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Autonomy in Use for Space Situation Awareness

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ABSTRACT

Advancements in artificial intelligence, information communication, and systems design are potential for autonomous systems emerging for space situation awareness (SSA) architectures. Examples of architecture designs are autonomy in motion (AIM) for dynamic data assessment systems (e.g., robotics) and autonomy at rest (AAR) for static data collection systems (e.g., surveillance). However, there is a need for data architectures which are tailored to the SSA missions, which necessitates autonomy in use (AIU). AIU requires pragmatic use of message passing and data flow architectures, contextual and theoretic modeling, and user and information fusion. Information fusion provides methods for data aggregation, correlation, and temporal assessment and awareness. Together, AIU accesses the dynamic data for autonomy in change (AIC), information fusion from AAR in order to make AIM real-time decisions. The paper discusses issues for space situation awareness directions focusing on autonomy in use.

Keywords: Space Situational Awareness, Machine Learning, SATCOM, Autonomy in Use (AIU)

1. INTRODUCTION

Space situation awareness (SSA) has many elements divided into areas of sensors, objects, and threats. The sensors monitor the environment from optical, radar, and magnetic sensing, among others. Sensing provides a picture of the situation; however, it is not pristine due to sensing environmental constraints [1] and subject to communications continuity [2]. The objects include resident objects, debris, and satellites; however, space is getting crowded, which exposes vulnerabilities to systems functions [3]. Moreover, the space environment encompasses many untapped opportunities from the global perspective, but it is subject to space weather such as radiation. Together the hazards, environment, and threats (HEAT) require pragmatic use of sensing data, Figure 1.Building on previous discussions [4], we discuss autonomy for space situations, Figure 2.

There is a need for information management techniques [5] to support various applications such as SSA [6]. The key aspect for SSA [7] is to track the many resident space objects (RSO), ranging from satellites, debris, or space transportation support [8]. To enable the space environment assessment, many attributes include communications, space weather, and conjunction analysis as well as using non-tradition data [9]. Key elements of SSA include: (1) RSO tracking and characterization [10], (2) satellite health monitoring and communication [11], (3) information management sensing, and navigation [12], and (4) data visualization [13]. Various applications include deep space exploration, global satellite positioning (GPS) navigation, and disaster response analysis. Four related issues that correspond with these areas include (1) command and control (e.g., tracking), (2) cyber security (e.g., satellite health monitoring), (3) connectivity and dissemination (e.g., communications), and (4) processing and exploitation (e.g., remote sensing) that require autonomous use of data [14].

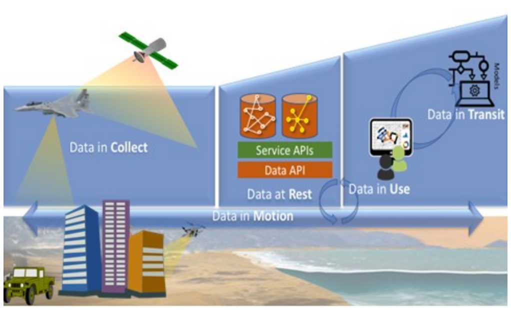

Figure 1– Elements of Data for SSA

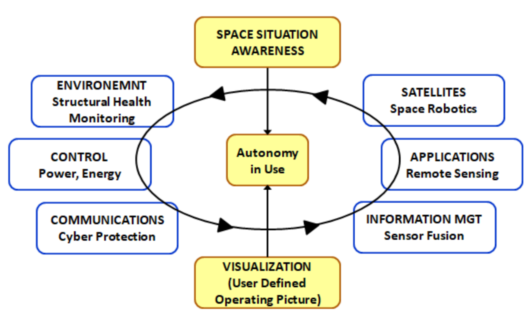

Figure 2 –SSA Functions

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The SSA environment roughly consists of two major areas: ground operations and space situation awareness (as shown in Figure 2). Effective satellite operations focus on the *local* perspective to include understanding the space environment to enable continuous operations by understanding the space weather (e.g., solar radiation) and building components that support satellite health monitoring (SHM). Collected data for SHM is then coordinated with the on-board power requirements and solar panel energy acquisition for efficient operations. Finally, satellites are routers of information such that communications of data (up-link and down-link) can be optimized for bandwidth and network bounds.

