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Artificial Intelligence — An Enabler of Naval Tactical Decision Superiority

Bonnie Johnson

■ *Artificial intelligence, as a capability enhancer, offers significant improvements to our tactical warfighting advantage. AI provides methods for fusing and analyzing data to enhance our knowledge of the tactical environment; it provides methods for generating and assessing decision options from multidimensional, complex situations; and it provides predictive analytics to identify and examine the effects of tactical courses of action. Machine learning can improve these processes in an evolutionary manner. Advanced computing techniques can handle highly heterogeneous and vast datasets and can synchronize knowledge across distributed warfare assets. This article presents concepts for applying AI to various aspects of tactical battle management and discusses their potential improvements to future warfare.*

Tactical warfare is complex (Bar-Yam 2004). The complexity, range, and speed of war are driving us to new technologies to remain competitive. Successful tactical operations require agile, adaptive, forward-thinking, fast-thinking, and effective decision-making. Advancing threat technology, the tempo of warfare, and the uniqueness of each battlespace situation, coupled with increased information that is often incomplete and sometimes egregious, are factors that cause human decision makers to become overwhelmed (Zhao et al. 2015). Advances in AI methods, increased amounts of data, and improvements in computational capabilities lead to a potential solution to address this complexity — through improved tactical knowledge, automated decision aids, and predictive capabilities.

There are many real-world challenges that AI technologies can address. These challenges include self-driving cars, air traffic management, finance and market analysis, as well as issues pertinent to telecommunications, hospitals, medical insurance, and marketing. One aspect of the tactical domain that sets it apart is the existence of the adversary whose objective is to outthink and overtake our military. This adversarial stance adds another dimension to the challenge of gaining situational knowledge and making effective decisions — as the adversary is intentionally attempting to obfuscate our knowledge and counter our actions. As illustrated in

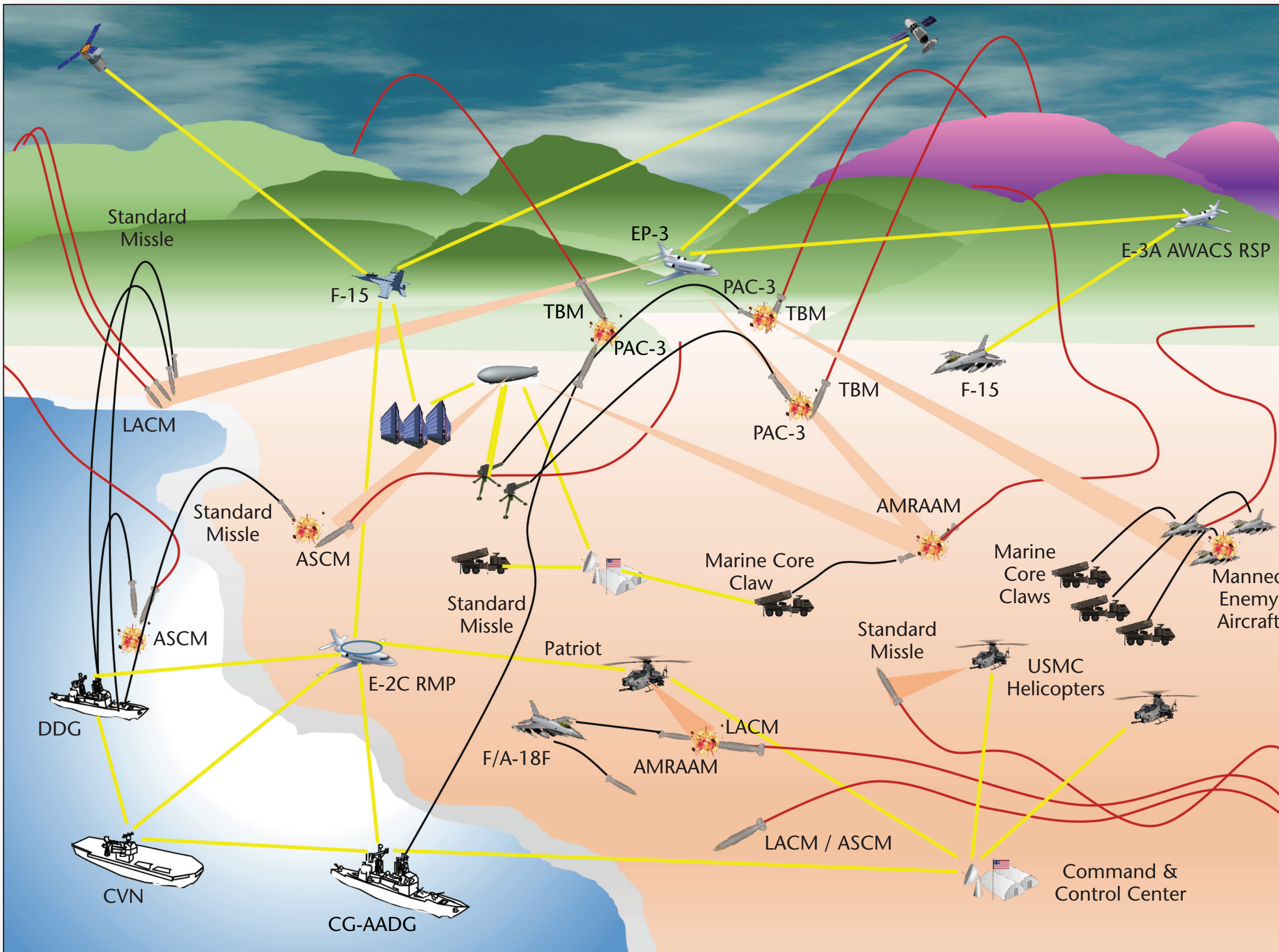

Figure 1. The Complex Tactical Environment.

figure 1, the complexities inherent in the tactical domain include unexpected and rapidly escalating events; deadly threats of many types; a variety of missions involving defensive and offensive operations and rules and policies dictating courses of action; inaccurate and incomplete knowledge of the situation; and courses of action that produce a range of potential consequences and adversarial reactions. AI technologies can support human decision makers in facing such a complex decision space.

The goal of AI is to create systems that can function intelligently and independently. In broad terms, AI encompasses the computer processing of images using symbolic learning to enhance what is seen, the processing of data using machine learning for speech, object, and pattern recognition, and cognitive learning and analysis for classification and prediction. Advances in sensors, communications, big data, and computers offer a prime opportunity for AI solutions. With large amounts of data from different sources and increased processing speeds, AI methods can provide the means to greatly improve tactical knowledge and enable automated decision aids or battle management aids (BMAs) to support the warfighter.

AI technologies have the potential to pay big dividends for naval tactical decision superiority. AI enables BMAs for improving combat identification, identifying and assessing tactical courses of action, coordinating distributed warfare resources, and incorporating predictive war-gaming into tactical decisions. AI is not an off-the-shelf, one-size-fits-all, or self-contained solution. Additionally, AI will require a systems of systems (SoS) approach. This arti-

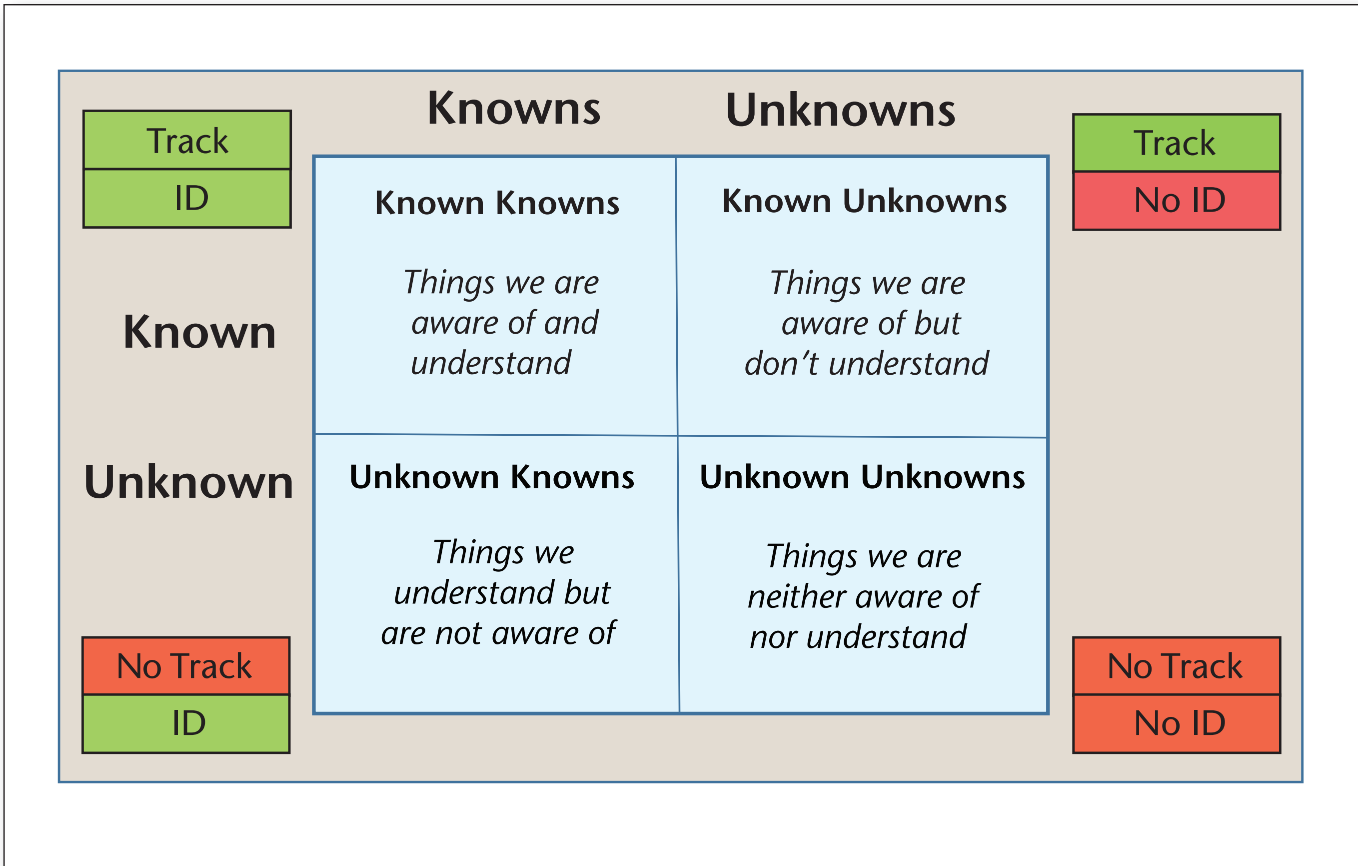

Figure 2. Knowns and Unknowns.

cle describes concepts for incorporating AI methods into decision aids to improve naval tactical knowledge and achieve decision superiority.

