR, we had computed a-priori's in a pre-run process. We chose to compute them dynamically in the SBIR to research the added benefit of using more localized probability universes. This is partly necessary due to the large surveillance ranges that might be required, having perhaps vastly different region-by-region a-priori's. This approach is also required because the OB is dynamic, not static, this is it evolves or is "learned" as the prototype runs. This is in contrast to currently deployed systems where OB is a static file, updated from an ashore INTEL

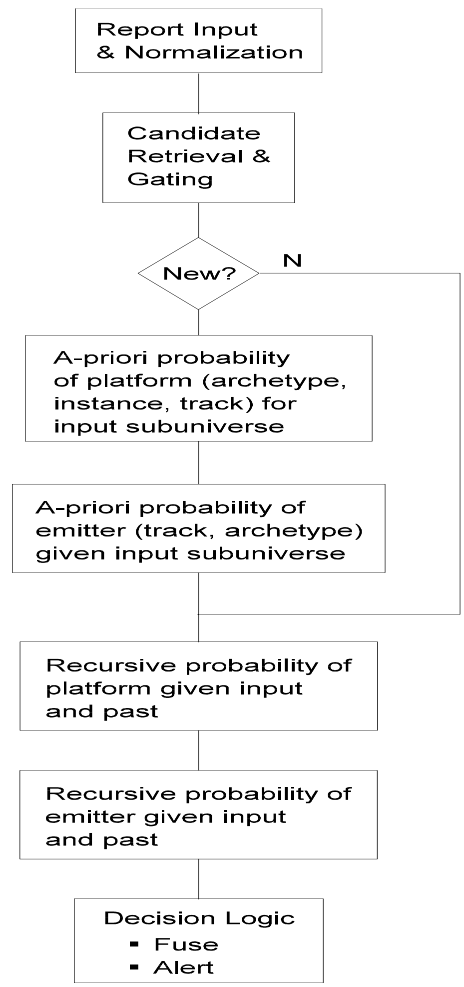


Figure 3. Design Overview

center (e.g., AIC) periodically (e.g., quarterly). Dynamic a-priori's are computed for platform and emitter candidates using OB, Characteristics and Performance data, and other parameters.

The next steps are recursive probability calculations using the just-computed a-priori's and the values in the track file that were computed on a previous update cycle. In addition to OB, C&P, and the other parameters, this process uses the EW library and interpretive models of the meaning of the library parameters.

The output is an identification vector for each target, conveying probability estimates for the target of the emitter and platform. The knowledge base is derived from various Navy Warfare Tactical Data Base (NWTDB) standardized sources[2]. The databases are structured and utilized as a-priori knowledge bases of emitter parametric ranges, emitter-platform fit, Order-of-Battle (OB), Characteristics and Performance (C&P), and terrain[3]. Other sources such as Military Integrated Intelligence Data System (MIIDS) Integrated Data Base (IDB)[4], DMA Air Routes, and flight schedule databases are planned to be used to provide additional or more complete knowledge.

In this section, we present a more detailed level of description. The design for the EWID prototype is a shown in Figure 3. This figure shows only the core process for identification. Not shown are processes for NERF preprocessing, geotailoring, and loading, TADIL-J taxonomy linkage to DIA, simulators, and tactical display. The major functions shown in Figure 3 are described in the following subparagraphs.

3.2 Parametric Candidate Selection and Gating

As can be seen, the primary gating criteria for all ESM and ELINT reports is waveform parameters. This "gating" is by virtue of the bitmap retrieval scheme which instantaneously retrieves RF, PRI, SCAN_CHR and MOD_TYPE candidates which are then logically "ANDED" to create the final candidates list. We chose this as the first discriminant over kinematics because, for ESM and ELINT, waveform parametrics will normally be more discriminating[5]. However, a kinematic hash subsequent to the parametric hash may be added later in EWID development if necessary for real-time requirements.

The mode/ST candidate bitmap is then decoded into a scratchpad ST and ST-ST candidacy links. This function uses the same utilities for ST-ST link maintenance as are used in other parts of the programs. Scoring begins by chaining up the ET-ST and IT-ET physical links to identify IT candidates linked to the ST candidates. Of course, multiple IT's per ST candidate are typical; even multiple ET's per ST are typical.

3.3 Kinematic Probability Scoring

For IT-ST kinematic scoring, the input ST kinematic data (LOB or AOP) is converted to a discrete PDF. LOB conversion considers the sensing origin, max detection range of that sensor against the ST candidate's Maximum Effective Radiated Power (from NERF), horizon versus altitude of the linked IT candidate, and seeker-turn-on-range for active weapons IT candidates. Time since initial detection by that sensor (if the ST report is a coherent track report) is also used to "count down" the approximated initial ranges.

IT-ST scoring recurses if the IT is an archetype, thereby necessitating estimating its probability density about its host ship, aircraft, or airbase. For ships that have not been detected by a sensor but could be within surveillance range according to NOB, an expected max range from homeport is looked-up based on IT TADIL-J Specific Type, or if the Specific Type value is NS, the next level up, Platform[6]. For weapons,

[2] NWTDB is the Navy data and message standardization process for warfare systems, tactical, INTEL, etc. Its components include: Characteristics and Performance (C&P), Electronic Warfare, Order of Battle including facilities and sites, Cryptologic, Meteorological, Mapping. It is directed by [cno3].

[3] DMA World Vector Shoreline (WVS) being used in Phase I for display only. Terrain tailoring of probability density functions (described later) would ultimately benefit from Digital Terrain Elevation Data (DTED) or equivalent considerations.

[4] MIIDS IDB is the authoritative OB and facilities and sites database from DIA. Its size is roughly 3.5 Gbytes.

[5] Particularly true for ESM bearing-on (LOB) reports

[6] Hierarchical defaults are used throughout to accommodate incomplete INTEL data, an almost fundamental characteristic of INTEL databases.

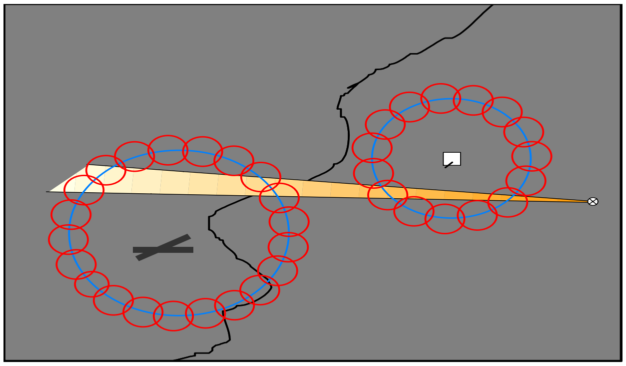


Figure 4. Knowledge Base Weapon Uncertainty Region

NID max-salvo-rate and max-range values are used along with other detected launches from the firing platform and the firing platforms weapons loadout (in NID and NERF). If the weapon candidate is launched from an aircraft, the PDF must also be iterated against the aircraft's max-combat-radius (from NID) from any airbase linked to the aircraft (via IT-IT links) that are within the kinematic gate of the reported ST, extended to account for aircraft and weapons radii. If the IT candidate is a track, then its PDF must be propagated (forward or backward). A real-time algorithm for this propagation is an area of continuing research. If history exists, backward would be the choice. Exceptions and large uncertainties in many of the input values are tolerable to the algorithms because they do not have a sensitive response to small variations. Despite uncertain or incomplete data, inclusion of these factors provides an advantage over current approaches which, in effect, assume uniform distributions and total pre-engagement ignorance.

Once the PDF's are generated and aligned, they are scored by taking the multiple sums of the products of the overlap discrete PDF elements:

$$\sum_i \sum_j PDF_1(x_i, y_j) PDF_2(x_i, y_j)(\Delta x_i \Delta y_j)^2$$

This involves determining a set of summing intervals for each degree of freedom that is the superset of the ST report and IT candidate discrete PDF intervals. (We did this already for parametric scoring in the demonstrator EWID.) The result requires no normalization -- it is the probability that two such PDF's could be manifested from the same target.

