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F-35 Information Fusion

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Information fusion is a set of algorithms that combines data from all sources to create an integrated view of the environment to provide situational awareness. Fusion is a core attribute of the F-35, designed into the mission systems from initial conception. The F-35 Information Fusion development leveraged experience from past fusion projects across the corporation and industry. However, there were some fundamental architectural decisions and algorithmic solutions that are unique to the F-35 concept of operation. This paper discusses some of the key design decisions and features that shaped the final F-35 Information Fusion solution.

I. Nomenclature

$\vec{D}$	=	vector difference between Observer 1 and Observer 2
K_k	=	Kalman filter gain
κ	=	Dempster-Shafer measure of conflict between two masses
$m(A)$	=	Dempster-Shafer probability mass of proposition A
$P_{k\|k-1}$	=	previous covariance estimate propagated to time k
R_k	=	measurement covariance for Z_k
$\hat{R}_1$	=	range estimate from Observer 1 to the target
$\hat{R}_2$	=	range estimate from Observer 2 to the target
Σ_1	=	covariance matrix for the target from Observer 1
Σ_2	=	covariance matrix for the target from Observer 2
Σ_{int}	=	covariance matrix for the intersection point
$\hat{X}_{k\|k}$	=	resultant state estimate at time k
$\hat{X}_{k\|k-1}$	=	previous state estimate propagated to time k
$\hat{u}_1$	=	unit direction vector from Observer 1 to the target
$\hat{u}_2$	=	unit direction vector from Observer 2 to the target
Z_k	=	measurement vector at time k

II. Introduction

In his 1982 book "Megatrends," John Naisbitt predicted that in the Information Age we would find ourselves "…drowning in information but starved for knowledge" [1]. For many aviation or military applications, as the amount of information increases, the sheer volume of data becomes overwhelming and results in the loss of situational awareness [2]. As the amount of data increases and control choices multiply, the pilot workload increases exponentially to a point where eventually even the most able pilots begin to miss important information or fail to recognize critical situations [3]. The loss of situational awareness degrades the reaction time of the user [4, 5]. Shenk coined the term *data smog* to describe the data overload caused by the dramatic increase in information without a means to readily incorporate this information or its significance [6]. In "Consilience: The Unity of Knowledge," E.O. Wilson predicted the need for a synthesizer that could combine relevant information at the right time to support critical decisions [7]. Kline identified fusion algorithms as this synthesizer to reduce information overload, improve situational awareness, and reduce user reaction time [8].

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5th Generation fighters, with their diverse sensor suites and multirole mission sets, require some form of information fusion to support the pilot's situational awareness (Fig. 1). The F-35 avionics suite comprises several complementary sensors and off-board datalinks but is a single-seat fighter with no weapon systems operator. Without some form of information fusion, the pilot would be left to manually correlate sensor and datalink tracks together, while executing tactical air, land, and sea missions while also trying to fly the aircraft. This combination of factors can increase pilot workload and quickly lead to an overwhelming amount of displayed information. Information fusion algorithms aggregate the onboard and off-board sensor information to provide a complete and accurate representation of the environment, resulting in an increase in situational awareness, which is the ultimate goal of fusion [9, 10].

Fig. 1 Information fusion is a set of algorithms that combines data from all sources to create an integrated view of the environment.

The terms *data fusion*, *sensor fusion*, and *information fusion* are often used interchangeably, and yet these terms have subtle distinctive connotations within the community. The Joint Directors of Laboratories (JDL) Data Fusion Model defines a useful categorization of fusion algorithms and techniques used in the solution of many general fusion problems [11]. They define *data fusion* as the combining of information to estimate or predict the current or future state of the environment. Level 1 fusion is focused on object assessment. Level 1 fusion algorithms include: (1) data association algorithms, which determine whether information from multiple sources describes the same object; and (2) state estimation algorithms, which estimate the current (and, in some cases, future) state of the physical object in the environment. The estimate includes both the kinematic state (e.g., position, velocity) and an estimate of the object's identification (ID). Level 2 fusion focuses on aggregating the Level 1 objects, inferring relationships between/among the objects and corresponding events, and assessing the unfolding situation. Level 3 fusion assesses the impact of perceived, anticipated, or planned actions in the context of the unfolding situation, for instance, in terms of lethality and survivability. Level 4 fusion is focused on process refinement, including sensor resource management or sensor feedback to modify sensor actions and refine the overall situational picture.

There are many published algorithms that offer methods to address each of these fusion functions. However, in the field the imperfect nature of data and the varying fidelity of disparate data sources make the fusion problem much more challenging to solve. To quote Yogi Berra, "In theory there is no difference between theory and practice. In practice, there is" [12]. For example, object refinement is relatively easy when there are a few well-separated objects, but as the number of objects increases and their spacing decreases, the data association problem can become much more difficult or even unsolvable. The potential for the object to perform maneuvers, coupled with a highly dynamic environment involving multipath, interference, signal blockage, and weak signals, can complicate the ability of fusion to make sense of the environment. Information fusion must be robust enough to provide reliable situational awareness, even in this challenging environment.

A. The Evolution of Fusion Technology

The first radar was introduced to a fighter in the mid-1940s. As confidence grew in this technology, pilots came to rely on the radar to provide situational awareness in the environment. A radar warning receiver was later added to give a coarse indication of the general direction of a hostile emitter. In the 1970s and 1980s, new sensors and datalinks added secondary sources of ranged tracks. This ushered in the initial generation of fusion technology, which used data association or correlation algorithms to identify tracks that most likely described the same object in space and then suppressed all except the most accurate copy of the track from the display (Fig. 2). This is sometimes referred to as correlation or display fusion. The accuracy of this technique was equal to the accuracy of the best track.