Combat Identification: Knowns and Unknowns

As Donald Rumsfeld put it: "There are known knowns. These are things we know that we know. There are known unknowns. That is to say, there are things that we know we don't know. But there are also unknown unknowns. There are things we don't know we don't know."[1]

A way of conceptualizing the challenge of combat identification (CID) is through the four categories shown in figure 2. In the upper-left quadrant, there are *known* knowns for areas of interest (AOI) that have been identified (assigned an identification or ID) and for which a track has been developed. A track is defined as a kinematic representation of the real-world object, based on sensor data that has been processed by a computer system. In the upper-right quadrant, there is a track of an object, but it hasn't been given an ID, which means that there is insufficient information to assign an identification to the object. So, we are aware that the object exists, but we don't understand what it is. These are our known unknowns. In the lower-left quadrant, we know that specific objects exist, but we haven't established a track, so we don't know exactly where they are located. These are our unknown knowns. Finally, the lower-right quadrant refers to objects that might exist in our AOI that we aren't at all aware of. These are our unknown unknowns.

Categorizing objects in the real-world AOI according to this known and unknown framework allows us to apply appropriate data analysis methods to each category. Figure 3 identifies different sensor and processing capabilities that could best apply to each of the four quadrants. The known knowns (in the upper-left quadrant), in general, can be analyzed using linear processes to gain ID and tracks of the real-world objects using structured data from onboard sensors. Known unknowns (in the upper-right quadrant) benefit from the collection and fusion of netted data from distributed sensors. In this case, multilinear processing might enable these unknown objects to be identified. For unknown knowns (in the lower-left quadrant), the use of multilinear processing, including correlation algorithms with increased data collection from multiple distrib-

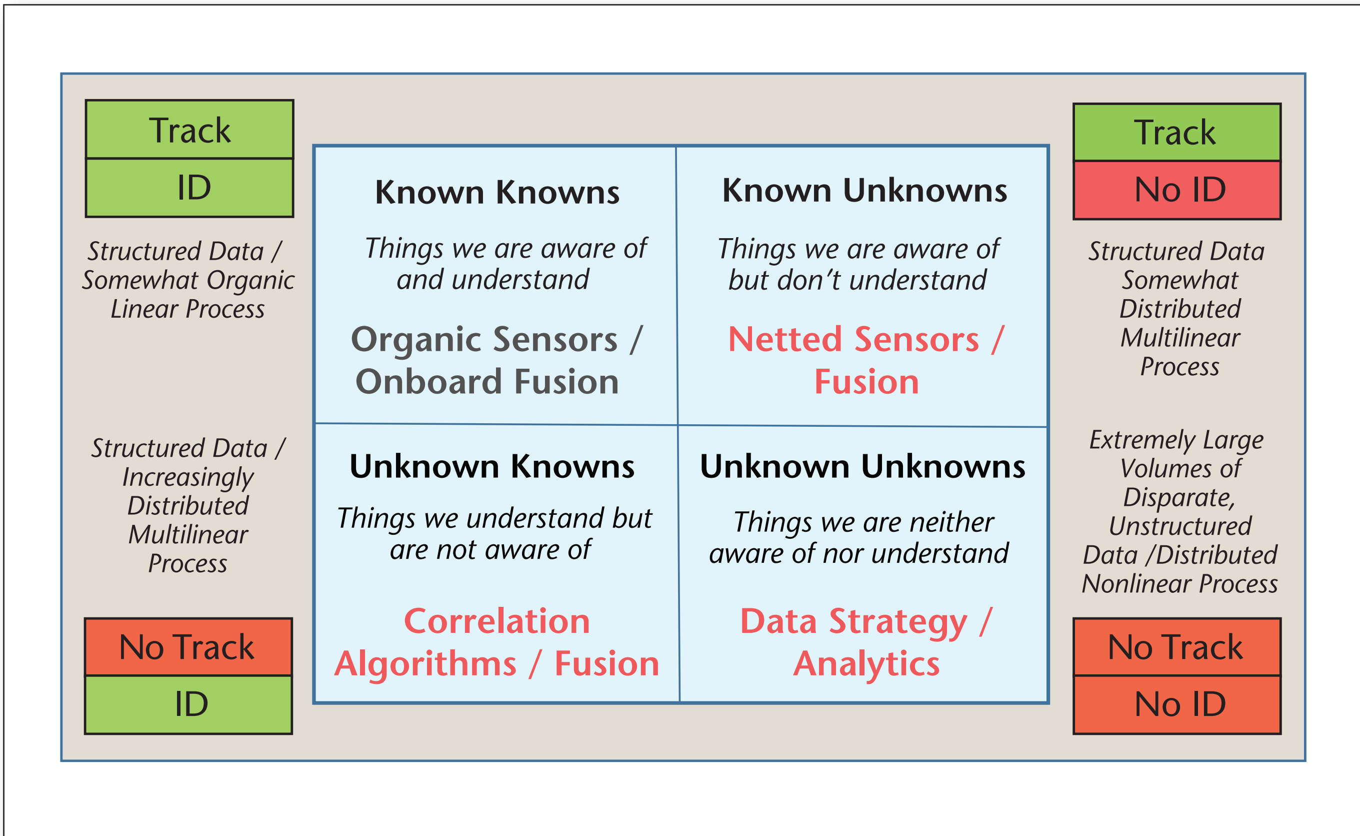

Figure 3. Data and Processing Strategies for Knowns and Unknowns.

uted sensors, might enable these objects to be located and tracked. Finally, the ability to become aware of unknown unknowns (in the lower-right quadrant) will rely on large amounts of disparate, unstructured data from distributed sensors and other information sources and will require data strategy and analytics that include AI and nonlinear processing.

To take it a step further, figure 4 shows the types of data analytics and AI methods applied to the four categories of knowns and unknowns. Here, we can see that simpler methods of fusing and applying statistics to data from news and wiki and onboard sensors is sufficient for the known knowns. As we shift to the upper-right quadrant, the use of forecasting, text and data mining, business intelligence, search engines, and some predictive analytics can support the identification of tracked objects. As we shift to the lower left, the use of knowledge discovery, collective memory, and findability algorithms can support finding the location of known objects. Finally, as we shift to the most challenging quadrant, the lower right, AI methods such as predictive analytics, machine learning, big data processing, and game theory might enable the identification and location of objects that are completely unknown.

Shared Situational Awareness

Gaining situational awareness is of utmost importance for both automated decision support systems and human decision-makers. "A CID [civil investigative demand] decision-maker is not interested in data or big data as such; but the knowledge it provides." (Zhao et al. 2015, 22). They are interested in actionable knowledge required to gain and maintain the tactical advantage. Situational awareness (SA), or knowledge of the tactical environment, must have low latency, high fidelity, and high confidence, and must cover a tactically relevant range. This knowledge or awareness of the situation can shorten decision times, and therefore response times. Warfighters want to increase the probability that objects in the operational environment are correctly identified, so decisions made for courses of action (COA) can rely on the best possible understanding of the situation.