As the ET-ST, IT-ET, and IT-IT recursions pass back values, they are combined according to conditionalization (total probability) and Bayesian inversion rules. In the process, previous pass values will be invoked. For the first score of an ST against an ST, ET, IT-ET, or IT, a-priori values must be used. Since a-priori values have meaning only within a specified universe, we take the universe as small as possible (3σ), resulting in dynamic "on-the-fly" a-priori's. This is in contrast to current identification and fusion systems that compute a-priori's pre-runtime. Our research led us to this approach when we looked into the universe size to be used for a-priori's. Since we anticipate a 2000 nm radius surveillance volume, we expect the a-priori's to vary significantly over the surveillance volume. It seemed best to choose as the universe for a report the smallest universe that we can be reasonably confident will always contain the track.

3.4 Parameter Probability Scoring

The parameter score is relatively easy since recursion through the ET's and IT's is not required, just scoring to the candidates the scratchpad ST holds. If the candidate ST is a mode, the min/max intervals are converted to 2σ discrete Gaussians (7 intervals currently). For ST tracks, it is planned for the history of hits will be maintained using some form of fading memory, state-transition detection, etc. The two sets of discrete PDF's are integrated in a similar manner to the kinematic integration. Missing parameters are handled using the geometric mean of the available parameter scores, the equivalent of χ^2 additive doping factors or multiple thresholds. Discretes are checked for compatibility using compatibility tables. Of course, presence of a parameter in one track/mode while it is Not Applicable in the other is cause for disqualification. Like the kinematic scores, the ST-ST scores are combined with a-priori's and, using conditionalization and inversion rules, the final set of ST-ST, ST-ET, ST-IT, and ST-ITET probabilities is formed. These are maintained for display, decision logic, and next pass recursion.

3.5 Decision Logic

Decision-making logic planned for Phase II is by multiple uni- and bi-modal thresholds for Semi-auto and Full-auto modes. However, since multiple ST's can be linked to an ET and multiple ET's can be linked to an IT, it is necessary to form a composite of the multi-source tracks to get a decipherable set of candidates for each IT and ET track. (Even if the ST had no identification candidates, it would result in a new ET and new IT linked to it.) This is done using ST composite scratchpad ST's in which to generate the composites for each ET that may be linked to an IT (currently parameter-wise max'd at 10). Composites are not maintained, they are generated only for decision making, either automatic or semi-auto. More sophisticated ambiguity resolution and decision logic schemes, along the lines of the "happy marriages" scheme we use for MTRACS, will be researched in Phase II.

If the mode is semi-auto or either of the auto-thresholds fail, the operator is notified of an identification ambiguity requiring more intuitive or subjective judgment. Our intention is to give the operator some level of control over the thresholds resulting in notification so he can level his workload or, alternatively, his confidence in the automatic algorithm. Of course, we could also monitor for overload indications such as alert queue backup.

Upon selection of an alert, the operator is presented with summary data on the IT with buttons for exploring its linked IT's and ET's, each resulting in popups. From the ET popups, ST's can be called up. Candidates are shown in scrolling lists in order of probability. A photograph of some of the popups for the pre-SBIR demonstrator is shown in Figure 8 and Figure 9. EWID displays the most probable Category, Platform, Specific Type, DIA platform, and Emitter types initially. As the operator scrolls the lists of candidates he wishes to explore and takes the select action, the hypothesis hierarchy tree switches to the selected branch. This is done using a variant of the composite scratchpad ST's called constraint scratchpads[7]. However, if the operator should need to see all the candidates, rather than just a branch, EWID provides an "ALL" button that displays all Platforms, Specific Types, DIA platforms, and Emitter types in probability order. The "ALL" display is just a text widget, not a scrolling list except for Emitter type. The reasoning for treating the emitter type differently was that for the highest ranking DIA platform, there would be few Emitter type candidates in the branch display. The operator, when analyzing a track from the emitter point of view, probably wants to know all the Emitter type candidates, not just the ones for the best platform. When the operator selects an Emitter type from the "ALL" popup scrolling list, the branch display then shows the highest branch given

[7] Meaning the operator selection imposes a constraint on the normal ranking logic.)

the selected Emitter type. Each popup has confirm buttons for confirmation of the identity candidate. When a low-hierarchy element is confirmed (e.g., specific type), the implied upper taxonomy levels are automatically confirmed.

3.6 Fusion

Upon an identification decision, whether automatic or semi-automatic, a number of adjustments take place. The hooked IT is merged into the selected candidate along with its linked ET's and their linked ST's. Kinematics are fused at the IT level. Parameter min/max's are updated in the ET for display purposes only -- the linked ST's fully convey the parameter data for identification and fusion purposes. If the candidate ET or IT is an archetype, its OB count is decremented. The most likely airbase or weapon launcher is used for aircraft and weapons. The archetype characteristics are then inherited by the track. For ET's, all the concurrent or transitional modes are inherited according concurrent and transitional groups of modes as indicated in the ET-ST links. The inherited modes will be indicated as dormant or undetected but will be available to match future incoming reports. The mechanism for the inheritance is to add links to the single mode records. Similarly, for IT's, IT-ET links are added for the undetected emitters so that if they should be detected, the IT track will become an identification/correlation candidate.

As this brief description should show, the candidacy and physical link structures and utilities play a continuous role in EWID. With this foundational effort completed in Phase I, many experiments can be run in Phase II.

4 Innovations

In the preceding section, the EWID design was described. In this section, we describe the innovative aspects of the EWID research. EWID research has and continues to encompass a judicious blend of experimental innovations with standard modern fusion concepts. The major innovations are:

- *Identification as an Estimation Problem*
- *Order-of-Battle and Surveillance Fusion*
- *Real-Time Recursive Bayesian Net Inference Algorithm*
- *ESM/ELINT/OB Fusion Knowledge Engineering*
- *Non-Gaussian Statistical Scoring*
- *Combined Identification and Kinematic Estimation*
- *Multi-Source Fusion*
- *Ambiguity Resolution*
- *Special Clues*
- *Real-Time Considerations*

Each of these innovations are described in the following subparagraphs.

4.1 Identification as an Estimation Problem

Owing to the success of state estimation theory in target tracking and other applications, we researched analogous formulations for the identification problem. State estimation typically addresses continuous state variables. The variables are always defined in metric space[8] [epst]. We introduced the notion of defining a metric on the discrete identification space in [nos1] and will research this fully in Phase II. In this view, identification vectors are analogous to continuous variable state estimates and covariances. To see this, consider a single dimension continuous variable. Its state estimate and 1-element covariance matrix convey the same type of probabilistic information as an identification vector. In fact, the continuous variable state estimate and covariance could be approximated as a probability vector by defining each vector element to correspond to an interval in the variable space and with probability values in the vector corresponding to the probability mass in that interval. In the EWID research, we attempt to draw parallels between the mathematics of these identification vectors and the standard mathematics of state estimation theory.