SSA is a *global* perspective. Data collected from ground and other space assets are used for RSO tracking, imaging and collision avoidance (e.g., satellite). Dynamic Data Driven Applications Systems (DDDAS) development include deep manifold learning [15], nonlinear tracking [16, 17], and information fusion [18, 19] show promise for advanced SSA assessments. With the global operations, there is a need for information management, remote sensing, and cyber analytics. Information management includes the types of data and signals being routed in the space network for coordinated control and sensing. Key elements of information management include ontologies, data base access, and graphical networks [20]. Remote sensing from satellite operations includes large data images (e.g., multispectral imaging [21]) for ground assessment. Cyber protection includes responses to threats such as signals jamming, spoofing, and contamination.

Various publications emphasize the importance of autonomy for future society [22], military [23], and industrial systems [24]. For example, autonomy is typically associated with self-governing behavior that resides in supervised, semi-supervised, and unsupervised systems. Users of autonomous systems require a level of trust before operating with software and hardware designs that exceed the capacity of individual users. The trust in design, development and coordination require many strategies for effective development for future man-machine autonomous systems [25]. Recent trends in autonomous systems include:

- *Artificial Intelligence/Machine Learning*: The confidence, scalability, flexibility, and data analytics of autonomous systems to provide information for effective analysis. Such an example is big data analysis and *sensor modeling* that determines which observations should support future collections.
- *Cognitive Echelon*: The accuracy, complexity, usability, and appropriate level of autonomous systems to support reasoning and thinking. Such an example is forecasting systems and *social/cultural modeling* that support course of action planning.
- *Human-Machine Design*: The throughput, reliability, maintainability, and control of autonomous systems to coordinate action for task completion. Such an example is *engineering modeling* that determines vehicle support during dynamic conditions.
- *Mission Focus*: The timeliness, availability, adaptability, and responsiveness of autonomous systems to augment roles to provide effect. Such an example is advanced *science modeling* capabilities that support operations to include weather, terrain, and materials variations.

The paper is organized as follows. Section 2 provides different definitions of autonomy. Section 3 discusses data requirements for effective autonomy. Section 4 discusses autonomy in use for information assessment and context awareness. Section 5 overviews the need for autonomy in use functions for SSA. Section 6 provides conclusions.

2. DEFINITION OF AUTONOMY

Typical automation assumes limited human involvement; however, most technology is employed for use by humans (automation) or for mission objectives (autonomy). The definitions of automation and autonomy are [26]:

- **Automation**: The system functions with no/little human operator involvement; therefore, the system performance is limited to the specific actions it has been designed to do. Typically, these are well-defined tasks that have predetermined responses, i.e. rule-based responses (with data-driven control for decisions).
- **Autonomy**: Systems have a set of intelligence-based capabilities that allow it to respond to situations that were not pre-programmed or anticipated in the design (i.e., decision-based responses).Autonomous systems have a degree of self-government, self-directed behavior (with the human's proxy for decisions).

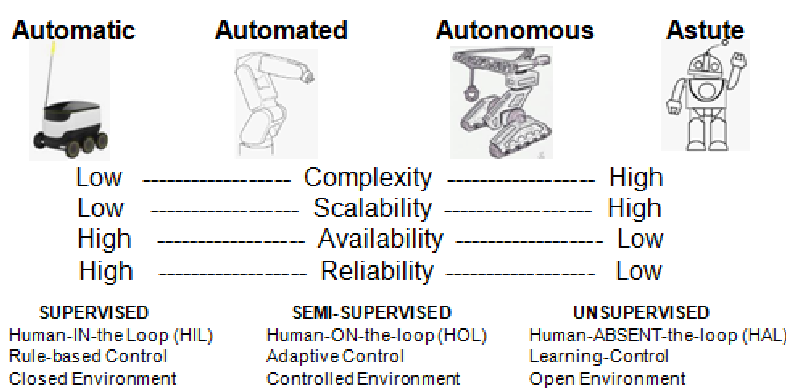

Figure 3 –Information Fusion System Design.