Deep learning techniques using big data can be used to specifically address the challenges of SA, including improving the classification accuracy and certainty of air objects by associating, correlating, and fusing heterogeneous data sources. This approach is related to machine vision, which recognizes objects using very high-dimensional data

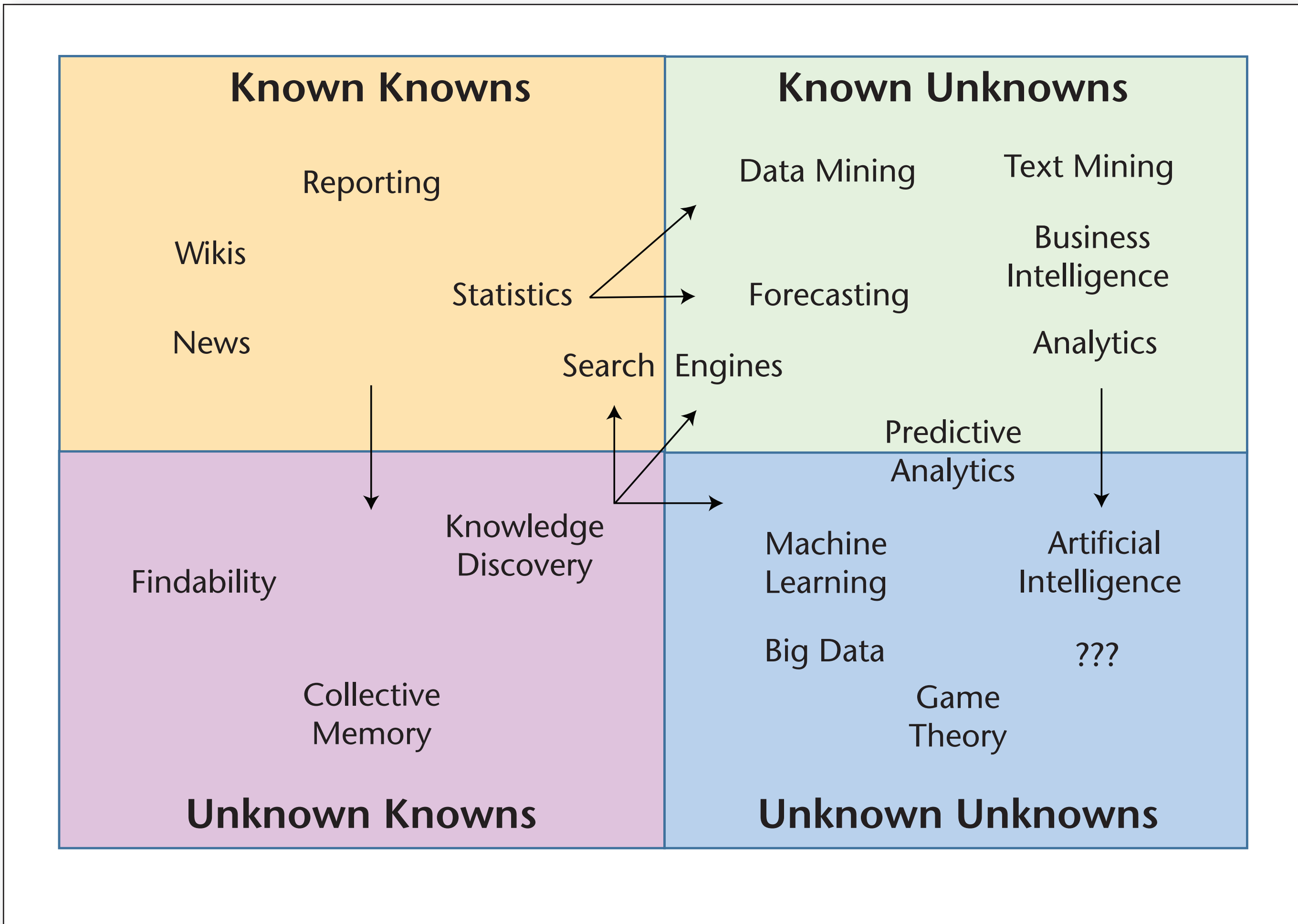

Figure 4. AI Methods for the Knowns and Unknowns.

attributes. In addition, association learning for diversified attributes from heterogeneous data sources (sensors and nonsensors) — which may not follow standard data definitions — can potentially improve object recognition tremendously (Zhao et al. 2015).

Activity-based intelligence (ABI) and object-based production (OBP) are computational methods that offer potential for SA.[2] ABI methods discover new entities and object relationships and behavior patterns based on the exploitation of all-source data at a massive scale. OBP methods organize and maintain knowledge around objects to discover things that exist and things that happen. The combination of these two methods leads to a tactical decision advantage.

The intended outcome of CID and SA capabilities is to provide actionable knowledge. Actionable knowledge is knowledge that is accurate, complete, and timely enough for warfighters to act upon, even to the point of making COA decisions that include weapon engagements. Another outcome is to produce knowledge that is shared across distributed warfare platforms, such as ships and aircraft. This shared knowledge enables a battle group to coordinate their actions, which further improves the tactical advantage.

The observe-orient-decide-act (OODA) loop is the basis for a conceptual systems of systems (SoS) architecture for a future tactical capability based on the AI methods in figure 5. The ABI and OBP methods support the ability to observe the real-world AOI. AI methods and data analytics combine with data fusion and processing to orient the situation and support decisions and actions. BMAs provide automated support to complex tactical decisions. The use of networks and multiple instantiations of this architecture enable shared SA and distributed warfighting coordination.

The desired outcome of the CID and shared SA processes is actionable knowledge. A notional display of CID determinations is shown in figure 6. An important feature would include computed confidence levels to indicate the goodness of the CID knowledge. This determination would be a combination of complex factors including weather conditions, sensor error, analytical approximation error,

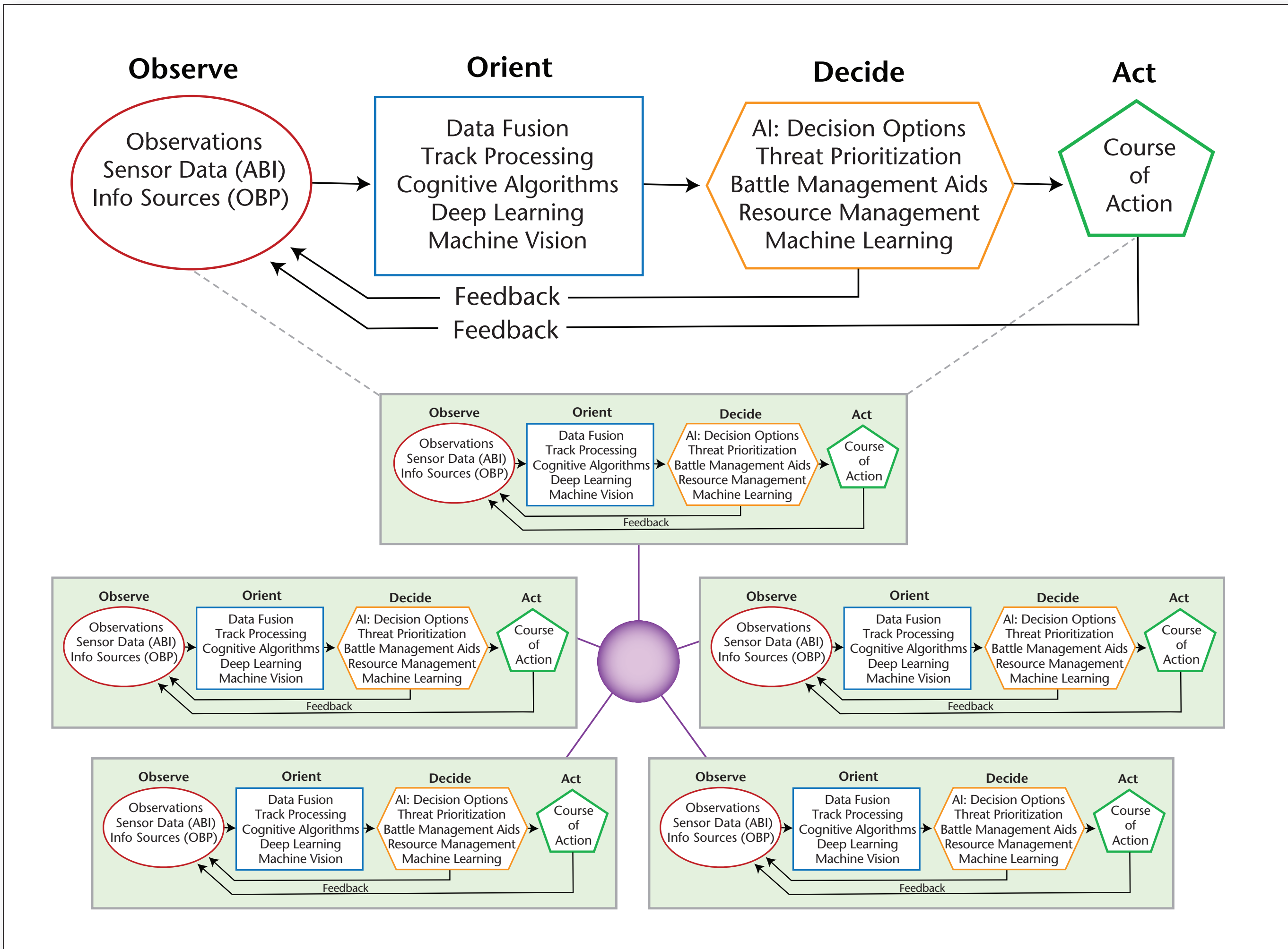

Figure 5. Conceptual Networked Architecture for Tactical Decisions.

and temporal effects such as track or ID stability over time. If higher confidence levels were required, actions could then be taken to gather more data and information sources or to apply additional data processing methods.

Holistic knowledge of the situation is a required input to effective tactical decision-making. In addition to achieving CID for the objects in the battlespace AOI, there are many other types of knowledge required to gain complete SA of the tactical situation. Figure 7 illustrates these "pictures," or categories of information. These various categories of information include knowledge of the warfare resources (weapons, sensors, communications, platforms, etc.), the weather conditions, operational missions and directives, C2 doctrine, rules and policies, and a model of what the adversary's awareness of the battlespace might look like. This additional information will greatly enhance tactical decisions — made by human warfighters with a range of support from BMAs.