Fig. 2 The evolution of fusion technology.

The next step in fusion technology was to combine the output of multiple sensor tracks into a blended system solution. By blending the tracks from two or more sensors, the resultant system track accuracy approached the accuracy of the best parameter of the contributing sensors. For example, blending tracks from a radar and an infrared search and track (IRST) sensor could have the range and range rate accuracy of the radar along with the angle and angle rate accuracy of the IRST. However, the accuracy of the resultant track remains limited by the track's update rate. If the track's update rate (fusion rate) is larger than the measurement's rate, then there is a loss of accuracy, even with optimal algorithms [13].

5th Generation aircraft are designed to process the sensor measurements rather than the sensor tracks, resulting in an integrated system track containing the most precise track accuracy and enabling cooperative sensing across aircraft. Measurement-level processing can provide earlier discovery of objects in the environment that are hard to detect. By processing the measurement-level data, the system can use detections from any sensor (or aircraft) to confirm a track before any single sensor can make the declaration. The focus on the measurement data rather than track data also means that combat ID information from a sensor is retained by the system track, even when the track is no longer in the sensor's field of view since the system track can be maintained by other sensors or aircraft.

In addition to improved accuracy and detection performance, the introduction of an Autonomous Sensor Management capability provided the ability to react and refine objects in the environment much faster than any human could respond [14]. The addition of the Autonomous Sensor Manager is referred to as Closed Loop Fusion. This capability provides the fusion process a feedback loop to coordinate the actions of the sensors in a complementary way to detect, refine, and maintain tracks based on system priorities [15]. The sensor management capability evaluates each system track, determines any kinematic or ID needs, assesses those needs according to system track prioritization, and cues the sensors to collect the required information. Analogous to John Boyd's Observe, Orient, Decide, and Act (OODA) Loop [16], which expressed the engagement advantage related to the pilot's ability to understand and react to an adversary, closed loop fusion accelerates the ability of the pilot to understand and respond to an object in space faster and often at a much greater range than legacy systems.

III. Fusion Architecture

The F-35 is not one but *three* highly common aircraft for the U.S. Air Force, the U.S. Marine Corps, and the U.S. Navy, designed to avoid the higher costs of developing, procuring, operating, and supporting three separate tactical aircraft designs to meet the services' similar but not identical operational needs. Numerous partner countries are also involved, and their needs are incorporated into one or more of these three basic variants. The mission system sensors and software, on the other hand, are common among all three variants. The F-35 sensor suite (Fig. 3) includes the APG-81 Active Electronically Scanned Array (AESA) radar, the ASQ-239 Electronic Warfare (EW)/Counter Measures (CM) suite, the AAQ-40 Electro-Optical Targeting System (EOTS), the AAQ-37 Electro-Optical Distributed Aperture System (DAS) system, and the ASQ-242 Communication, Navigation, and Identification (CNI) system. These five sensors provide object detection and measurements in the RF and EO/IR spectrum to F-35 Information

Fusion, resulting in more information about the objects in the environment around the aircraft than has been available to a fighter aircraft before.

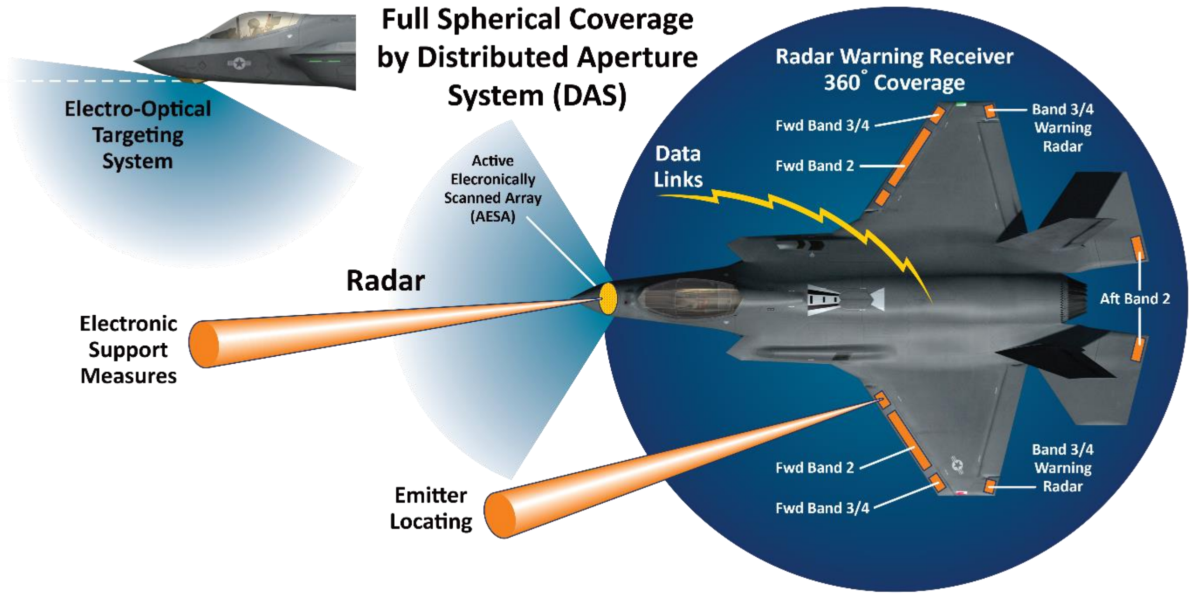

Fig. 3 The F-35 sensor suite.