EWID Phase I produces an identification vector with ranked probabilities for emitter and platform type as shown in Figure 5. The emitter type is categorized per ELNOT. The platform type is categorized as per DIA OB:

- EOB/GOB/MOB: specific lat/long site
- NOB: specific hull
- AOB: specific airbase
- A/C: aircraft model to alpha modifier
- Weapons: model to alpha modifier

Category Platform Specific DIA
Type OB

$$\begin{bmatrix} 0.9 \\ 0.1 \\ 0.0 \\ 0.0 \\ 0.0 \end{bmatrix} \left\{ \begin{matrix} air \\ surf \\ sub \\ land \\ space \end{matrix} \right. \quad \begin{bmatrix} 0.20 \\ 0.10 \\ 0.09 \\ 0.01 \\ 0.00 \\ 0.00 \\ \vdots \end{bmatrix} \left\{ \begin{matrix} fighter \\ bomber \\ attack \\ transport \\ AEW \\ EW \\ \vdots \end{matrix} \right. \quad \begin{bmatrix} 0.00 \\ 0.33 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.10 \\ 0.00 \\ \vdots \end{bmatrix} \left\{ \begin{matrix} F\ 5 \\ F\ 14 \\ F\ 15 \\ F\ 16 \\ F\ 18 \\ F\ 111 \\ F\ 117 \\ MIG\ 21 \\ MIG\ 23 \\ MIG\ 25 \\ MIG\ 27 \\ \vdots \end{matrix} \right. \quad \begin{bmatrix} 0.33 \\ 0.33 \\ 0.33 \\ 0.00 \\ \vdots \end{bmatrix} \left\{ \begin{matrix} F\ 14\ A \\ F\ 14\ A+ \\ F\ 14\ C \\ F\ 14\ D \\ \vdots \end{matrix} \right.$$

Kinematic State Covariance Estimate Matrix

$$\begin{bmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{xz} & \sigma_{x\dot{x}} & \sigma_{x\dot{y}} & \sigma_{x\dot{z}} \\ & \sigma_y^2 & \sigma_{yz} & \sigma_{y\dot{x}} & \sigma_{y\dot{y}} & \sigma_{y\dot{z}} \\ & & \sigma_z^2 & \sigma_{z\dot{x}} & \sigma_{z\dot{y}} & \sigma_{z\dot{z}} \\ & & & \sigma_{\dot{x}}^2 & \sigma_{\dot{x}\dot{y}} & \sigma_{\dot{x}z} \\ & & & & \sigma_{\dot{y}}^2 & \sigma_{\dot{y}z} \\ & & & & & \sigma_{\dot{z}}^2 \end{bmatrix}$$

Figure 5. Identification Vectors and Kinematic State Estimate Covariance Matrix

[8] A metric space, A, is one in which is defined a function ρ ∍ ∀ x, y ∈ A: (1) ρ(x, y) > 0, (2) ρ(x, y) = 0 iff x and y are identical, (3) ρ(x, z) < ρ(x, y) + ρ(y, z). [epst]

4.2 Order-of-Battle and Surveillance Fusion

Current ESM and C3I systems maintain Order-of-Battle (OB) as a semi-static file, independent of the track file (e.g., JMCIS, SLQ-32). This causes a schism in the systems knowledge bases as the encyclopedic pre-deployment OB becomes asynchronous with the surveillance track file. In the Phase I research we took the revolutionary approach of combining the OB file and track file into one coherent file. This involved initializing the track file with OB data. Part of the challenge was to find a common conceptual data model for OB, composed of NOB, AOB, EOB, aircraft, weapons, and their relationships, and surveillance tracks. Some OB elements, aircraft and weapons, are archetypal, not actual instances of aircraft or weapons. Aircraft archetypes are related to the actual individual aircraft via linkages to airbases, with the linkage indicating how many of that type of aircraft are typically located at that airbase. Then correlated surveillance reports are used to update OB data or instantiate OB archetypes. This has had enormous implications from knowledge engineering, inferential reasoning, and software engineering vantages.

This approach furthers the blurring of the distinction between INTEL and surveillance, a trend that increasingly benefits warfighters. In this case, the blurring is due to the fact that OB is based on some form of reconnaissance, analysis, or other intelligence surveillance at some point in time. INTEL is treated as merely previous surveillance. By capitalizing on the vast investment in everyday INTEL RECON, S&T analyses, etc., EWID's track picture is initialized with a comprehensive knowledge of the theatre of operation. Correlating surveillance against this a-priori track file is equivalent to identifying targets to a defined taxonomy since the OB defines the identification universe. ***Identification and correlation are accomplished by the same process.*** Additionally, this approach enables:

- ***Tactical EOB***. A dynamically adaptive EW "library" and EOB. Conventional ESM systems use pre-engagement EW libraries to identify contacts. EWID uses received ELINT as well as pre-engagement INTEL. The use of ELINT provides the parameter ranges actually being used by a platforms emitter instead of the generic ranges found in libraries. Also, use of ELINT provides better locational information over the general locations available via OB so that the more informational maximum a-posteriori likelihoods can be used instead of the conventional maximum likelihoods.
- ***Order-of-Battle Accounting***. The INTEL database is the initial track database, with sensor reports used to discover or account-for the pre-engage INTEL.
- ***Inheritance*** of archetype properties on instantiation even if there is no current sensor data detecting those properties. This allows for recognition of those properties as potentially belonging to the instantiated track if they do manifest themselves.
- Kinematic scoring between surveillance and ***OB kinematic information***. This is made possible a knowledge structure using C&P and other parameters to transform OB data to surveillance expectations.

- ***New track hypotheses*** can be based on local region populations suggested by OB that have not yet been accounted for by previous surveillance reports. This consideration allows the a-priori probability of target types (e.g., Mig-29, Mirage F-5) to vary geographically according to OB and other parameters. In currently deployed systems, the expected target density is static and uniform over the entire surveillance volume. EWID allows it to be more accurate: vary in time and by location and by non-kinematic parameters. This technique provides a way not only to update OB, but also to use OB as a universe for which surveillance reveals expected items. This is much more knowledgeable than conventional likelihood methods which use default uniform target density values for the entire universe of operation.

A key element of classification and identification processes, whether man or machine, is the use of a-priori knowledge databases. Human tactical analysts do not make fusion decisions based merely upon the sensor inputs. In subtle ways they consider INTEL, target characteristics, known adversary tactics, battle condition, etc. Databases exist that convey aspects of this information, most of which are within the "umbrella" of the Navy Warfare Tactical Data Base (NWTDB) database standardization program. These include the Naval Emitter Reference File (NERF), Navy Intelligence Dataset (NID), Military Integrated Intelligence Data System (MIIDS) Integrated Data Base (IDB), DMA DAFIS air routes, Joint Munitions Effectiveness Manual (JMEMs), and others such as JOPES, SORTS, and so forth. In EWID Phase I, we use only NERF and NID. As new INTEL or surveillance manifests itself, we in-effect update these databases by virtue of their inclusion in the track file and the consequent updates there. As more exotic knowledge is required for fusion, knowledge representation becomes a challenge. Technologies such as fuzzy sets could provide expressive power to the existing database technologies for data dictionaries (e.g., fuzzy data element definitions for such status as unit morale).

4.3 Recursive Bayesian Net Inference Algorithm

The core of the EWID approach is the recursive Bayesian algorithm applied as a series of Bayesian Net links using the an actual EW parametric database and the Order-of-Battle (OB) database. Bayesian nets are the state-of-the-art in probabilistic inferential reasoning (i.e., machine thinking). This provides a recursive maximum a-posteriori probability computation exploiting a-priori INTEL information such as OB and C&P and refining estimates over time and over multi-sensor ESM/ELINT updates. Bayesian techniques have been known as applicable to AI nearly since its inception. However, they were considered intractable for complex applications, requiring knowledge of too many joint probability distributions [char, barr]. The Bayesian net provides a methodology for modelling the probabilistic dependencies in the real-world problem space, thereby often enormously alleviating the requirements for joint probability knowledge.

We chose to research the Bayesian net because it allows us to build a model of the identification process that resembles human identification thinking. Additionally, the recursive algorithm is the discrete non-metric-space analog of a zero-process-noise

Kalman filter[9], thus encouraging our interest in generalizing the estimation problem, as we discussed previously. The recursive probability approach also has the desirable property that ambiguity decreases monotonically with updates. Also, Bayesian nets provide a basis for the representation of explicit knowledge, unlike techniques such as neural networks which are used to represent knowledge which is not explicit (i.e., pattern recognition).