A simple machine supports automatic functions such as data estimation with human control (Figure 3). Activities defined by human directives include manipulator control and data association [27]. The techniques for *autonomy* include control functions such as those supporting the data management to include retrieval, storage, and indexing affording decisions to data (D2D) [28]. An astute robot of the future would respond to dynamic sensor, environment, and target (SET) operating conditions for the user [29]. Hence, future robotic challenges [30, 31] seek:

- *Automatic* - working by itself with little or no direct human control, and
- *Astute* - having or showing an ability to accurately assess situations or people and turn this to one's advantage.

The US Army [32] looked at autonomy as the "delegation of decision-making authority". The Defense Science Board's role of autonomy task force report (2012) [33] delivered the *Autonomous Systems Reference Framework* (ASRF), which presses for the need of different levels of autonomy based on the application. A number of techniques exist for reducing the *amount of supervision* that learning systems require. These include:

- *Active Learning*: The amount of supervision required is reduced by automatically selecting only those examples for labeling that will most improve the overall system performance.
- *Transfer Learning*: Learning for a new "target" problem is aided by using knowledge previously acquired for related "source" problems.
- *Semi-Supervised Learning*: A mix of labeled and unlabeled data is used to learn accurate knowledge with a limited amount of supervision.
- *Cross-modal training*: One sensory modality is used to automatically train another; for example, visual information acquired at short range can be used to train radar interpretation from a much longer range.

Additional basic research in these and other approaches to reduce supervision in machine learning [34] would decrease the time and expense needed to develop autonomous systems. As such, these suggestions support the Autonomy in Use (AIU). To verify the need for AIU, it is important to address the levels of autonomy from different perspectives.

2.1 Levels of Autonomy (National Institute of Standards)

The National Institute of Standards and Technology (NIST) sought to develop a taxonomy of autonomy to have a common understanding of the meaning of autonomy. The *Autonomy Levels for Unmanned Systems (ALFUS) Working Group,* defined the cognitive, fusion, and perception functions [35]. An example of these levels is from Albus [36], as shown in Figure 4, which calls out the operator for AIU.

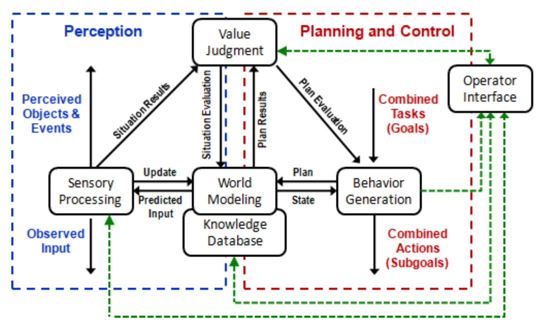

Figure 4 – 4-D/RCS Reference Model (Albus, 2002)

The cognitive levels determine what an unmanned autonomous system (UAS) can know or understand, based on its sensory processing capability:

- **Level 1 – data**, initially processed after measured by sensors.
- **Level 2 – information**, resulting from data processed, refined, and structured that is human understandable.
- **Level 3 – intelligence**, knowledge, and actionable information that is further processed for particular mission needs.

2.2 Levels of Autonomy (Society of Automotive Engineers)

Current trends in society include self-driving cars. The Society of Automotive Engineers (SAM) as well as the National Highway Traffic Safety Administration adopted a standard going from driver control to full autonomy. The autonomous vehicles community taxonomy for automation towards future systems is shown in Table 1.

Table 1: Autonomy levels from Society of Automotive Engineers (SAM)

Car	Automation	Autonomy	Automotive Example	SSA Example
0	None	Rest (no data)	- Driver controls the car	- Space vehicle docking [37]
1	Control Assistance	Rest (sensing)	- Steering and cruise control	- Space telerobotics [37]
2	Partial (monitoring)	Use (navigation)	- Hands-off functions e.g., lane-changing	- Satellite active information management
3	Coordinated (intervene)	Use (safety-critical functions)	- Car responds to environmental situations	- Satellite responds to space weather
4	High	Motion (self-driving)	- Car conducts all functions in nomral trips	- Satellite health monitoring
5	Full	Motion (route planning)	- Car performs all functions for most paths	- Satellite cyber protection

As with the ALFUS levels, the self-driving car community is developing automation towards autonomy in incremental steps. Hence, these incremental steps should include the human user with increasing autonomy and complexity in determining the verification and validation, risk and benefit, as well as the cost and comfort in the deployment of UASs.