In addition to the onboard sensors, F-35 transmits and receives tracks via the Link 16 datalink and the Multifunction Advanced Data Link (MADL). Link 16 provides connectivity with legacy aircraft and command and control systems, which allows the aircraft to transmit information about selected tracks and receive surveillance information from command and control centers. Designed primarily for cueing, information about the quality and timeliness of the track is limited.

The F-35 MADL communication link was designed explicitly for the F-35 to support the sharing of information among the flight group. Unlike legacy datalinks, MADL bandwidth supports passing fusion-quality information on all air and surface tracks to other members of the flight group. This data includes a locally derived track state, track covariance, ID measurement history, and RF history, as well as other metadata associated with each track. The amount of potentially redundant off-board information provided by MADL was one of the largest challenges for fusion design. It was now possible to have many copies (in some cases greater than 10) of the same track from onboard and off-board sources simultaneously, creating a high potential for clutter. The fusion of this spatially diverse data offered a significant improvement in situational awareness and cooperative sensing.

IV. The F-35 Information Fusion Approach

Prior to the introduction of the 5th Generation fusion systems, fusion historically only referred to the data association and estimation processes. The earliest partitioning of the F-35 fusion capability envisioned the sensor management capability to be independent of the fusion process. However, there was already strong evidence that the autonomous sensor manager was fundamental to efficient fusion performance and sensor optimization. During the early stages of design, the sensor manager was repartitioned to the F-35 fusion design. Figure 4 shows the top-level functional architecture of the F-35 fusion design, highlighting the data association, estimation (both kinematic and ID), and sensor management functionality.

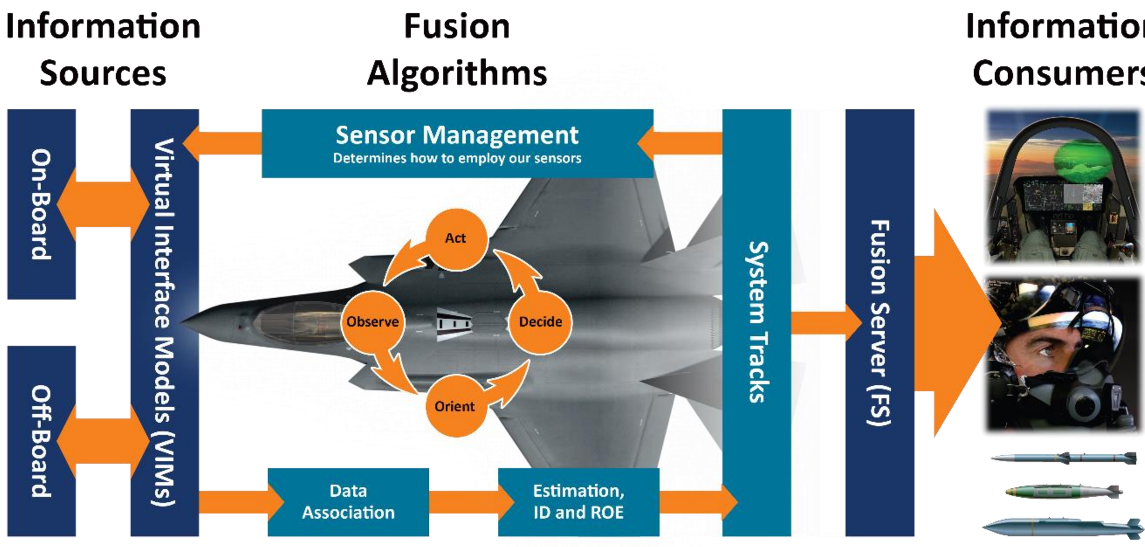

Fig. 4 F-35 fusion architecture.

The F-35 Information Fusion design isolates fusion algorithms from both the sensor and datalink inputs, as well as any consumers of fused data. Essentially, the fusion algorithms comprise a black box, known internally as the fusion engine, and sensor inputs and data consumers are encapsulated in external software objects known as virtual interface models (VIMs). For incoming data, the sensor-specific or datalink-specific VIMs fill in missing data (e.g., navigation state, sensor bias values), preprocess the information, and translate it into a standard form for the fusion process. For data leaving fusion, the outgoing VIM, known internally as the fusion server, provides data to the various consumers of fused information, both onboard and off-board. The fusion server isolates users of the fused information from both the fusion process and data sources. Legacy fusion implementations reported fusion tracks as a monolithic block (i.e., one size fits all) where all data consumers received the same message. Any propagation of the data or conversion was the responsibility of the recipient. This created a coupled interface between fusion and the data consumers. When a new data source was introduced to fusion, the interface changes to make this data available impacted all consumers of that message, whether the data was used or not, making changes to fusion very costly. The fusion server sends each information consumer a tailored message that contains only the information required to support that consumer. This isolates that consumer from changes to any data source or to the fusion algorithm. The use of VIMs enables the fusion architecture to be extensible to new sensors and data sources, as well as new data consumers, over its lifetime.