We modelled the EW, OB, surveillance, and identification hypothesis domain using semantic net concepts. This net becomes a Bayesian net by attributing probability formulas for traversals through the net. The relationships encoded in the NERF (or other EW parametric and OB databases) are ideally represented as Bayesian nets because Bayesian nets faithfully represent the dependencies between variables.

One of the challenges in EWID research is the programming of the algorithm as a real-time algorithm. The mathematical formulation is recursive over all candidates. This would not result in real-time performance. EWID retrieves the initial candidate set by parametrics (discussed in more detail later) using a non-standard bitmap technique. The mathematical formulation is IT's and ET's downward; the real-time implementation is ST's upward. Hence, it has been necessary to implement the functional equivalent of the mathematical formulation in the reverse order of candidate selection. Research on implementation of inferential, knowledge-based, inferential, and fusion algorithms for real-time requirements is an import aspect of the EWID effort.

[9] In the sense that the recursion is applied to the last cycle "state estimate". There is no process noise because the process model for identification has no assumptions analogous to the assumption of constant velocity. The model is static, not dynamic.

4.4 ESM/ELINT/OB Fusion Knowledge Engineering

The degree to which a computer can be used as a part of a system controlling some environment, in the cybernetic sense [scho], depends on how much of that understanding is embedded in the computer. A knowledge representation embeds that understanding through a "combination of data structures and interpretive procedures that, if used in the right way in a program, would lead to knowledgeable behavior" [barr]. Similarly, conceptual data models provide a means for achieving knowledgeable behavior by defining "a number of symbol structures and symbol structure manipulators which...are supposed to correspond to conceptualizations of the world by human observers" [borg].

EWID research has involved knowledge engineering the Battle Force surveillance environment, the physical and fusion hypotheses universes, by encoding INTEL knowledge bases as semantic nets upon which Bayesian net mathematics are attributed. EWID's reasoning capabilities and logic are built upon a powerful organization of the EW track files in three tiers as shown in Figure 6. The intercept/sensor level, Sensor/Intercept Track File (STF), corresponds to a reported sensor track or a tracked set of contacts from a reporting source. In EWID's unique approach, the STF also includes the EW "library" emitter modes. Combining library and sensor data in a single file allows a single process to match new reports against previously received reports and pre-engagement INTEL and for the EW "library" to dynamically adapt to the real-time tactical electronic situation. An underlying concept in this is the treatment of pre-engagement INTEL as previous surveillance, a concept that introduces powerful new reasoning capabilities into the data fusion problem.

Representation of the relationship between knowledge base elements is important and semantic nets provide a powerful tool for representation in a high fidelity manner. Most conveniently, Bayesian net mathematics can be conveniently overlaid on the semantic net, thereby creating not only a knowledge representation, but also a reasoning method and a way to manage uncertainty.

The Emitter Track File (ETF) is the consolidated representation of the fused STF's into emitters. This is the first level operators would normally be interested in. The Intermediate Track File is the consolidated representation of the fused ETF's into platforms. The term "intermediate" is used to convey that cross-discipline fusion to other INT's (e.g., COMINT, IMINT, RADINT) is still to be performed to create the final all-source fused track.

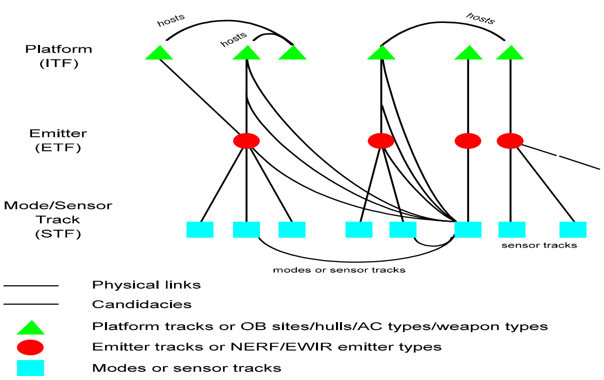
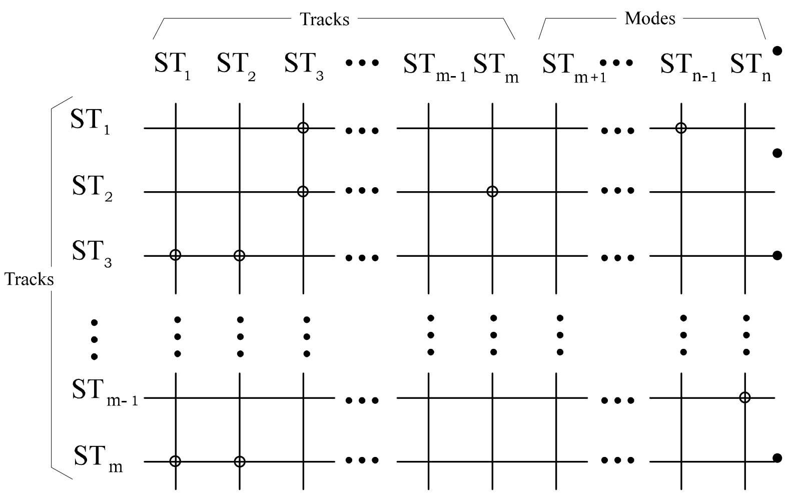


Figure 6. EWID Track and Fusion Structure

The levels are related in EWID via two-way ITF-ITF links, ITF-ETF links, and ETF-STF links. The first two are many-to-many; the last is one-to-many. The levels and the links are related in EWID via candidacy links, indicating and storing possible identification and correlation candidacies. Candidacy links are STF-STF, STF-ETF, STF-ITF, STF-ETF/ITF. Candidacy links store the probability values for recursion. Candidacy links and their half-rules are shown in the following pages. As can be seen, the links explicate or reveal the nature of OB, ESM, and ELINT fusion over all categories of target via the logical constraints[10] governing their formulation. For instance, the first diagram, showing ST-ST links shows how input track reports (running down from ST_1 to ST_m have candidacy links to other tracks and also to modes. The filled nodes at the crossings exemplify a candidacy link. In the next diagram, both candidacy links and physical links are shown, the former as filled nodes, the latter as small squares. In the EWID software, a standard set of link utilities provide a consistent means for adding, dropping, updating, and traversing physical and candidacy links.

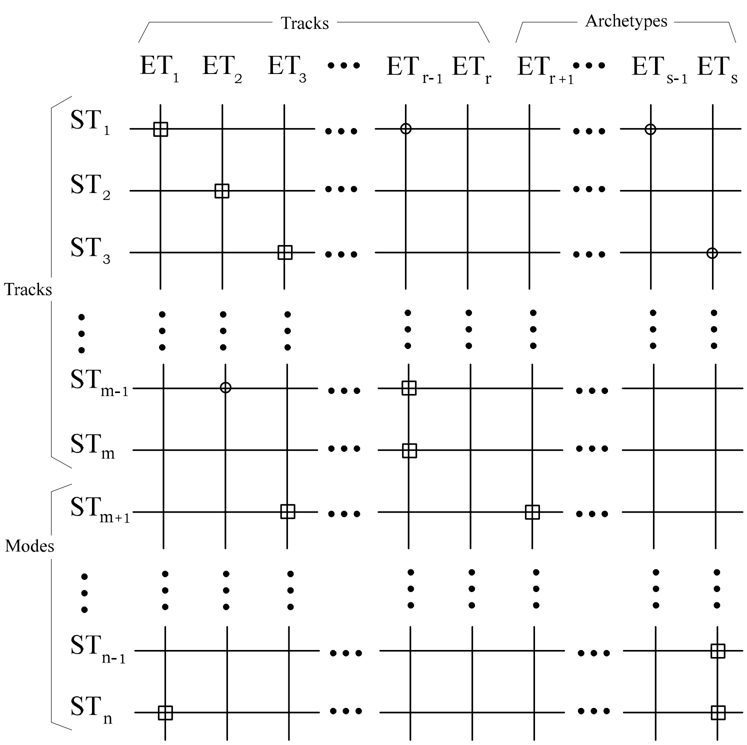
[10] The logical constraints play a role similar to "half-order theory" in mass spectroscopy [barr].