2.3 Autonomy Complexity Factors

Context is an important aspect of the types of autonomy useable for different situations. There are a variety of issues concerning complexity including: environmental, mission, and man-machine interaction as shown in Figure 5. For the *environmental factors*, various situations include different knowledge types. The static environment includes the ground soil, known roads, and terrain. Dynamic factors include object frequency, density, and types [38]. As assets are deployed, the congestion of systems in the airspace and ground include operational challenges of rural versus urban terrains, fixed and moving threats, and weather and social changes.

Mission requirements dictate the level of complexity desired. Pragmatic design of autonomous systems can mitigate the complexity. At the simplest level, the command of the system could be monitoring with known rules based on knowledge and tasks. As a mission unfolds, there is a need for more collaboration among systems to respond to changes. At a more complex level, situation awareness requires continual dynamic planning and analysis to respond to emerging threats that could cause danger or harm.

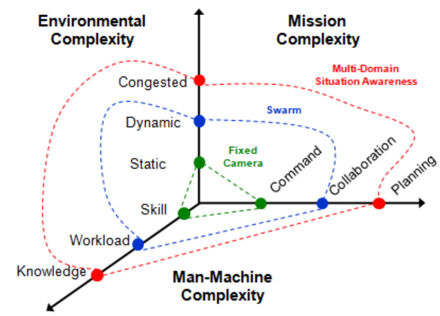

Figure 5 – Autonomy Complexity Factors

Man-machine complexity affords the command and control of future engineered systems. Human factors design is based on skills, rules, and knowledge. Various human operators differ in the skill levels from naïve to experienced. Depending on the skill level, autonomy workloads can be designed to account for rules of tasks to on-demand management. In situations of the unknown, knowledge requires experience and preparation to make decisions and take action with UASs.

When considering the level of autonomy, complexity and context determines the appropriate system to use (see Table 2). Hence, *autonomy in use* (AIU) is based on the environmental, mission, and man-machine complexity. For example, AIU is a swarm of UAVs is controlled by a user in collaboration based on a dynamic environment [39]. As the environment changes, the swarm operator workload increases to direct the swarm in a collaborative fashion [40]. A complex scenario for AIU is multi-UAS situation awareness [41]. Much has been written about situation awareness, but effectively it is about understanding the operational environment [42]. Humans, that are prepared and trained, gain knowledge about previous situations (as in fighting fires); but as the scenario changes, complexity arises. For example, in a congested environment with many engineered assets (e.g., UASs), planning for multi-domain (space, air, ground, sea) operations is needed. The various examples above showcase that autonomy is more than autonomy of rest and motion, but the intended use determines the appropriate autonomous system to employ for the collection, transmission, and artificial intelligence/machine learning of data, features, and information [43]. Self-aware autonomous vehicles interact with humans, build conceptual knowledge [44], and utilize contextual data [45].

Table 2: ALFUS Contextual Autonomy Capability (CAC).

Level	Autonomy	Non-contextual Levels of Autonomy
1	Non-	**Perception** of physical sensor system
2	Partial	**Modeling** (mapping, localization, detection)
3	Semi-	**Planning** (paths, behaviors)
4	Full	**Execution** (mobility, response)
5	Complete	**Mission** operations (adverse conditions)

3. DATA REQUIREMENTS FOR AUTONOMY

The types of autonomy relate to the data concerns such as ML future trends including [46, 47]:

- **Data Quality:** Use more valuable and contextual data before trying to change the model.
- **Data Augmentation:** Utilize normal data extension techniques and unsupervised generative models.
- **Class sampling:** Model relevant context parameters with equivalent numbers of samples per class.
- **Realistic Analysis:** Ensure validation set and test sets come from the same distribution.
- **Scalability:** Design computing methods that expand with more data and model complexity.
- **Human-level performance metrics:** Employ domain experts to compare system performances.