V. Information Tiers

> "Sensor fusion can result in poor performance if incorrect information about sensor performance is used: A common failure in data fusion is to characterize the sensor performance in an ad hoc or convenient way. Failure to accurately model sensor performance will result in corruption of the fused results." [17]

One of the key architecture decisions for F-35 fusion is how to share information among aircraft. Independent data can be incorporated optimally into a filter for the highest accuracy. However, if dependent data is incorporated under the assumption of independence, the result will be track instability and, eventually, track loss [18]. Data consumers on the F-35, including the pilot, receive the kinematic and ID estimate of each track based on all available data sources, both onboard and off-board. This is referred to as the Tier 3 solution. However, when sharing information with other aircraft, each F-35 shares the information describing a track based solely on measurements from onboard sensors. This is referred to as the Tier 1 solution. By ensuring that the information received from MADL is independent, the track information can be converted into equivalent measurements [19] by the recipient supporting both track-to-track and measurement-to-track of the information. The sharing of Tier 1 data ensures that the information is not coupled to any specific fusion algorithm and provides a method for dissimilar fusion platforms to share optimal fusion data in the future (Fig. 5). In late 2016, Lockheed Martin and the U.S. government used this technique to share an F-35 fused track of a target drone across MADL to a surface-based weapons system that had no line of sight to the drone. The surface-based weapons system converted the F-35 MADL Tier 1 information into equivalent measurements that were consumed by the native engagement tracker. Together, the networked systems achieved a successful acquisition, guidance, and kinematic intercept of the track using a surface-to-air missile.

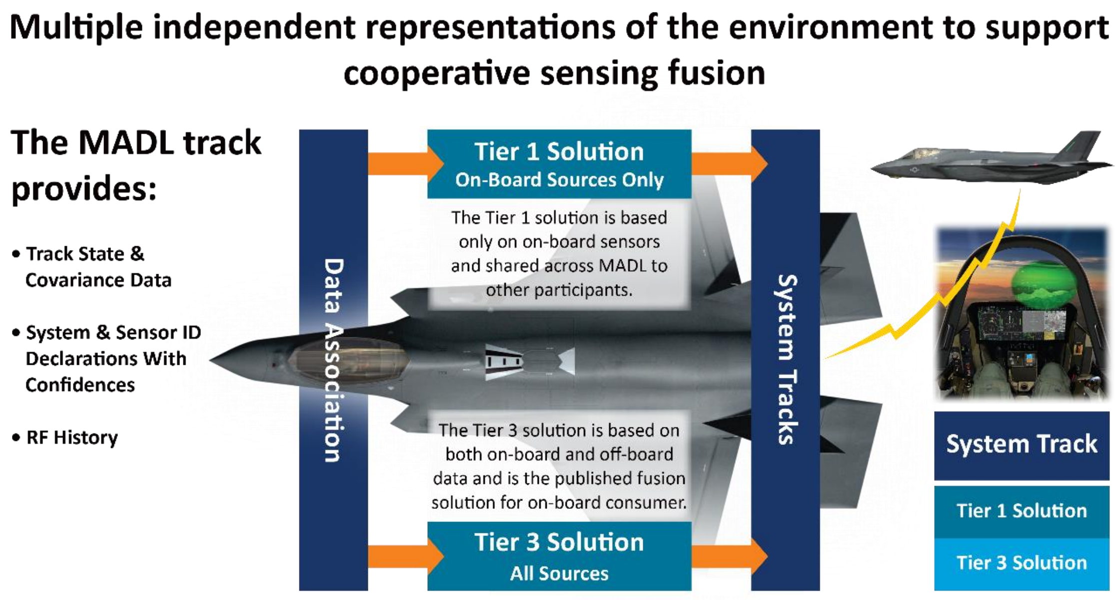

Fig. 5 Information tiers.

To incorporate dependent information or unknown pedigree information into the F-35 estimate, fusion includes a covariance intersection update that is more tolerant of re-broadcasted data [20]. The covariance intersection algorithm reduces the error of the estimate when novel information is introduced but does not improve the error with redundant data. This technique provides flexibility for incorporating data from many different datalinks in the future, where the pedigree of the data is not known.

The integration of legacy datalinks uncovered other challenges to optimal fusion. When system tracks are sent off-board over a datalink, it is important to send the most precise error characterization available for the system track. The covariance matrix provides this sensor characterization to other users of the data. However, in many legacy datalinks, quality factors are used to describe track errors rather than multidimensional covariance matrices. These quality factors denote a maximum area or volume uncertainty value for the data. This lack of specificity in dimensional accuracy requires the recipient to assume the worst possible accuracy for the data in all dimensions to ensure stable tracking behavior under all conditions. From an algorithmic perspective, the pessimistic error characterization leads to a higher incidence of false correlation and a de-weighting of the off-board data [21].

Given the off-board data has successfully correlated to the correct system track, the reported error of the remote track is used to weight the influence of the data. Recall from the Kalman filter that the optimal gain (K_k) is used to determine the blending of the new measurement [22, 23]. Equation (1) is an alternative form of the Kalman filter, showing how the optimal filter gain blends the propagated system estimate and the observation data. As the gain increases, the observation data (Z_k) has a larger influence on the new estimate.

$$\hat{X}_{k|k} = K_k\, Z_k + (1 - K_k)\, \hat{X}_{k|k-1} \tag{1}$$

The gain for a Kalman filter is determined by the estimated system track errors and the measurement errors, as shown in Eq. (2).

$$K_k = P_{k|k-1}\left[P_{k|k-1} + R_k\right]^{-1} \tag{2}$$

If the measurement errors are pessimistic, the filter gain decreases and results in a natural de-weighting of the measurement influence on the new estimate. Conversely, if the measurement errors are optimistic, the filter gain increases, and the measurement has too large an effect on the track. The use of quality factors on legacy datalinks leads to smaller gain values and reduces the potential accuracy of the resultant track. The F-35 MADL datalink reports the track covariance for each track, allowing for accurate weighting of the off-board contributions.

VI. Evidence-Based Combat Identification

Combat ID is the process of attaining an accurate characterization of detected objects in the joint battlespace [24]. Characterizations may include affiliation, class, type, nationality, and mission configuration. The F-35 employs a probabilistic, evidential reasoning approach to ID in a fundamental departure from heuristic algorithms employed on other tactical platforms. The decision to switch to a probabilistic formulation was driven by lessons learned from those platforms to eliminate misidentification due to forced declarations and the inability to handle ambiguous information sources. The transition to a probabilistic framework forced design changes throughout the rest of the information fusion design, including sensors, pilot displays, and sensor tasking.