A Sensor Track (ST) has Candidacies with Other Tracks and NERF/EWIR Modes

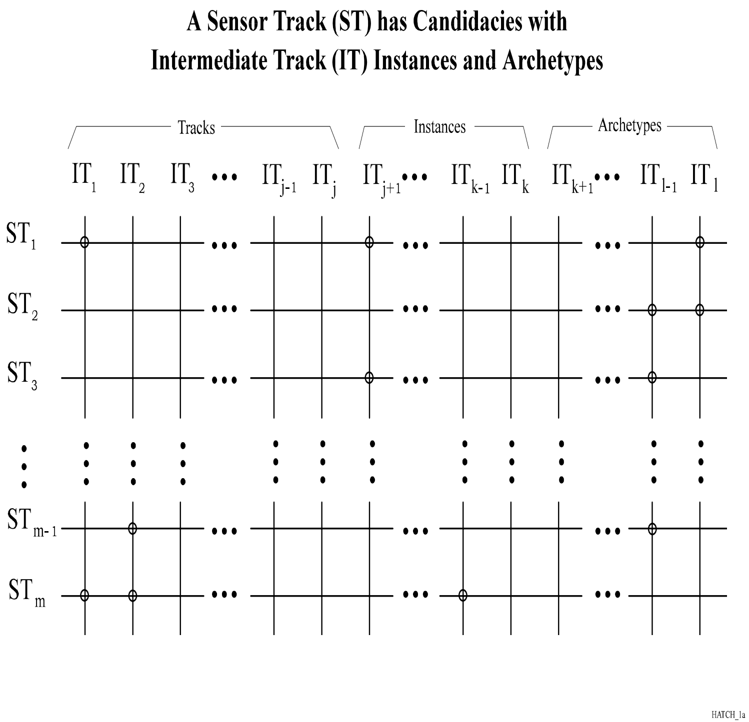


- Usually, if B is a candidate of A (i.e., A "likes" B), B likes A but not always (ST_m likes ST_1 but ST_1 doesn't like ST_m)
- It is possible for a track to not like any other tracks implying new track (ST_{m-1})
- It is possible for a track to not like any modes implying a new mode (e.g., WRM)
- Probabilities based on mode/track parameter probabilities and kinematic probabilities with linked ET, linked IT, and IT-IT basing and loadout links, and C&P, geopolitical, and other parameters.
- Holds $P(ST \mid ST_\zeta, \text{past })_{-1}$

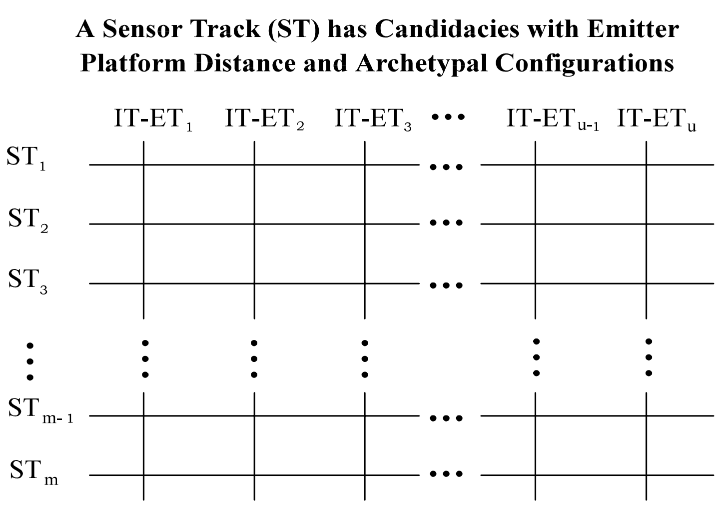
A Sensor Track (ST) has Candidacies and Links with Emitter Tracks and Emitter Archetypes



- An ST always has a least one ET link and vice-versa
  - Each mode links to a single archetype and 0-to-many ET tracks
  - Each ST track links to one and only one ET track
- Only the concurrent and transitional modes are linked to ET tracks via inheritance
  - Allows mode tracking
- Multiple ST tracks linked to a single ET track are the result of a correlation decision
- An ST track can have candidacies with 0-to-many ET tracks and/or archetypes
- Candidacy scores are a function of ST track/mode score, IT track/instance score, ST-ET and ET-IT links containing mode-emitter, basing/loadout defaults, and C&P, political and other parameters
- Holds $P(ST \mid ET_k, \text{past })_{-1}$

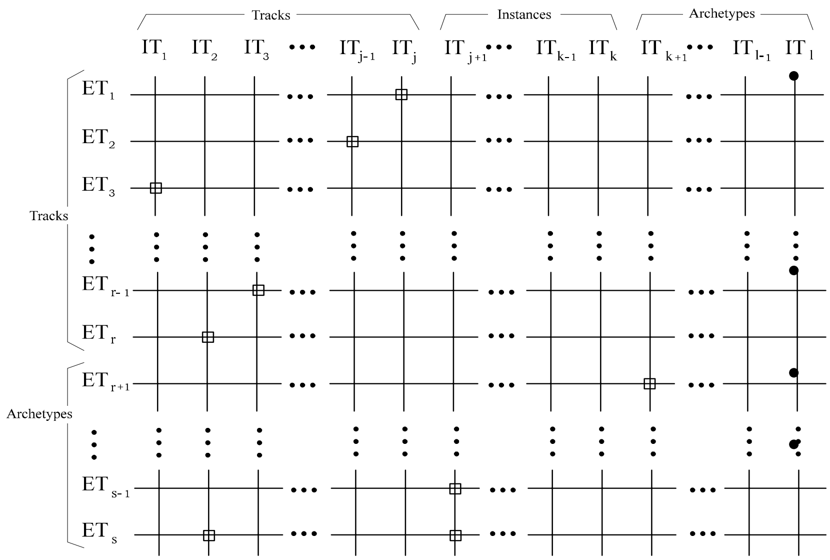


- An ST track can like 0-to-many IT tracks, instances, and/or archetypes
- Holds $P(IT_j \mid past)_{-1}$



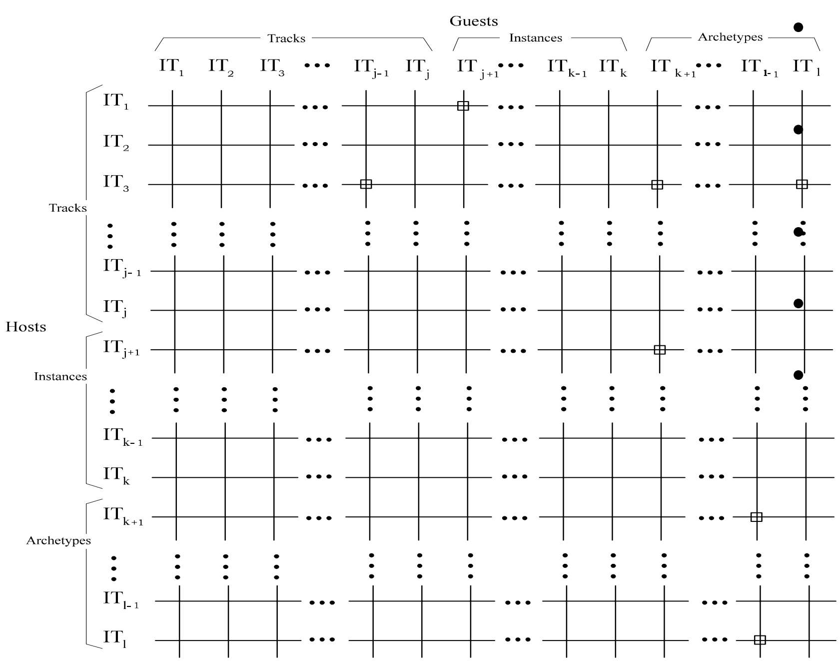
- Holds $P(ST \mid ET_k, IT_j, past)_{-1}$

IT - ET Linkages Convey Radar "Fit"



- For example track IT_2 is a ship of same class as instance IT_{j+1} with ET_{s-1} radar discovered as ET_r and ET_s dormantly linked via inheritance at confirmation (auto or manual)
- In EWID all IT tracks have a linked ET since only sensors are ESM/ELINT
- An IT track can have 1-to-many ET tracks and/or archetype links
- An IT archetype can have 1-to-many ET archetypes links

IT - IT Linkages Convey Theater Information



- For example, Airbase IT_{j+1} hosts A/C type IT_{k+1} which hosts weapon type IT_{l-1}
- For example, Ship track IT_3 hosts archetype A/C IT_{k+1}, archetype weapon IT_l, and track IT_{j-1}
- Tracks can host tracks, instances, and/or archetypes
- Archetypes can only host archetypes
- Upon confirmation (auto or manual), instances become tracks and tracks inherit instance data. Archetypes get OB count decremented.