The ability to foster different levels of autonomy is based on the data that supports command, control, and coordination (Figure 6) for autonomy in use:

- **Data at Rest**: Provide *structure (i.e., translations)* between data for integration, analysis, and storage;
- **Data in Collect**: Leverage the *power of modeling* from which data is analyzed for information, delivered as knowledge, and supports prediction of data needs;
- **Data in Transit**: Develop a *Data as a Service (DaaS)* architecture that incorporates contextual information, metadata, and information registration to support the systems-of-systems design;
- **Data in Motion**: Utilize *feedback control loops* to dynamically adapt to changing priorities, timescales, and mission scenarios; and,
- **Data in Use**: Afford context-based *human-machine interactions* based on dynamic mission priorities, information needs, and resource availability.

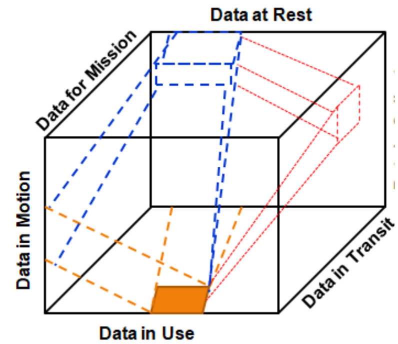

Figure 6 – Data types

One example of data management methods (Table 3) for AIU occurs in physics-based and human-derived information fusion (PHIF)[48] that coordinates data collections through a user defined operating picture (UDOP) in support of situation analysis [49]. Contemporary issues concern contextual reasoning, knowledge management, and command and control for artificial intelligence (where "A" in AI could extend to automated, autonomous, or augmented).

Table 3:Data Management for Context AI

Data	Method	Example	Ref
Data at Rest	Statistical algorithm	Image fusion	[50]
Data in Collect	High-dimensional model learning	Road networks	[51]
Data in Transit	Systems software computing	Container-based agents	[52]
Data in Motion	Instrumentation, sesning and control	Imagery and data collection	[53]
Data in Use	Human-Machine AI	UDOP	[46]

The challenge for the deployment of autonomous systems requires a pragmatic understanding of how these systems would be planned, used, operated, and maintained. Hence, different types of autonomy include:

- **Autonomy at Rest (AAR)**: sensing for mission-level planning;
- **Autonomy in Motion (AIM)**: robotics and unmanned systems for platform control;
- **Autonomy in Change (AIC)**: high-performance and cloud computing for enterprise-level services; and
- **Autonomy in Use (AIU)**: Command and Control (C2) for multi-domain flexibility.

4. AUTONOMY IN USE

4.1 Autonomy in Use Information Assessment

SSA utilizes sensor fusion by including external source information for context assessment [54]. The use of context (e.g., source data from geophysical, cultural, and historical databases) requires information fusion and management [55]. Low-level information fusion (LLIF) consists of filtering, estimation and control, whereas High-level information fusion (HLIF) consists of sensor, user, and mission (SUM) management [56]. *Context-based management* of information includes all resource data gathered or developed from internal and external sources [57].

Information fusion affords context provided from the user (e.g., mission) to the machine, and the machine provides analytics to the user [58]. Information fusion consists of Level 1 (object tracking and classification), Level 2 (situation assessment), and Level 3 (impact assessment). To support analysis, context focuses attention on the issues over the sensor, target, and environment operating conditions [59, 60]. Typically, *context assessment* is associated with Level 1-3 fusion functions [61].

Context information includes geospatial intelligence (e.g., road networks and locations of interest [62]), target types (e.g., vehicles), cultural factors (e.g., social networks), and mission objectives (e.g., target following) that is data as autonomy at rest (AAR). In each case, context provides autonomy in change (AIC) information to guide the assessment of real-time collected information [63] for autonomy in motion (AIM). Likewise, new information (e.g., target classification and identification) can be derived from context information (e.g., models) or given from content reports such as Priority Information Requests (PIR) [64] for autonomy in use (AIU).