Early in the F-35 design, a trade was performed between Bayesian and Dempster-Shafer inferencing algorithms. Ultimately, Dempster-Shafer was selected due to greater robustness to conflicting data, less reliance on a priori target distributions, and a more natural formulation of relationships between sensor attributes and corresponding platform sets. Algorithms based on Bayes' rule provide intuitive probabilistic confidence values. However, Bayesian inference places a higher dependence on a priori probabilities, the $P(A)$ term in Eq. (3), to seed the probability of a given target ID declaration. Accurate a priori information can be difficult to obtain in practice.

$$\mathrm{P(A|B)} = \frac{P(B|A)P(A)}{P(B)} \tag{3}$$

In contrast, Dempster-Shafer belief theory does not require explicit a priori information. Further, Fixsen and Mahler have shown that Dempster-Shafer probability masses can approach Bayesian probabilities [25] when probability masses are chosen appropriately. In our Dempster-Shafer formulation, each sensor declaration maps to a set of platform disjunctions, or a list of disjunctions in the case of ambiguities. These sensor disjunctions are combined using Dempster's rule of combination, shown in Eq. (4). Inconsistent propositions, designated by κ in Eq. (5), are removed and their confidence is distributed across the consistent terms through normalization.

$$m(A) = \frac{1}{1-\kappa} \sum_{B \cap C \neq \emptyset} m(B)m(C) \tag{4}$$

$$\kappa = \sum_{B \cap C = \emptyset} m(B)m(C) \tag{5}$$

Implementation of the Dempster-Shafer algorithm requires first defining the frame of discernment: the set of objects over which the algorithm reasons. Previous approaches to combat ID have been forced to limit their platform set due to processing and memory constraints. By contrast, the F-35 design took a holistic approach to include all tactically relevant platforms in the theater, minimizing misidentification of platforms that are not in library. Platforms are interconnected in a strict hierarchical taxonomy with levels in the taxonomy labeled subtype, type, class, and affiliation, as shown in Fig. 6. The algorithm creates ambiguity lists and associated confidences for each level of the taxonomy. The type ambiguity list is inferred from the subtype ambiguity list; the class ambiguity list is inferred from the type ambiguity list; and the affiliation ambiguity list is inferred from the class ambiguity list. The strictly enforced hierarchy allows for processing simplifications and ensures that the confidence at a higher level in the taxonomy is always greater than to or equal to the confidence at lower levels [26].

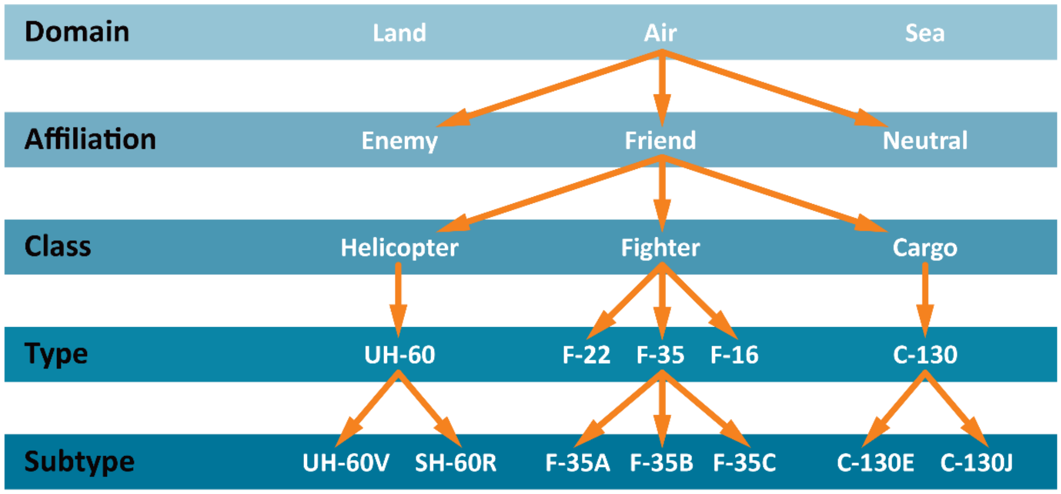

Fig. 6 Platform taxonomy levels.

The platform taxonomy also provides the framework for mapping sensor attributes to a platform set. This mapping, contained in an onboard relational threat database, encodes the transitional probability of observing a feature given a particular platform subtype. Each sensor declaration must also have an associated probability or confidence so the input to fusion is weighted based on its relative merit in the same way a kinematic report is weighted based on its covariance matrix. At the beginning of the F-35 program, none of the sensor modes produced confidence values, so these needed to be generated. Called the basic probability assignment (BPA), the generation of confidence values proved to be one of the more challenging aspects of the design. It should go without saying, the generated error must also correctly bound the true error distribution. Continuing with the kinematic tracking analogy, it does no good to report a track range error as having a standard deviation of 1 meter when the true error statistics are 100 meters. Similarly, the ID probabilities must accurately reflect the true target uncertainty.