Another SA challenge that AI methods can address is the ability to maintain a continuously changing model, or picture, of the continuously changing tactical environment. An adaptive data strategy is required to update and maintain accurate and timely SA that includes all of the types of knowledge shown in figure 7. Data from heterogeneous sensor and nonsensor data sources must be fused, processed, and managed as it is continuously received. The SA picture must be updated accordingly. As tactical operations unfold and data becomes outdated and no longer relevant, the system must recognize this and manage the data and picture accordingly. AI methods can be used to recognize and learn which parts of the data model are outdated and to manage the model as it continuously changes and adapts to the incoming data.

Effective tactical operations also depend on gaining a shared knowledge of the battlespace among distributed warfare platforms (such as ships and aircraft).

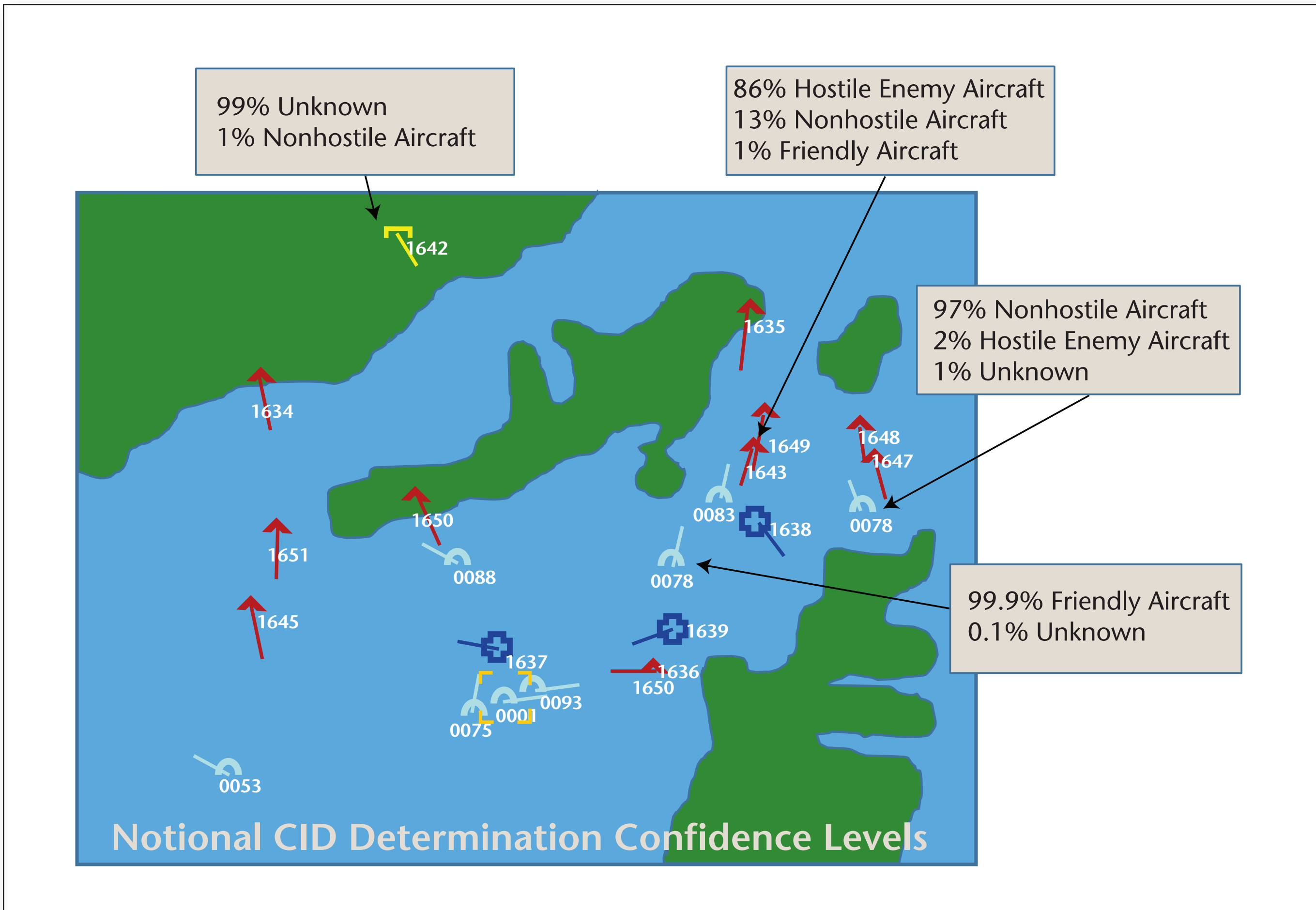

Figure 6. Conceptual CID Confidence Levels.

AI and its associated computational and data communication and management capabilities can enable the achievement of shared SA. A SoS approach, as depicted in figure 8, is necessary to implementing a shared SA. In order for distributed ships and aircraft to achieve a common tactical picture, it is necessary for the tactical knowledge (that is, CID determinations) to be common on each platform. If each platform hosts an independently operating decision aid (that operates in isolation), the tactical knowledge will vary from platform to platform depending on what data is available at each platform. Implementing a common set of collaborative AI-enabled decision aids that communicate and synchronize with each other will achieve shared SA. A SoS approach to the data strategy for managing and distributing data among the platforms is also required.

Automated Battle Management Aids

Automated BMAs are computer-aided decision support systems that are meant to enhance and improve tactical decisions. BMAs may improve decisions by speeding up the decision process, providing greater confidence in the knowledge that decisions are based on, developing more decision options, providing greater understanding of decision consequences, developing options with greater probability of success, and/or improving the optimization of resource usage. The military currently uses BMAs to share and process data to develop operational pictures and situational awareness. With the support of AI technologies, BMAs of the future can be expanded to enhance all aspects of tactical decision-making.

Decision Complexity

Military tactical operations involve a great variety of battle management decisions. Tactical decisions involve the use or placement of warfare assets that include platforms (ships, aircraft, submarines, and so on), weapons, sensors, communication devices, and people (Johnson, Green, and Canfield 2001). Decisions to use warfare assets are complicated by a number of decision complexity factors. Figure 9 illustrates four types of warfare decision factors: the temporal domain, the spatial domain, the proactive/reactive

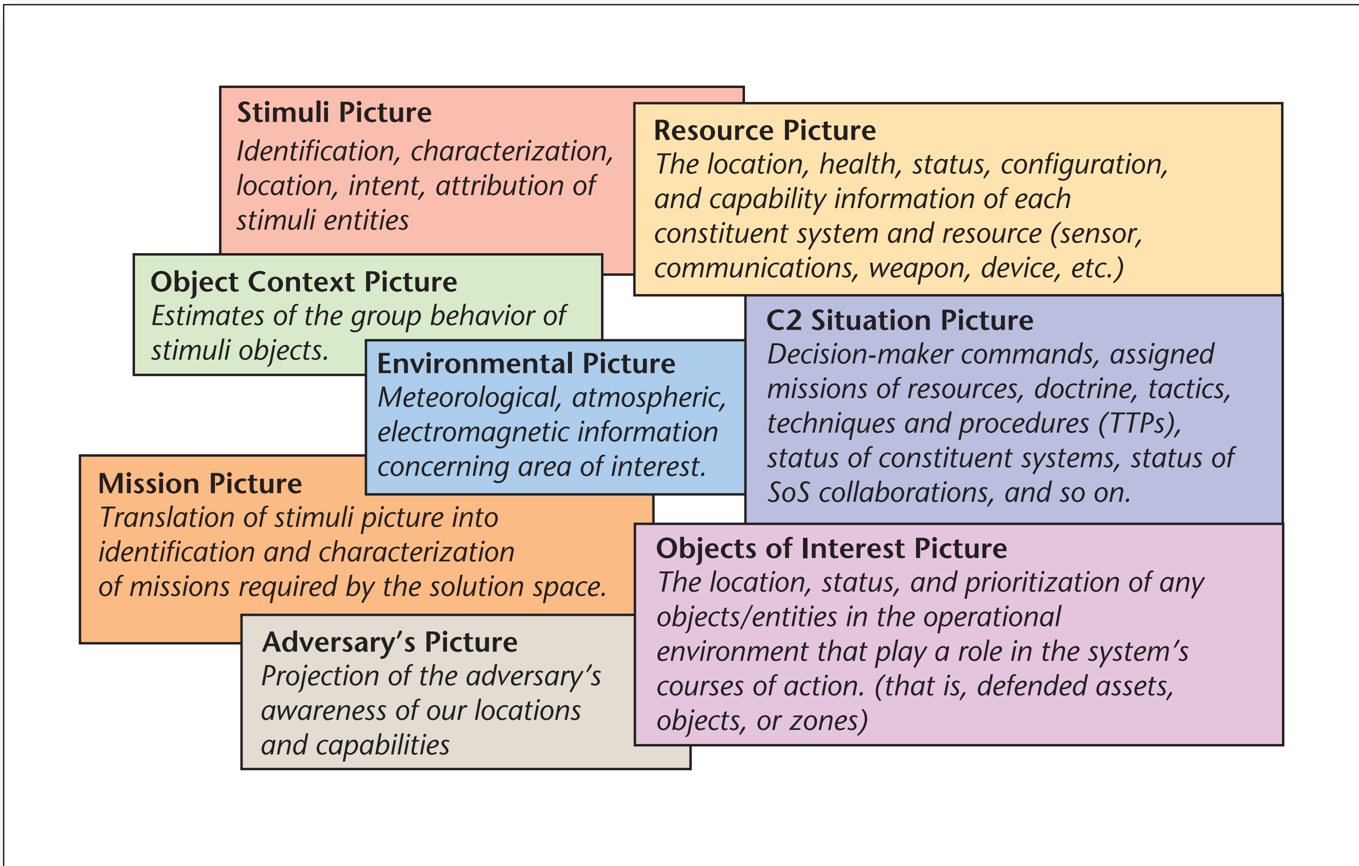

Figure 7. Types of SA of Knowledge.

domain, and the domain of rules and policies. Each of these domains affects the decision-making process and leads to increased decision complexity. These factors lead to a decision space that overwhelms human decision makers and requires an AI technology solution.