4.5 Non-Gaussian Statistical Scoring

Many ESM input reports are kinematically in the form of Line Of Bearing (LOB) or bearing-only reports. These are only awkwardly representable in Cartesian covariance matrices since there is no know range, necessary for the coordinate system conversion. Cartesian trackers of bearing-only inputs have known behavioral anomalies. We were involved with this problem in the Tomahawk weapon system which represented LOB's as high eccentricity ellipses. Later, on ACDS Block 1, we analyzed the performance of LOB/AOP trackers using models. The major problem was dubbed "range runaway" in the ACDS project and it resulted in the range estimate for single source LOB tracking to converge to zero. This was due to the difficulty in making a good initial range guess, the ambiguous interpretation of a bearing change in terms of the target motion model, and, in linear Kalmans, the linearization in the observation equation[11] [nos2, nos3]. Modern computing speeds and memory capabilities allow radical approaches to these problems. In particular it may not be necessary to coerce bearing-only measurements into Cartesian form, but to maintain the probability density values individually over a grid. Consequently, EWID Phase I has researched,

- ***Non-Gaussian Kinematic Scoring***. Kinematic scores are calculated using non-parametric statistics, treating uncertainty regions as non-Gaussian ***Locational Probability Densities (LPD's)***. Non-Gaussian LPD's will be valuable in the littoral area where coastlines, mountains, waterways, etc. can preclude the location of certain types of platforms [arp]. Such representation is advantageous for multiple-LOB and AOB data correlation scoring and fusion and also for terrain tailoring, a proposed Phase II feature. In particular, uncertainty regions for confirmed ships should be zeroed over land and redistributed to the oversea elements as shown in Figure 7. Computational techniques for transforming to/from parametric representations and scoring over widely varying levels of granularity are being devised.
- ***Non-Gaussian ESM Parameter Scoring***. This technique is also used one-dimensionally for scoring parameters, allowing for increased future abilities for parameter range non-Gaussian shaping for, say, channelized transmitters or uniform distributions. Multiple frequency radars have been around for some time. PRI often appears as stagger groups. The non-Gaussian parametric representation also provides a more accurate learning of or history keeping for observed emitters. ESM/ELINT/INTEL parameter scores use non-parametric statistics to allow high-fidelity representations of the parameters. This is especially beneficial for HULLTECHable crystal oscillators.

The probability mathematics of the discrete PDF's are conceptually straightforward. Correlation scores are computed as approximate integrals over the overlapping PDF's[12]. Kinematics are fused as normalized element-by-element products of the PDF grids.

[11] Ultimately, the project settled on a non-linear Kalman, called the Multi-State Space (MSS) tracker that, in effect, used a Cartesian motion model and a polar observation equation. This was verified to perform roughly equivalently to the iterated extended Kalman described in [gelb].

[12] The number of discrete PDF elements maintained is a compile-time parameter that could vary depending on the real-time requirements, data update rates, computational resources available, and mission accuracy requirements.

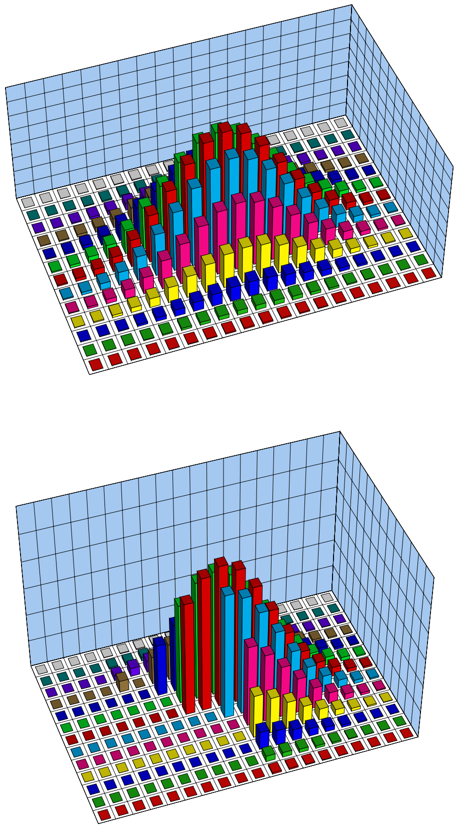


Figure 7. Non-Gaussian Kinematic Uncertainty Representation & Terrain Masking

4.5.1 Combined Identification and Kinematic Estimation

Current estimation techniques are primarily for kinematics. This design is innovative in combining both. It is expected that this design's results will be more accurate and less ambiguous through the full use of all available clues.

4.5.2 Multi-Source Inputs

This design accepts inputs from sensors such as:

- Ownship: SLQ-32, WLR-1H, ALQ-142
- Link (11, TADIL-B, or JTIDS): ALR-73, ALR-66(V)3, SLQ-32, ALQ-142 (via SLQ-32), ...
- National: TRE/TRAP

This design scores new reports against previously received reports/tracks from other sources using the same processing and algorithms as it uses to score against "library" emitter modes. This is possible because modes and sensor tracks are uniformly maintained in the STF. The advantage is that reports/tracks from one source that become identified aid the identification of subsequent reports, supporting, for example, HULLTECing. The integrity of the sensor report/track is maintained in the STF in a "normalized" format, with the fused emitter and platform estimation embodied in the ETF and ITF.

Parameter types can be mismatched. For example, one report could contain RF, PRI, and Scan Rate while another contained RF, PRI, and PD. For the Phase I research we used the geometric mean of matched types. This is functionally equivalent to other schemes we have used: multiple χ^2 thresholds or a χ^2 "doping" factor, an additive factor to neutralize the absence of a missing comparison degree of freedom. There are a number of other methods for treating mismatched parameter types via similarity measures that will be considered in the Phase II research.

4.5.3 Ambiguity Resolution Aids

EWID resolves ambiguity beyond the basic gating or lookup levels by mimicking human reasoning. EWID cannot, of course, mimic advanced cognitive capabilities. EWID can, however, consider and collate vast amounts of data in its reasoning that can aid an analyst/operator in resolving these high-ambiguity tracks. One aid for resolving ambiguity is ranking of ambiguous candidates. EWID Phase I ranks candidate identifications based upon kinematics, OB, parametric fit, weapon and A/C ranges, and emitter effective radiated power. Another method of handling ambiguity is hierarchical abstraction. When, after ranking, ambiguity still remains, EWID can present and output tactically useful results by abstracting the platforms hierarchically. The hierarchy EWID uses is the JTIDS joint taxonomy which provides three levels of hierarchical abstraction over the DIA OB platform taxonomy. The DIA-JTIDS taxonomy links are included in Phase I.