Although the soft decisions developed by fusion provide a more accurate representation of what is known and not known about a given target's ID state, the pilot requires actionable information, which requires that the soft decision be converted into a hard declaration. The Dempster-Shafer algorithm produces support-plausibility intervals that bound the estimate of probability but do not directly provide platform declarations. The F-35 design converts the probability masses into pignistic probabilities that effectively distribute the platform disjunction confidence across all elements of the disjunction [27]. The system makes a hard ID declaration when the translated confidence exceeds a user-defined threshold. The taxonomy is traversed from lower nodes to higher nodes until the confidence threshold is exceeded. The F-35 combat ID output, shown in the second row of Fig. 7, is flexible enough to allow a display of information from any level in the taxonomy. The output also contains ID declarations from other sensors and off-board sources, which helped to develop trust in the fused outputs and transition from legacy platforms. In this example, a Link 16 declaration of fighter was combined with the MADL declaration of F-35 to produce a high-confidence type declaration of F-35 and a friendly confidence of 1.

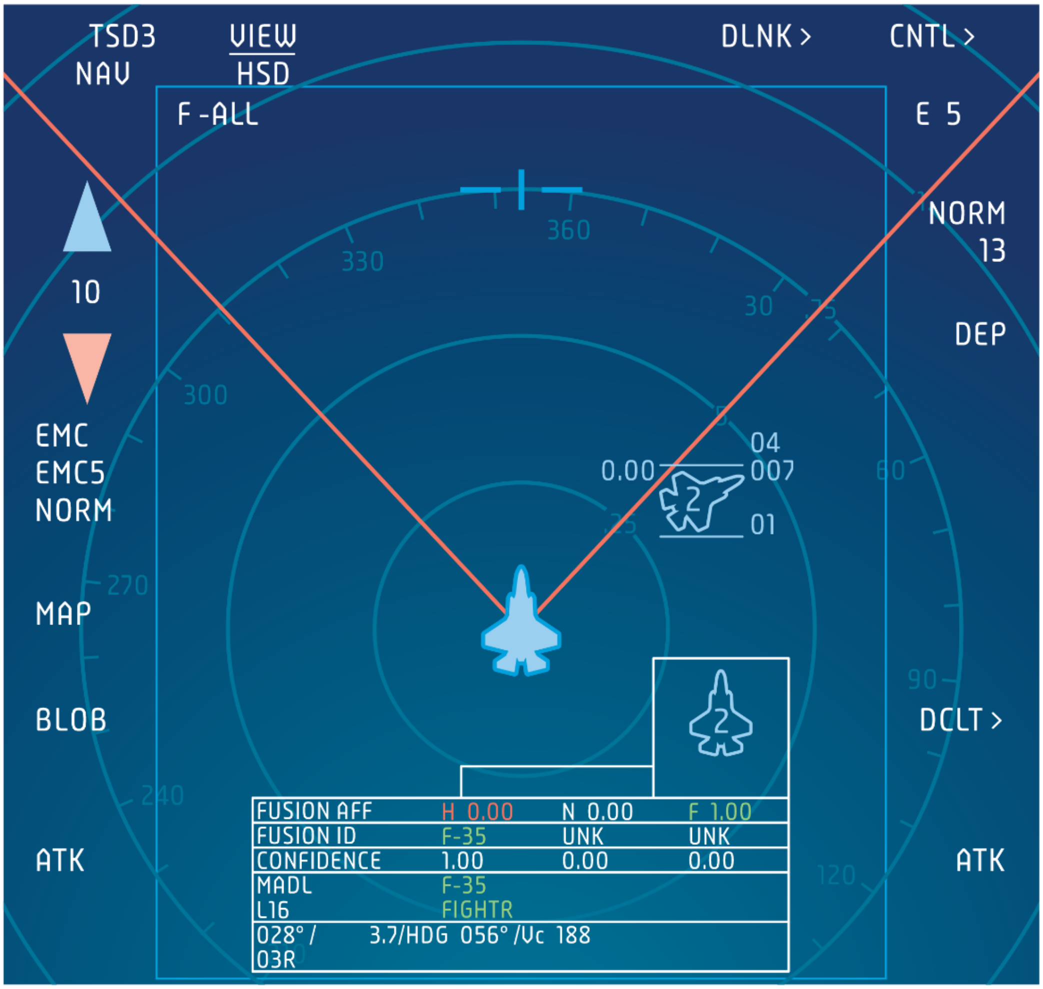

Fig. 7 F-35 expanded data window.

VII. Autonomous Sensor Management

Technical advances in the capability of modern sensors, increases in the number of multiple sensor systems, and the migration to increased connectivity have led to a sensor network that has exceeded the ability of a human to efficiently control them [28]. This performance gap led to the development of an automatic feedback mechanism in the closed-loop fusion model that autonomously modifies the actions of the sensor suite to achieve a mission-level objective or behavior. The use of an algorithm to task or modify the behavior of the information sources is referred to as process refinement and is categorized as JDL Fusion Level 4 [29]. The goals of the sensor manager are to: (1) reduce pilot workload by automating sensor actions and selection; (2) prioritize information requests (including pilot requests, background volume searches, and fusion information needs), and (3) reconfigure sensor assets to compensate for individual sensor loss or unavailability [30].

Sensor management strategies focus generally on the control of heterogeneous collocated or spatially diverse sensors to achieve a desired goal (e.g., track accuracy). An autonomous sensor management system requires an objective function to optimize sensor utilization to select a preferred action over many possible alternatives. Many early strategies [31-33] were ad hoc or rule-based, having a strong coupling to sensor requirements. Others [34-38] explored information-theoretic approaches that sought to minimize uncertainty in the track covariance, thus decoupling the objective function from a specific sensor suite. The advantage of information-theoretic solutions is their adaptability to many problems. However, they are focused on optimizing the information of a given track while neglecting the value of that information to the mission objectives [39]. For a fighter aircraft, the primary objective is to provide situational awareness to the operator during a complex and changing environment to support critical mission decisions [40].