Planned or proactive decisions include positioning forces (like ships, battlegroups, and aircraft), stealth operations, offensive attacks, and denying enemy operations through jamming or other force measures. Examples of reactive or responsive decisions include defending against an active threat, moving platforms into a defensive posture, retreating from a threat environment, and assessing battle damage. Effective battle management must recognize when proactive or reactive decisions need automated support.

The nature of military decisions shifts over time and can be viewed as hierarchical. Strategic decisions have a longer time horizon and must take into consideration high-level objectives — sometimes spanning years. Planning-level decisions have a shorter time horizon and are proactive even when arranging a defense. Tactical decisions, which are the main focus of battle management, have the shortest time horizon and involve very near-term planning or proactive decisions as well as reactive decisions in response to enemy actions. Consistency is desired among the three temporal decision domains to effect compatibility among tactical, planning, and strategic decisions. Likewise, plans and strategies need to support effective tactical warfare and reflect major changes in tactical threat environments. Automated BMAs should be designed to support a hierarchical decision paradigm, as well as one that supports and adapts to varying decision time horizons.

One of the results of the hierarchical temporal decision domain is a set of rules and policies that guide tactical decisions. These rules are one of the methods by which near-real-time decisions can align with longer-term plans and strategies. The rules and policies support effective tactical decisions that are consistent with the higher objectives. Automated decision aids must support dynamic and adaptive decision-making across the temporal and hierarchical domain to enable consistency among levels; consideration of how changes at various levels might affect other levels; and effective promulgation of guidance across levels.

A fourth way to categorize battle management

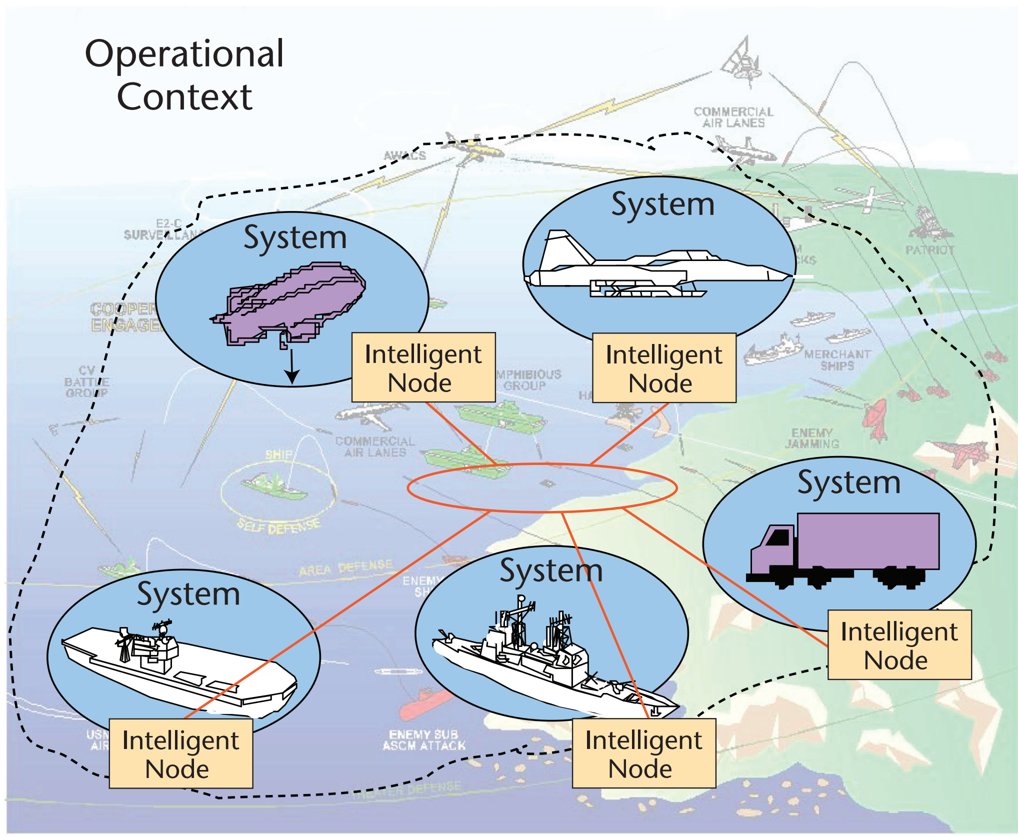

Figure 8. SoS Approach to Shared SA.

decisions is by spatial domain, that is, space, air, sea, underwater, or land. Threats vary greatly in each of these operational environments. Likewise, warfare systems are developed to address specific threats or threat types that naturally reflect their spatial environment. Naval battlegroups must address threats in all spatial domains, and at times, simultaneously. Automated BMAs have the potential to address this complexity through gains in cross-spatial-domain situational awareness and through the development of decision alternatives that prioritize missions and engagement strategies.

Ultimately, the battle management decision space fluctuates from simple to complex as operations range from peacetime to multidomain threat encounters. Examples of changes to the problem space that affect the complexity of the decision space include battle tempo (or reaction time), the number of simultaneously occurring threats (or battle events), the severity of the consequences of battle events, the heterogeneity of threats (due to threat type or spatial domain), and the scope of the event or events (in terms of area or population affected). All of these operational factors translate into multidimensional variables that comprise a decision space. As the decision space complexity increases, military human decision makers become overwhelmed. At this point, automated BMAs are necessary for effective decision-making.

Human-Machine Decision-Making

The amount of information in the battlespace has increased due to more sensors, networks, participants, reach-back and intelligence. Human decision makers become overwhelmed with information and shortened decision times. Automated BMAs are a necessary capability required for effective tactical decision-making.

Automated decision aids, or machines, as depicted in figure 10, can support human decision makers in a number of ways. Three models for human-machine decision-making interaction are shown (Johnson, Green, and Canfield 2001). The manual decision-making model encompasses situations in which

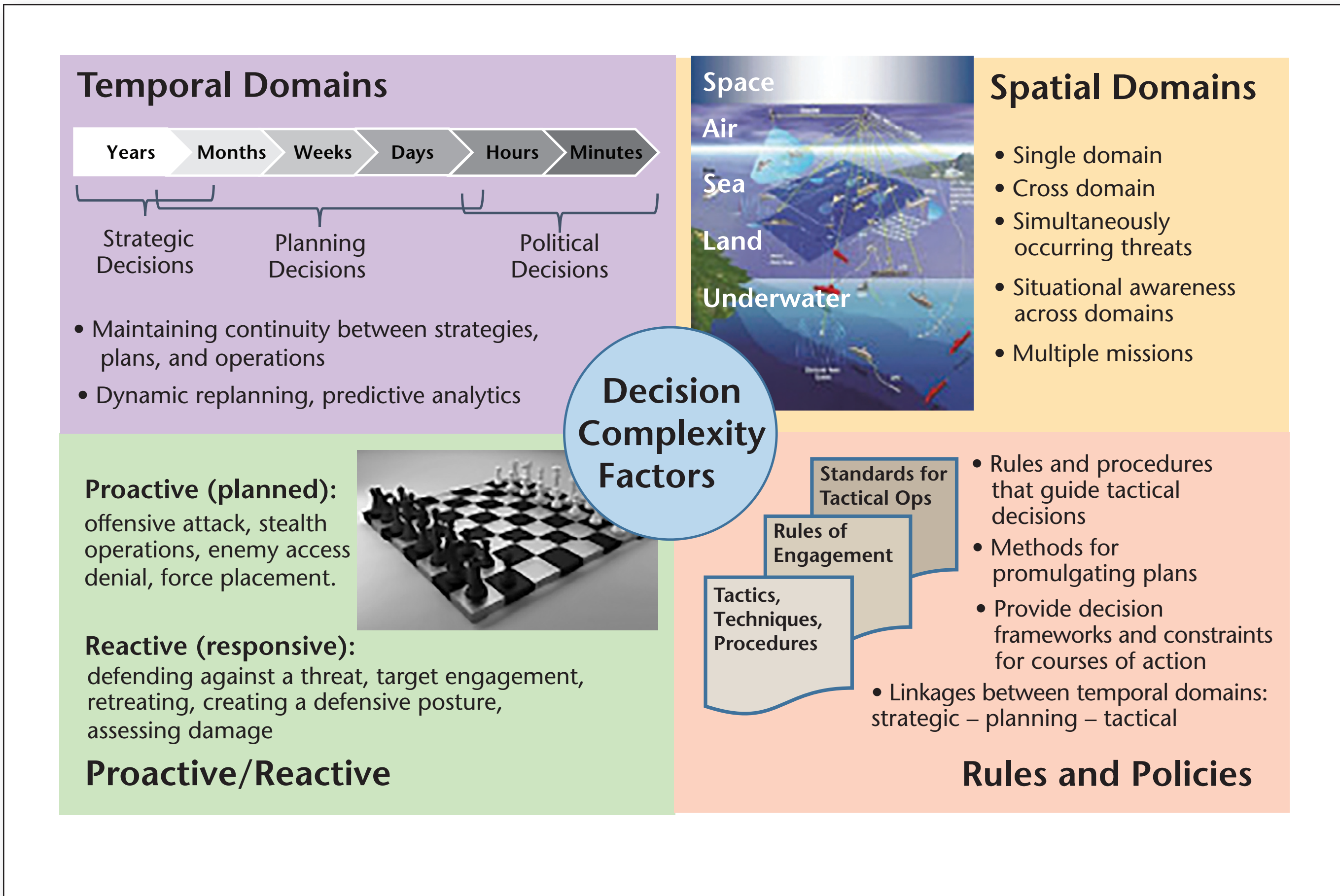

Figure 9. Tactical Decision Domains.

humans collect and store relevant information, as well as perform the decision analysis (processing and decision-making), in their heads. This model implies a fairly simple and straightforward decision space in which the amount of data and number of variants is manageable manually. In the semiautomated model, the human decision maker can rely on machines to manage, store, fuse, and process the input information to display decision analytics to the human. Decision analytics may consist of knowledge of the battlespace and threats, COA options, and quantitative measures of expected event successes and consequences. Finally, in the fully automated model, the role of the human is to monitor the automated machine decision processes and to override or change decisions when necessary.