The management of information comes from Level 4 (Process) and Level 5 (User refinement). The user must deduce judgment (i.e., intuition, experience, decision making) using contextual understanding of the situation [65]. Hence, autonomy in use (AIU) includes contextual data (AAR), dynamic data (AIM), being collected which requires users to correlate and associate the information. AIU displays the correlation of data [66], from which *context management* is fundamental for information refinement, situation awareness [67], and target tracking [68].

An example of AIU is *contextual tracking* as related to context-awareness [69]. Contextual target tracking approaches include classification [70], relations to other targets [71], and intent. Context can also be road constraints, filtering models [72], and world features [73]. Context helps to select the sensor modality [74], covariance information [75], and measurement source data [76]. An example of the use of context is in Wide-Area Motion Imagery (WAMI) [77, 78]. Specifically, methods have been explored for spatial context [79], temporal context [80], signature context [81], and dynamic context [82]. Autonomy can leverage the human, social, cultural, and behavioral semantics of a situation, such as the handover of control in autonomous cars [83].To determine the context of a situation, natural language processing (NLP) provides understanding, narratives, and missions [84].

4.2 Autonomy in Use Context Awareness

Two approaches for AIU context analysis include *procedural* (do-act) and *self-aware* (do-decide-act) methods. Procedural systems run open loop (do-act). Some procedural systems have sought to include beliefs and intents into reasoning as a form of context. Procedural systems (or imperative/implicit) seek data to perform a task. Procedural tasks are different than declarative tasks as a system learns by doing (e.g., from empirical data). The declarative (propositional) approach includes problem domain understanding that works to help in knowledge acquisition. Declarative examples include logic, learning from experience, intuition, and observing the natural world (cultures, geography, etc.). Declarative approaches work to aid in situation understanding and wisdom.

Another approach for AIU is *self-aware* (observe-decide-act). Self-awareness requires decision making as connected to contextual data of operating conditions – sensor, target, and environments. Other contextual opportunities include self-adaptation for transfer learning such as using domain knowledge for tracking objects (e.g., humans walking or running) as explicit technical knowledge. A self-aware system is

- *Introspective* - observes itself, reflects on its behavior and learns;
- *Goal-oriented* – incorporates missions and sub-functions determines how to get there;
- *Adaptive* - analyzes observations, computes differences between the goal and observed state, and takes actions to optimize its behavior;
- *Self-healing* - continues to function through faults and degrades gracefully; and
- *Approximate* - does not expend any more effort than necessary to meet goals.

Self-aware analysis is related to service-oriented architectures as information fusion systems gather the context information needed as a service [85]. Many different users are collecting information, some which leads to a prior information to guide the contextual collection of future information. For example, imagery data can be used for *perception* of target tracking and semantic data for situation *comprehension*. These processes support machine-level projection and mission-level resolution.

A motivation for AIU is that a dynamic scenario includes uncertainty such as the changing actions of multiple entities and actors, such as in game theoretic methods [86, 87]. AIU requires an ontology [88], not only structuring the information, but describing the uncertainty. Reducing the uncertainty can impart credibility to the measurement source [89] and the trust in the situation beliefs [90]. One aspect of situation beliefs is measurements of effectiveness [91] that includes classification [92] and kinematics [93]. These measurements are compounded by the cognitive capabilities of a user [94] which requires advanced methods of decision making over conflicting reports [95]. As the text helps to classify target behavior, contextual analysis aids in information fusion assessment and refinement. The deployment of systems for autonomy in use (AIU) requires context assessment (CA) as autonomy at rest (AAR) as well as context management (CM) for autonomy in motion (AIM).

5. AUTONOMY IN USE FOR SPACE SITUATION AWARENESS EXAMPLES

SSA includes many entities, functions, and attributes of the space domain. Figure 7 presents key functions in support of assessment and awareness. Space assessment includes functions in support of “things” such as space object tracking and characterization as well as data on network and social information. Space awareness concerns “processes:” such as entities (e.g., debris), objects (e.g., satellites), health (e.g., cyber), and knowledge (e.g., information fusion). To bridge the need to access the right data about things for processing, “autonomy in use” requires that among all the data in motion and at rest, the essential information is made available.