Endsley [41] defines situational awareness from the perspective of the fusion customer (pilot), which could then be decomposed further into times or distances where key decisions must be made. The necessary information to support these key decisions are independent of the sensor's ability to meet these needs. The information boundaries and associated information needs define a dimensional space that can be used to derive a global objective function to support autonomous sensor management [42] and can be used to define the sensor and fusion capabilities necessary to support these decisions. A benefit from this mapping is that the mission goals can be directly related to the sensor capabilities in terms of range, accuracy, and latency. This allows the designer to trace system-level fusion situational awareness requirements to individual sensor performance requirements.

For the F-35, the automated sensor management function is responsible for efficiently managing the sensor suite to provide critical information about the objects in the environment to the pilot, supporting critical decisions and actions. It does this by prioritizing the systems tracks, autonomously directing system resources to maintain existing tracks, gathering mission ID and rules of engagement (ROE) information, and balancing track maintenance with new track discovery through searching. System priorities, track information needs, and track accuracies are based on the track type, pilot emphasis (if any), and information boundaries around the aircraft. The autonomous sensor manager also provides methods for the pilot to collaborate with the fusion system, both for refinement or reprioritization of existing tracks, or to cue the system to search for new objects in the environment. The pilot can designate a line of sight (air) or area (surface) and command a cued search. The sensor manager will direct a series of active and passive scans focused on the detection of new air or surface objects. If the pilot selects an existing track, sensor management will raise the priority of the track and will cue sensors to meet the information needs associated with the tactical zone (full state).

The autonomous sensor management algorithm focuses on providing the information needs for every track based on priority. The goal is not to drive each track to the best accuracy, but to instead drive it to sufficient accuracy and information content. In practice, for situational awareness, there is a level of component accuracy (e.g., range, angle) where the information is sufficient to support the pilot's understanding of the environment to decide. Additional accuracy beyond this point does not significantly improve the pilot's awareness or decision-making ability. Therefore, information gain above a sufficient level does not support the mission objective and should be directed toward other objectives in the environment, such as searching for new objects. This concept of sufficiency can be used to define a new constrained objective function that incorporates the concept of sufficient information and targets specific information needs. The addition of the sufficiency constraint removes the dependency of the objective function on the accuracy of the sensor making the update, as long as the sensor can provide the required accuracy. This objective function encapsulates the mission goals in terms of situational awareness while incorporating the constraint of sufficiency. The definition of sufficiency changes at each boundary based on the pilot's needs to make critical decisions. The closed-loop nature of the autonomous sensor manager enables the system to respond more rapidly to changes in the environment and to optimize the sensor behavior, freeing the pilot from the sensor manager and returning him/her to the role of tactician.

VIII. Cooperative Sensing

The F-35 MADL was designed to support full sharing of information among aircraft. MADL bandwidth supports the exchange of all air and surface tracks between/among participants within the flight group. Given that each F-35 has multiple sensors detecting multiple targets – and sometimes spurious signals – this can lead to the exchange of numerous, potentially duplicative tracks over MADL. Therefore, the F-35 places limits on the kinds of tracks and associated information that can be transmitted over the link.

For MADL distribution, a single F-35 system track is divided into three messages: the basic MADL surveillance track, extended combat ID (XID), and RF parametric extensions. The basic surveillance track provides the independent kinematic state estimate and track covariance at the time of the last measurement update. It is important to note that the kinematic estimate for a sent track can be either ranged or angle-only (no observed range). This distinction becomes important for advanced multi-ship tracking techniques, such as angle/angle ranging or time difference of arrival (TDOA), described later. The MADL surveillance track also includes a list of sensors contributing to this track, as well as ID summary data. The XID message contains a higher-fidelity ID ambiguity list, in addition to ID measurements (e.g., IFF). The RF parametric message contains the electronic signal measurement (ESM) data correlated to this track. The sharing of this detailed information allows each aircraft to leverage the spatial diversity of the flight group.

One of the initial multi-ship capabilities of the F-35 was the ability to cooperatively range airborne emitters by finding the intersection (or point of nearest approach) for angle-only tracks on two or more different aircraft (Fig. 8).

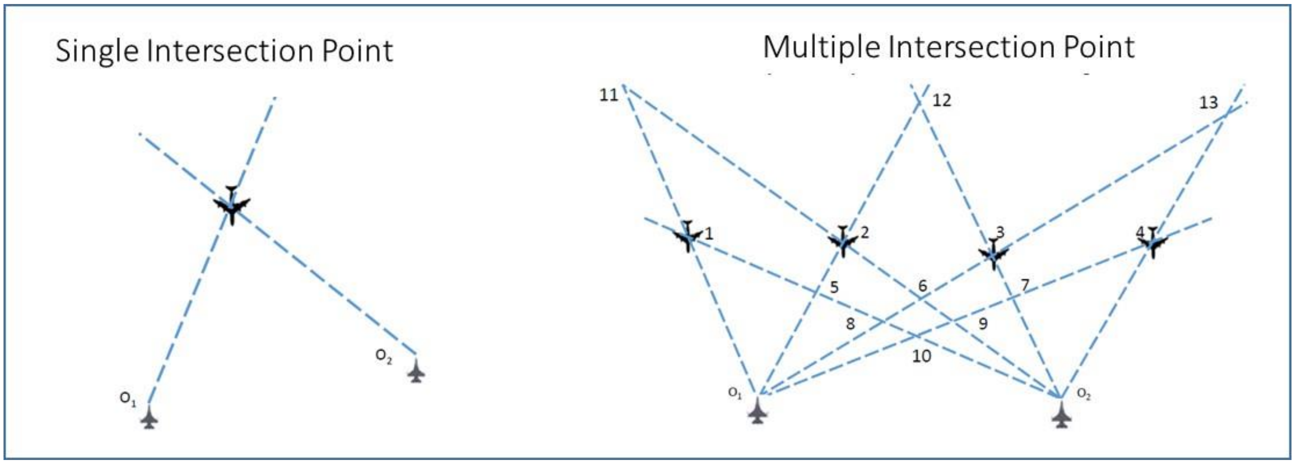

Fig. 8 Passive angle/angle ranging of airborne emitters.