It is important to establish the appropriate mechanism for the type of decision being made. In general, decision-making can be performed manually when the problem space is relatively simple and the number of factors to be considered and the amount of information is manageable by the human decision maker. For some types of decisions, a semiautomated human-machine interface (HMI) mechanism is most appropriate. This approach is effective for more complex decision spaces with potentially critical or dire consequences, requiring the support of automated BMAs, but with significant human involvement. A fully automated human-machine interaction is appropriate for decision spaces that are complex in terms of large amounts of information that must be processed and fused, but very straightforward in terms of the types of decisions being made. Fully automated decision modes are for peacetime operations where decisions do not have dire consequences or for highly complex operations where the decision reaction time is too compressed for humans. Fully automated decision modes are appropriate when there is very high degree of confidence in the information and knowledge of the situation. For example, when it is known with high confidence that a tracked object is in fact an enemy threat target.

A future capability for battle management decision support systems could select the appropriate decision model for the given decision space. Such a system would require a flexible decision-making architecture to accommodate the three human-machine models and apply them as needed. The superstructure itself

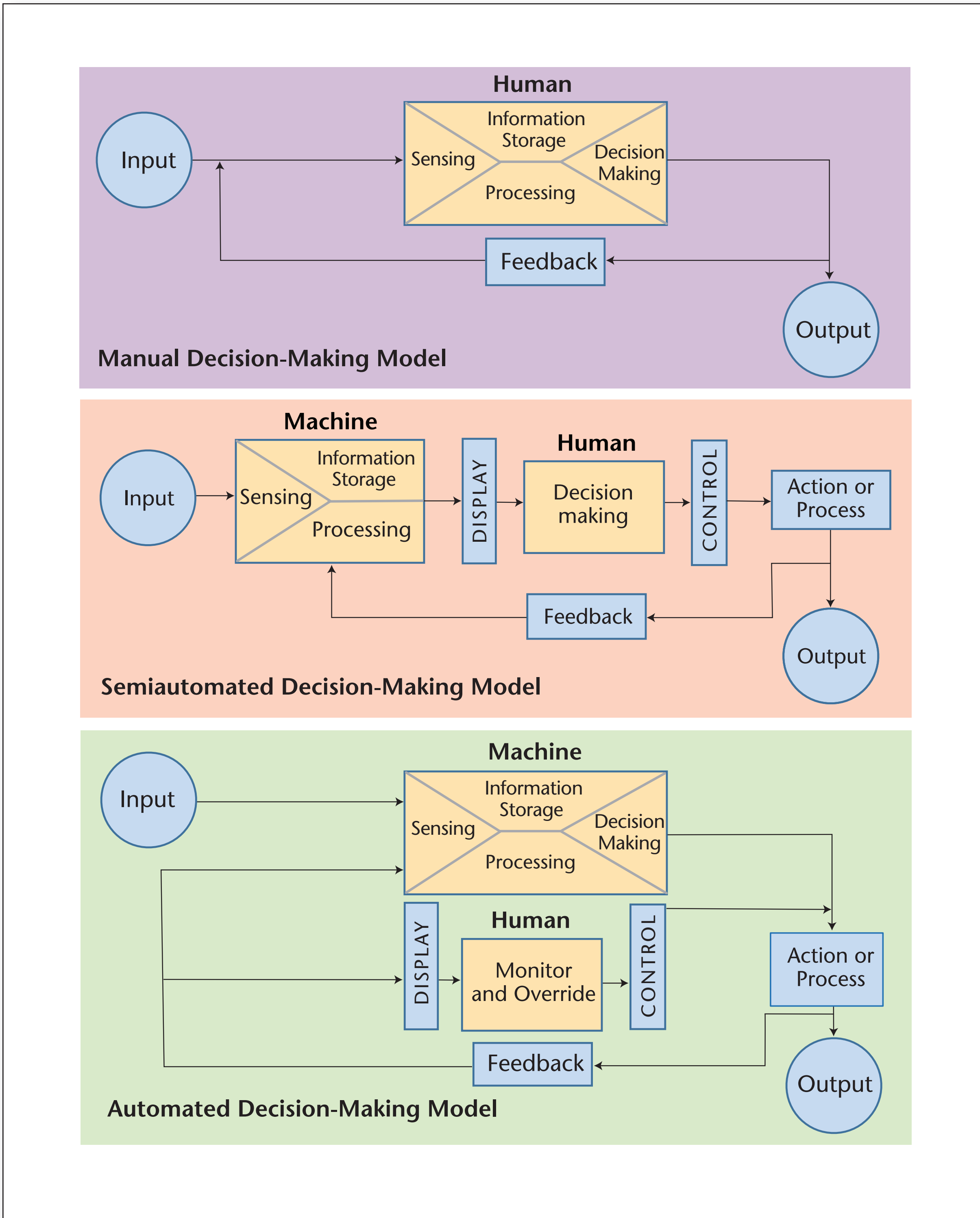

Figure 10. Human-Machine Models for Decision-Making.

would be monitoring the decision space and evaluating what kinds of decisions needed to be made and then determining the appropriate interaction between the human and machine to make each decision. The superstructure would rely on AI methods to learn and assess the situational complexity to enable adaptive responses in the appropriate human-machine mode.

Force-Level Decisions for Distributed Warfare Coordination

Battle management operations are complex (Young 2012). And "a high complexity task requires a system that is sufficiently complex to perform it" (Bar-Yam 2004, p. 99). The tactical environment can range from peaceful to highly dangerous given a multitude of varied threats from many different directions. This mutability translates into a complex decision space for battle management. The state of the decision space must flexibly shift from linear and straightforward during normal nonthreat operations, to highly nonlinear and multivaried during combat operations.

Characteristics of a complex problem space include complex objectives, complex environments and/or operations, adaptation, collective behavior, and unpredictable outcomes of decisions (Braha, Minai, and Bar-Yam 2006). Each of these characteristics is inherent to tactical operations (Young 2012). The battlespace presents multiple objectives that are generally inconsistent and changing. Military systems must weigh their individual battle objectives, such as self-defense, against force-level missions that may include area defense, stealth operations, or defense of specific assets. Complex operations are required, as adverse and widely varying environments result in changing target priorities and multiple cross-spatial domain missions. Adaptation is a required characteristic of warfare systems as they respond to the complex and changing threat environment. Military operations must adapt effectively to threats to improve their chances of survival and meet tactical and strategic goals. The collective, or force-level, behavior of distributed warfare assets must be properly orchestrated to avoid collisions and friendly-fire incidents and ideally to benefit from their cumulative contributions. Finally, the unpredictable outcomes of tactical decisions, ranging from misfires to misidentifications to misassessments of battle damage, result in a problem space made more complex through inaccurate knowledge and a ripple effect of actions and unforeseen consequences.

AI has the potential to support human decision makers by characterizing the level of complexity in the operational environment and translating this knowledge to the decision space. Ideally, a complete and accurate picture of the battlespace will provide situational awareness to the decision space. BMAs using AI could monitor the picture and develop assessments of the complexity characteristics of the problem space. This knowledge could support effective and timely use of decision aids, as well as enable the effective interplay of human and machine decision-making.

AI technologies support a multidimensional approach (Gharajedaghi 2011) to the problem space, enabling a force-level solution by viewing the battlespace as a set of interacting systems. The ability to exploit the multidimensionality supports collaborative force-level behavior that spans spatial and temporal domains. It enables layered defense and integrated fire control strategies involving distributed weapons and sensors. Automated BMAs, relying on AI methods, can provide the quantitative analysis to determine collaborative resource utilization when complex multidimensional objectives exist.

Decision Scope and Systems of Decision Systems

Complex tactical environments require a holistic perspective to manage warfare resources from a force level. As the environment becomes more complex, events are occurring more rapidly and in parallel. The numbers of decisions are increasing, as are the number of courses of actions required. More demands are being made on the finite set of warfare resources, and their missions, objectives, and courses of action are becoming more interrelated. Gaining a holistic understanding of multiple threats and missions, as well as the possible options for addressing them, along with the possible consequences, provides a more effective military response and might be required to effectively address demanding threats. The idea of battlespace perspective can be characterized as decision scope, that is, setting a boundary around the problem space and solution space. A more holistic decision scope includes an area, or theater, and all threats and warfare resources in this geospatial area. A narrower decision scope may only include a particular threat and a particular platform and its associated assets.