GDSS evolution is as systems that are tools for analysis rather than "truth" machines [haf]. This is particularly true for identification, where own system limitations, natural factors, ambient environment, adversary techniques, and so forth can conspire to create problems requiring massive information processing and high-order human decision making. EW identification is an information intense activity. EW operators evaluate measurement data on their CRT's, signal modulations on audio, other sensor data on their PPI's, and intelligence data via system lookups, briefings, messages, intelligence documents (e.g., EPL and EW OPTASK), and open source documents. The research prototype provides alternatives for presenting data in an organized manner that supports cognitive recognition of the information. The technique for accomplishing this is shown in Figure 8. On initial presentation, the workstation shows the most probable "branch" of the JCS/DIA taxonomic hierarchy. That is, the most probable Category's Platforms are presented followed by the most probable Platform's Specific Types, etc. The operator can explore other branches of the hierarchy using the X-Windows scrolling lists by selecting a lesser probability item (e.g., a lesser probability Category). Upon such an event, the entire hierarchy instantaneously switches to the operator-selected branch. While hierarchical organization supports cognition, it sometimes is insightful to view non-hierarchically. Hence, the EW classification workstation provides X-Windows buttons for selection of all Platforms, Specific Types, NERF Platforms, and Emitters resulting in pop-ups of the selected cross-section.

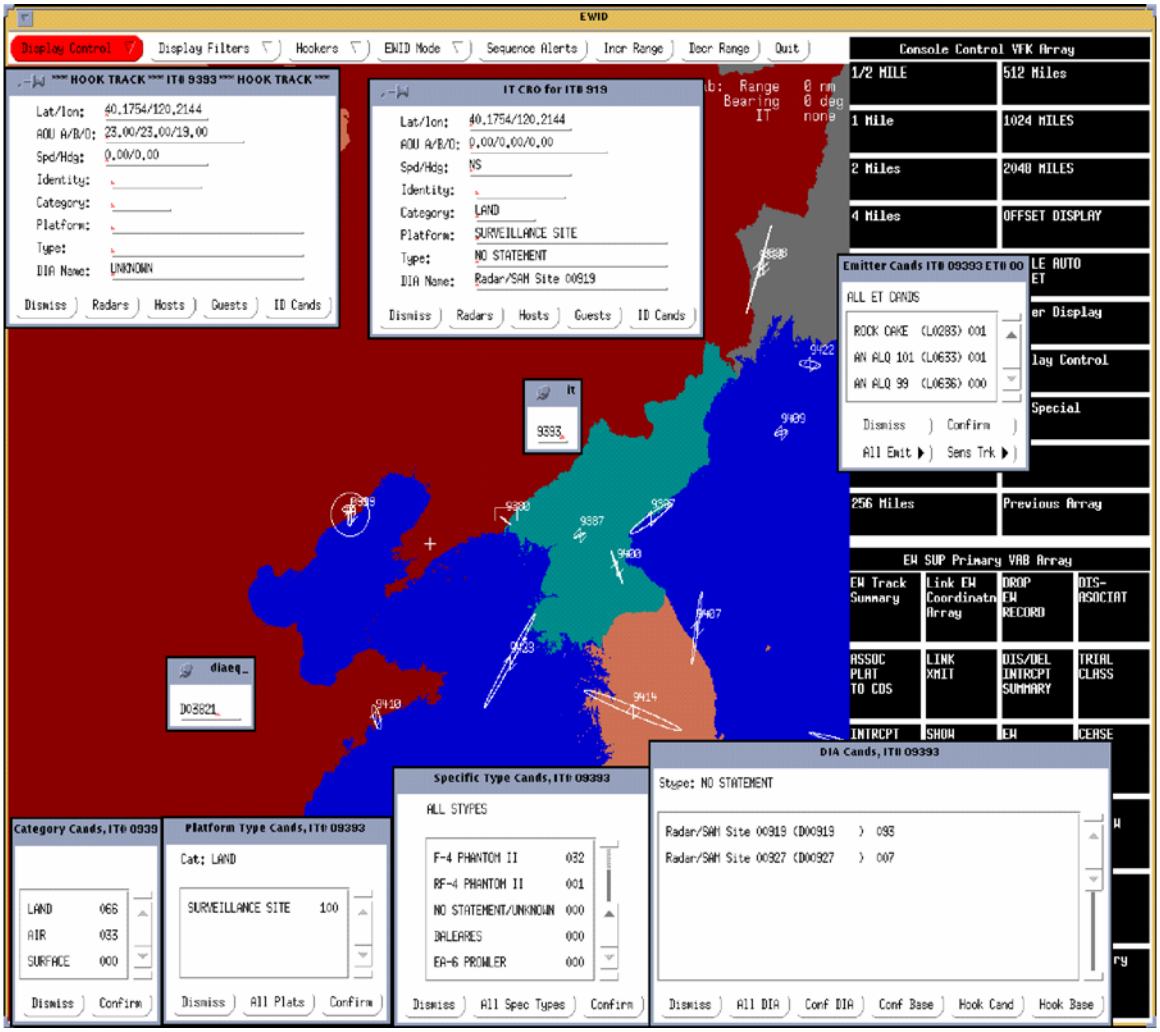


Figure 8. Bayesian Net Hierarchical Alternatives Display. *This is a basic hierarchical Bayesian Net example. For the hooked track (9393), the ID Cands button was depressed resulting in the hierarchical ID alternatives popups in the lower part of the display. The Bayesian Net estimates the Environment/Category as 66% Land, 33% Air and less than 1% Surface. Given Land, the only alternative is Surveillance Site (100%). Normally, the Specific Type scrolling list would show the alternatives given the selected or most likely Platform but in this example the operator had selected display of All Spec Types. This is sometimes necessary to cut across the alternatives hierarchy horizontally because branch-by-branch analysis may be too tedious. Whenever a platform or emitter candidate is selected, at any level in the hierarchy, the entire set of alternatives is redisplayed to be consistent with that selection. The operator confirms the alternatives at any level. This set of displays would be used in manual mode, high ambiguity semi-auto mode, or to review a target's fusion decision and current alternatives. Of interest to note is the EA-6B candidate which makes the list because of its jamming pod. Its probability is low however, less than a percent.*