On the receipt of a MADL angle-only track, the receiving fusion system determines possible intersection points with its own onboard angle-only tracks. It is possible for a given MADL angle-only track to intersect with multiple ownship tracks. In truth, only one of the intersections is correct. These alternate angle/angle candidates are referred to colloquially as ghosts. Once all ghosts have been eliminated, the range of the track from each participant can be calculated in Eqs. (6) and (7) as [43]:

$$\hat{R}_1 = \left\|\vec{R}_1\right\| = \frac{|\vec{D}\times\vec{u}_2|}{|\vec{u}_1\times\vec{u}_2|} \tag{6}$$

$$\hat{R}_2 = \left\|\vec{R}_2\right\| = \frac{|\vec{D}\times\vec{u}_1|}{|\vec{u}_1\times\vec{u}_2|} \tag{7}$$

Rotating the covariance of each observer into a common reference frame, the range error in the common reference frame is approximately the intersection of the two error covariance matrices, which can be expressed in Eq. (8) as:

$$\Sigma_{int} = \left({\Sigma_1}^{-1} + {\Sigma_2}^{-1}\right)^{-1} \tag{8}$$

For surface emitters, fusion incorporates a TDOA capability for precision location. The TDOA capability provides the ability for multiple aircraft to synchronize ESM dwells in time and frequency. Upon initiation, the autonomous sensor manager configures the dwells across the network, and then all aircraft send the time of arrival of any received pulses to the initiating aircraft. Fusion processes these pulse streams from the cooperating participants to detect common pulse pairs. Common pulse pairs form a surface of constant delta-time that, when intersected with the Earth, produce a hyperbola of constant time difference called an isochrone. Multiple pulse pairs represent the intersection of one or more isochrones and produce range estimate (Fig. 9).

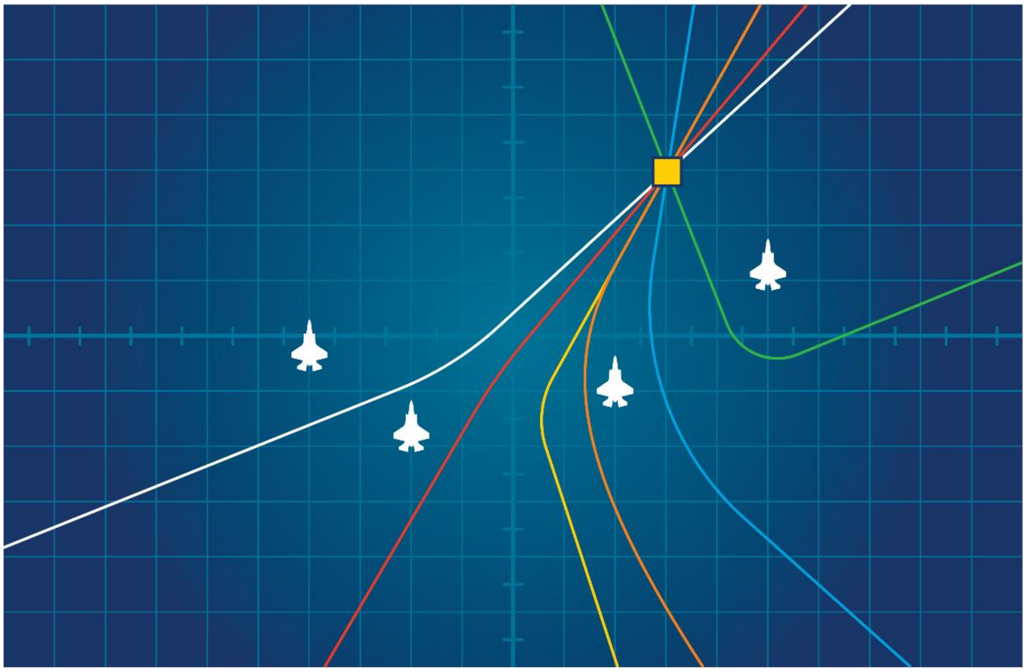

Fig. 9 Passive ranging of surface emitters using TDOA techniques.

IX. Summary

The F-35 Information Fusion software combines information from both onboard and off-board data sources, providing the pilot with advanced capabilities not available on legacy aircraft. Further, this extensible approach to information fusion leverages the spatial and spectral diversity among multiple F-35 wingmen, creating an innovative tactical network where data is shared instantaneously with other F-35s and legacy aircraft. The F-35 Information Fusion implementation of data association, state estimation, and combat ID ensures that the pilot has accurate situational awareness, allowing for advanced target detection, tracking, and tactical employment. The autonomous sensor manager provides timely reaction to a changing environment and ensures that all tracks are refined to a prespecified quality based on priority, allowing the pilot to return to the role of tactician. The F-35 MADL provides sufficient bandwidth for complete sharing of detailed fusion solutions and accuracies for all air and surface targets, resulting in improved situational awareness for all pilots in the MADL network. Using data-sharing methods to ensure that the data pedigree is maintained, the MADL information can be processed like a remote sensor, resulting in improved accuracies and new capabilities.

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