Establishing decision scope is both a limiting factor and a necessary enabler. Tactical decisions become more interdependent and messy in terms of cause and effect as the operational environment becomes more complex (Jackson and Keys 1984). Making a particular weapons engagement decision or sensor-tasking decision is simpler when there is one threat to kill or one area of interest to view. However, narrowing the decision scope to firing a single weapon system or managing the sensors on one ship loses its overall force-level effectiveness when several tactical missions need to be addressed or many threats need to be prioritized and engaged. The principle of holism, applied to decision-making in this context, involves including "simultaneously and interdependently as many parts and levels of the system as possible" (Jackson and Keys 1984, p. 480). In other words, widening the scope of the decision space to perhaps consider a tactical area, or theater. Determining the decision scope is a decision in itself. The goal is to design future force architectures that support a flexible decision scope that can widen as force-level missions become more complex and might benefit from distributed warfare asset collaboration. AI methods can enable and manage an adaptive architecture — identifying complexity and

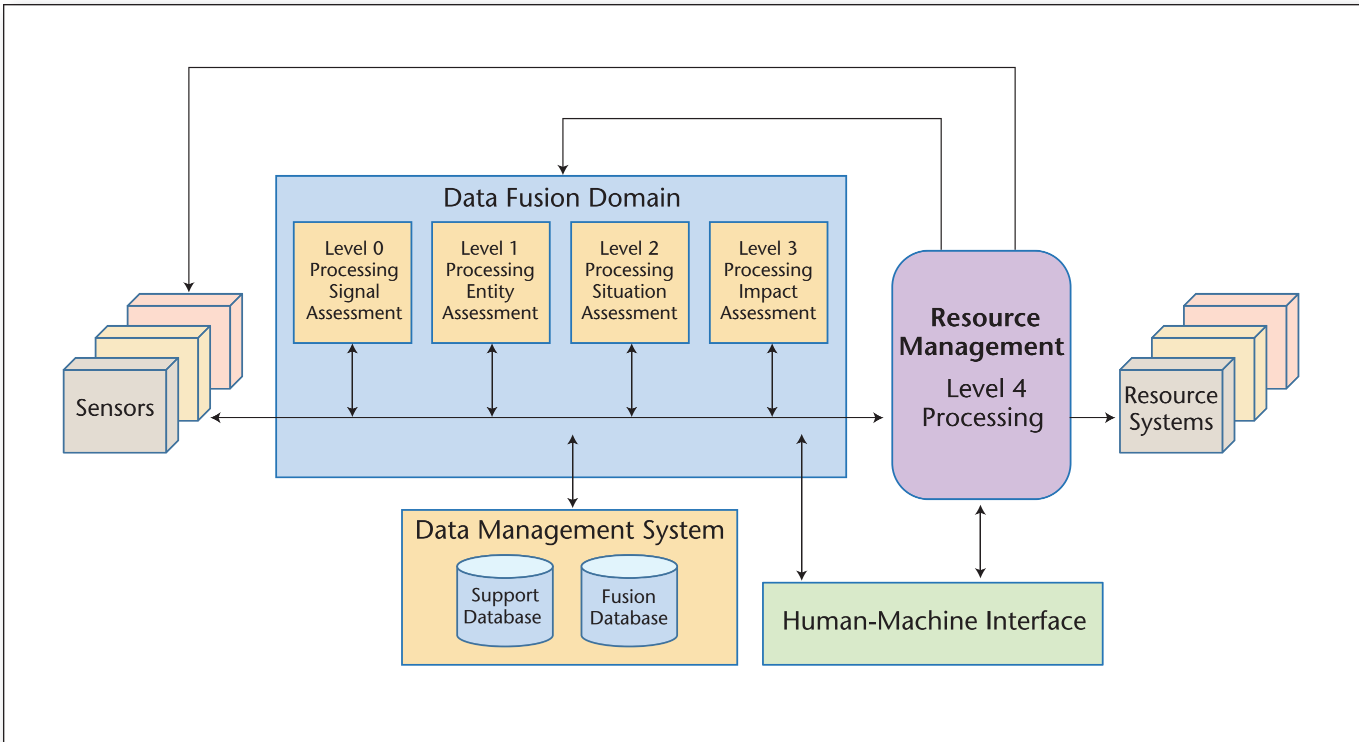

Figure 11. Resource Management within the Data Fusion Architecture.

adjusting decision scope and managing missions at the force level.

Once a tactical military force faces a complex operational problem space, future automated BMAs could establish a more holistic and wider decision scope and support resource management at both the platform and force levels. Ultimately a variety of automated BMAs could support resource usage at different levels. BMAs supporting specific sensors and weapons could be orchestrated by a higher-level BMA architecture. Thus a system of BMA systems could be implemented.

Resource Management

Resource management is a primary focus of tactical decision-making and, consequently, a primary application for automated BMAs. The previous section characterized the battle management problem space in terms of decision-making; made the distinction between decisions made by humans and how automated decision aids can support those decisions; and characterized battle management complexity. This section looks at some specific concepts for how AI technologies and concepts can enable and improve resource management.

Defining warfare assets (ships, aircraft, submarines, weapons, sensors, communication devices/networks, data processing, and jammers) as systems allows them to be considered as resources and viewed in terms of their functions, performance, behavior, structure, and interfaces. It enables quantitative analyses to be performed based on resource characteristics such as location, status, and expected capabilities. As operations grow in complexity, AI methods could be used to determine the effective use of warfare resources when multiple objectives exist that overlap and conflict. Warfare resource utilization could, with the aid of BMAs, include forming collaborations among systems to enable systems of systems (or force-level) behaviors and capabilities to better address complex tactical missions.

Resource management as part of the data fusion process (Steinberg, Bowman, and White 1998) is highlighted in figure 11. In this architectural concept, resource management is considered as level 4 processing — assessing the products of data fusion to determine how to best manage or task resources. Resource management also provides feedback to the data fusion process, tasking the level 0–3 processes. This data fusion architecture is still a useful paradigm for implementing AI methods in each processing level. Given significant advances in computing power and many new sources of data, the use of machine learning and deep learning can improve resource management — especially given complex operational situations and distributed warfare resources.

Another way to conceptualize resource management is in terms of systems or data models.

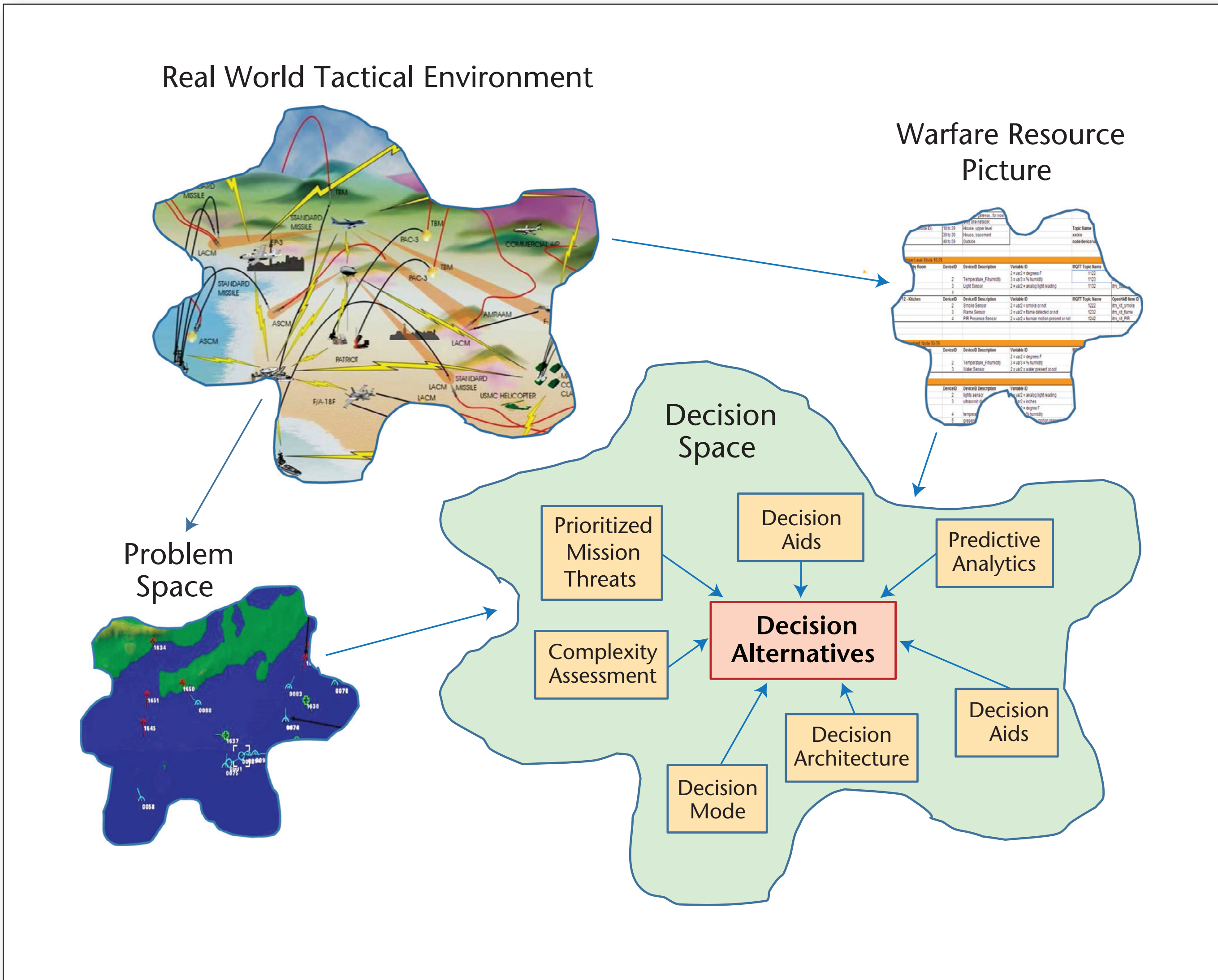

Figure 12. Tactical Models and the Decision Space.