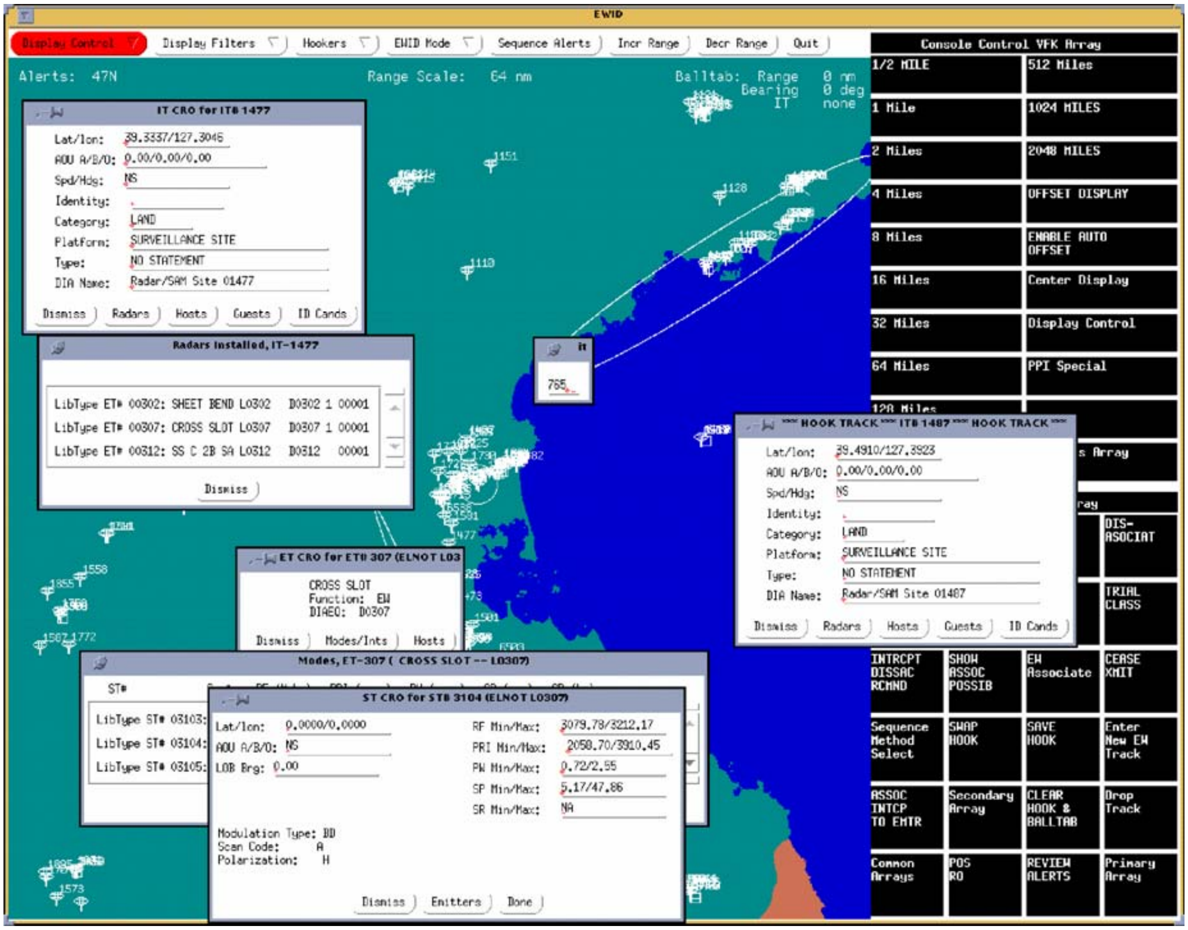


Figure 9. OOB, Fit, and EW Parameters Review & Update. *This figure shows how an operator can review OOB knowledge base information in the exact same manner as displaying details about the realtime track file. In this figure, an OOB "track" had been hooked (# 1477) and its radars had been asked for. These were displayed in the scrolling list, "Radars Installed". The first entry had been selected by double-clicking, resulting in the "ET CRO" display, showing the emitter's function code and DIA Equipment Code and allowing for display of the modes (or intervals if the "track" is realtime.) The modes are displayed in summary fashion in a scrolling list and it is again possible to select a mode for more details, as is shown in "ST CRO". This is the exact HMI that is used to analyze a realtime track, providing a single paradigm for OOB, near-realtime, and realtime analysis.*

4.5.4 Dynamic A-Priori's

Bayesian ***a-priori's are computed dynamically (on-the-fly).*** We researched this by computing a-priori's as new track reports are received for sub-universes about the new track report. To circumscribe the subuniverse, we used weapon platform locations (with uncertainties), airbasing, INTEL data on aircraft and weapons ranges, INTEL platform-weapons capabilities, weapons firing rates, and geopolitical readiness posture.

4.5.5 Special Clues

EWID also uses a variety of additional minor clues to further influence the probability vectors and reduce ambiguity. These are:

a. ***Effective Radiated Power*** (ERP) INTEL data is used along with estimated track range and known sensor detection sensitivities using estimates sucah as in [vacc]

b. NID Platform Operating Ranges

c. Platform Operating Range Defaults

d. NID salvo size and firing rate

e. Best geo-locational estimate (JMCIS if available; OB otherwise)

4.5.6 Real-Time Considerations

Even with the use of modern workstations, EW classification requires the use of real-time techniques. For a ship with SLQ-32, WLR-1H, and an active EW datalink (e.g., JTIDS EW subnet), future ESM track data update rates in the neighborhood of 25/sec. can be expected although current rates are more like 5/sec. maximum. The primary real-time concern is that each input sensor report requires access to min/max values for RF, PRI, etc. for possibly hundreds of modes/sensor tracks. Using standard non-real-time RDBMS SQL queries is infeasible even if the database is indexed by each parameter min and max since the matches still have to be "AND"ed. Real-time techniques avoid searching by using pre-encoded match maps. For the EW Classification workstation, we implemented a method illustrated in Figure 10. This method uses an index by measured parameter into a mode "bitmap" that can then be "AND"ed with the other measured parameter lookups thereby resulting in a bitmap, all of whose entries correspond to modes/sensor tracks whose parameter ranges include the input report. The result is no searching or sorting -- all such work is done ahead of time. This real-time technique is appropriate not only for shipboard command and control and ASMD, but also for any environment in which there are quick react or high data flux requirements such as C3I systems and aircraft RWR's.

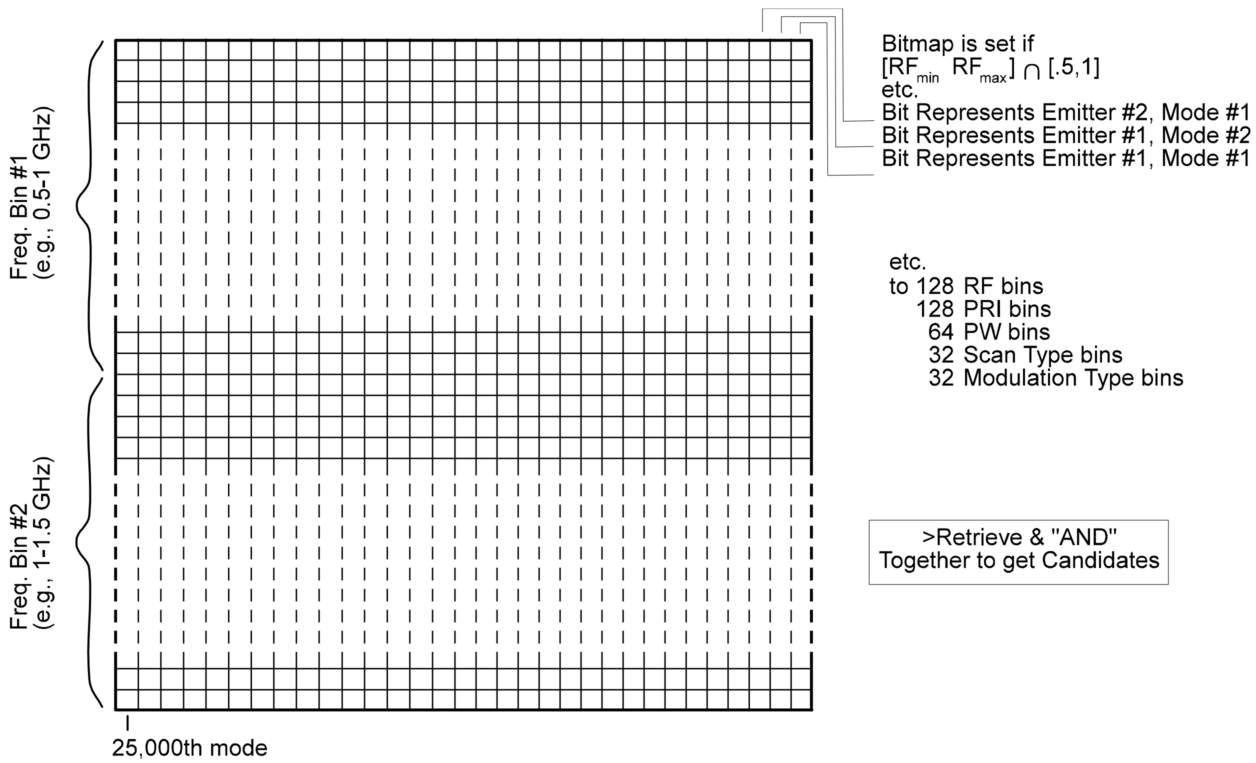


Figure 10. Real-Time EW Library Mode Candidates Retrieval Method

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