The decision space itself can be viewed as a system or model. Taking a systems approach to the decision space enables the definition of a boundary, inputs and outputs, functionality, performance, and structure. Figure 12 illustrates the decision space in its contextual environment. The actual real world is illustrated in the top left. Knowledge (or situational awareness) of the battlespace is developed and maintained as the problem space (or operational tactical picture). It includes tracked threat objects as well as terrain, weather, defended assets, and all other physical entities in the real world. These entities are modeled in the form of data representations. A resource picture must also be developed and maintained that includes up-to-date status, health, readiness, and projected capabilities of the warfare assets. The problem space and resource picture comprise the primary inputs to the decision space.

The decision space is the model of all of the factors going into the decision process to formulate tactical courses of action. The boundary of the conceptual decision space model surrounds the decision architecture and the decision analytics, which include decision aids, assessments, prioritizations, alternatives generation, and overall decision management. The primary function of the decision space system is to develop decision alternatives. These alternatives provide recommendations to manage the warfare resource assets, such as sensor tasking, courses of action, weapon scheduling, and the movement of platforms. Secondary functions include estimating the confidence levels associated with decision alternatives and the many types of analyses that feed into the alternatives. Examples of analyses include prioritizing threats, evaluating war-gaming possible consequences, estimating sensor error, estimating knowledge accuracy and completeness, evaluating operational complexity, and recommending optimum human-machine decision-making interaction. The interaction between the human and automated decision space is not illustrated in the simplified concept shown in figure 12, but this interaction would be significant in tactical operations.

The outputs of the conceptual decision space system would include decision alternatives, estimations of predicted consequences, estimated probabilities of success and failure, and the confidence levels associated with source information, options, and knowledge in general.

To coordinate tactical decisions across the force, a system of distributed decision systems is needed. A future concept that relies heavily on AI technologies is to integrate identical intelligent agents onto distributed warfare platforms. These agents would share data and information and each develop decision alternatives for both individual resource management and force-level battle management options. The distributed agents would share decision alternatives and synchronize their selections. This system of decision systems would enable distributed warfare coordination with the objective of optimizing warfare resources at the force level. This futuristic concept would depend on intelligent analytical methods as well as intelligent and self-aware data strategies and data architectures. Ultimately, such a system of AI systems would enable huge gains in tactical decision superiority.

Predictive Analytics

Using methods of machine learning to process and analyze large amounts of heterogeneous data and information, AI technology can make predictions about probable effects, outcomes, and responses. These AI methods, referred to as *predictive analytics* (PA), can provide a powerful capability for tactical decision-making. Armed with the knowledge of possible effects and adversary responses to courses of action, warfighters can leap ahead in terms of applying longer-term strategy to near-term warfare decisions.

A PA capability enables strategic operations within the tactical domain — enabling projections of possible consequences and effects of decision alternatives. Conceptually, PA can develop what-if and if-then predictive scenarios to shape the synthesis of future intelligent decisions and coordinated resource management. PA would identify projected short-term and long-term effects of different course of action options. It would enable BMAs to assess these projections and weigh them as courses of action are selected.

Figure 13 contains some of the notional capabilities of a future PA capability. Given tactical knowledge of the operational situation and warfare assets, as well as COA options developed by the resource management capability, PA could assess the consequences of COAs and develop projected future states of the environment and warfare assets. These projections would be used to support the selection of COAs with the most desired consequences. A PA capability would support tactical actions that best align short- and longer-term objectives. It could also assess the possible effects of weather predictions and the availability, depletion, and projected capability of warfare resources. It could also assess and predict the overall readiness, resilience, and warfare capability of a tactical battle group.

A PA capability could employ game theory methods to perform war-gaming assessments to predict enemy responses to tactical actions. A model of the adversary's predicted knowledge, capabilities, intents, and strategies would have to be developed and maintained based on our knowledge and predictions of the enemy. In addition, it would be necessary to develop and maintain a predicted model of what the enemy knows about our forces, based on assumptions and any tactical knowledge we have. This war-gaming capability could conceptually be part of the operational BMA capability for tactical decision-making.

Conclusions

In summary, the battle management problem space is complex and it will only continue to grow in complexity with the addition of more sensors, more information, more unmanned threats, more non-state adversaries, and advances in technology. This ever-increasing complexity places a greater demand on tactical decisions — requiring them to be made both more quickly and more effectively. The level of complexity can easily exceed the abilities of human decision-making. Fortunately, the increase in sensors and information systems is also creating an opportunity for AI as a capability enhancer and improver for tactical decision support. This paper introduced some concepts for using AI to improve combat identification, shared situational awareness, battle management, resource management, and operational war-gaming. Employing AI effectively will require a holistic systems of systems approach to create an adaptive architecture of decision aids that synchronizes distributed knowledge and decisions across the force, establishes and maintains decision scope, identifies levels of situational complexity, and self-assesses to manage human-machine interaction modes and determine levels of confidence in knowledge and COA. The effective use of AI in support of human warfighters provides the foundation for tactical solutions and decision superiority.

Notes

1. A response US Secretary of Defense Donald Rumsfeld provided at a US Department of Defense news briefing, February 12, 2002.

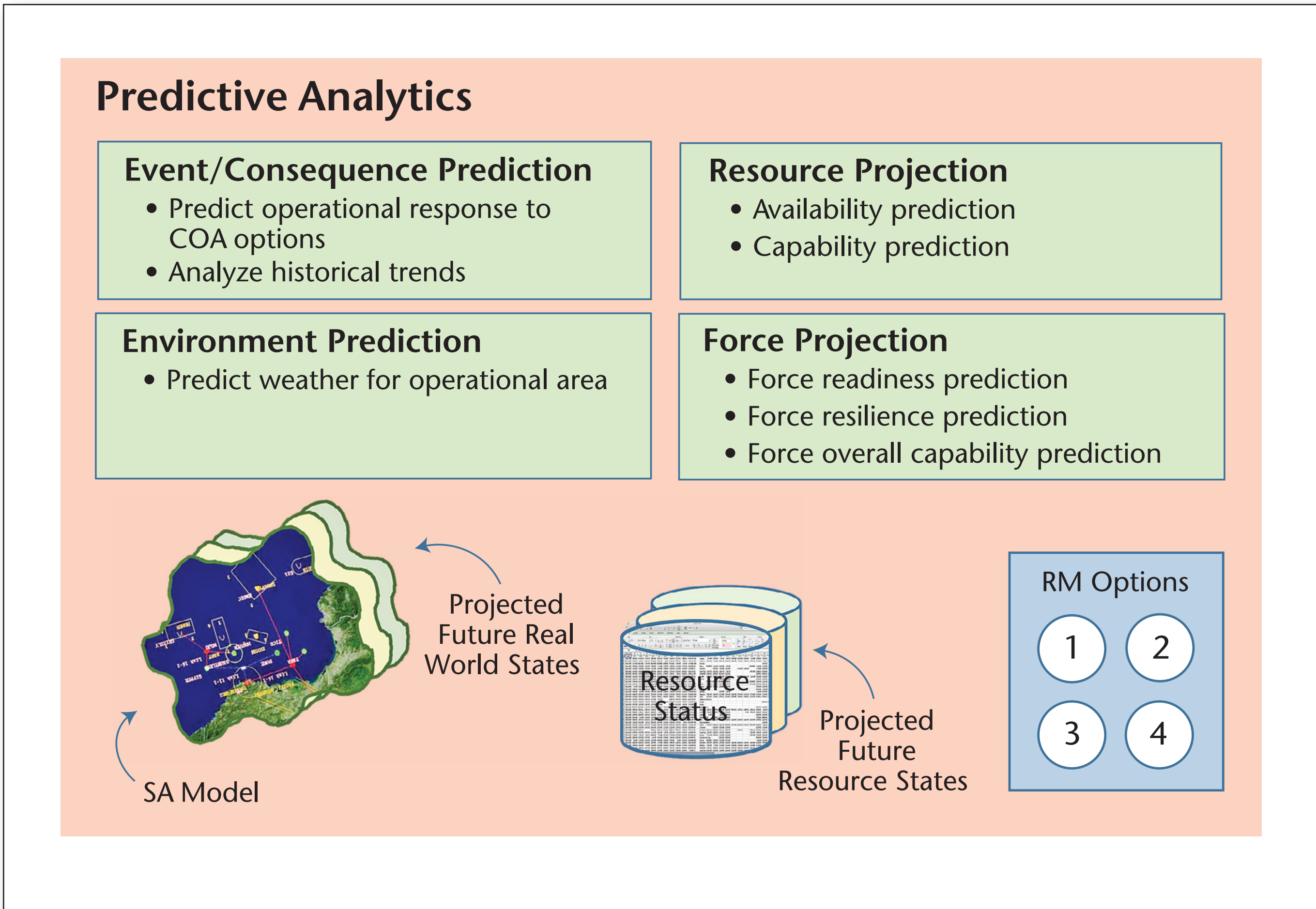

Figure 13. Predictive Analytic Concepts.

2. Decision Advantage Based on Activity-Based Intelligence and Object-Based Production. Vencore Inc. Presentation.

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