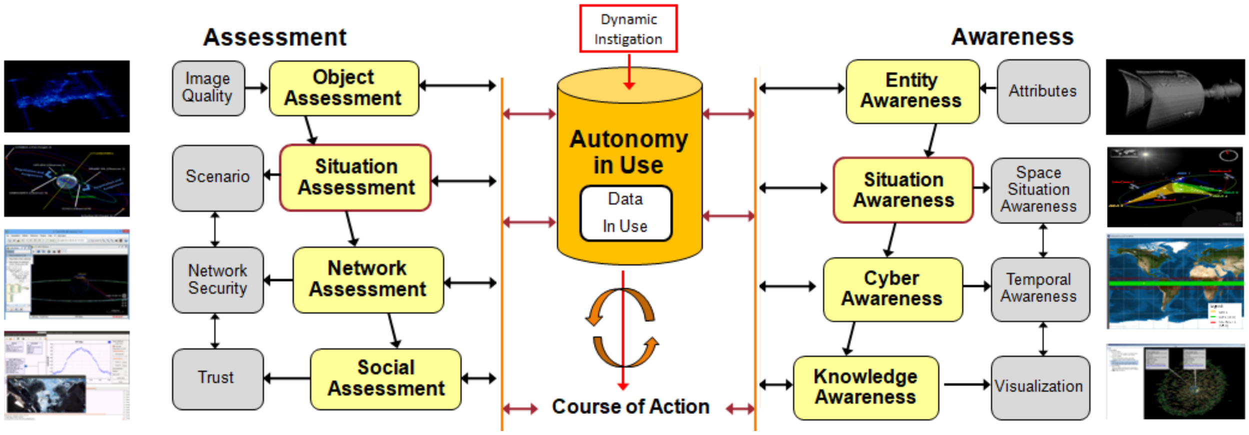

Figure 7–Autonomy in Use Concerns for SSA

5.1 Space Object Assessment

When SSA is generally described, it includes the large data being collected to sense the locations of satellites from either ground [96] or space platforms [97].Many tracking algorithms have been proposed and evaluated [98, 99], typically using the two-line element (TLE) information. Since the orbital information is generally known, then deviations in the track estimation need to be determined for attitude estimation [100]. Crassidis, *et al.*, developed methods using the unscented filtering for the nonlinear dynamics [101]. Using additional estimation information beyond the mean and covariance from the Kalman Filtering adds data complexity while enhancing accuracy associated with the non-oval covariance uncertainty [102, 103, 104]. These tracking techniques can be combined with sensor management to direct the collection of data to enhance tracking performance [105]. Current trends in SSA tracking include locating both the known and unknown (e.g., debris, [106], e.g., deceptive evaders [107]) objects from which context-aided tracking can enhance SSA track accuracy.

5.2 Space Object Situation Assessment

Space object characterization situation assessment includes using the detection of position to update the knowledge of the RSO. A popular example is to use radar and optical sensors to image the RSO for advanced object recognition, classification, and identification. In addition to the radar and EO data, there are other data sources such as multispectral, astrometric and photometric [108], and infrared features [109]for determining subparts, area, and mass. Two emerging themes in DDDAS that support big data analysis include ontologies [110, 111, 112] and deep learning (DL) methods. A space ontology [113] brings together the unstructured information into a common taxonomy of the physical sensed data and the object semantic definitions for RSO characterization [114].

5.3 Space Network Assessment

RSO tracking and characterization assume that the data has not been corrupted. To ensure the integrity of the data collected for SSA, cyber protection is needed. Cyber protection methods [115, 116] include data security, privacy, and assurance which are made more complex for situation awareness [117]. These attributes require information architectures (e.g., cloud services, layered sensing), data protocols (e.g., formats, hashing), source characterizations (e.g., diversity, location), and transmission formats (e.g., speed, bandwidth). Space security includes SSA, space domain mission assurance (SDMA), and cyber-space protection.

A key attribute for cyber protection is response to the effects of electromagnetic interference, jamming, or denial of service attacks. Examples for cyber protection include game theoretical methods [118] for robust communication and RSO survivability [119]. An intelligent system seeking not be detected can maneuver to avoid observation or corrupt the data for miss-characterization between multi-player low-earth orbit (LEO) and geosynchronous earth orbit (GEO) SSA [120], as illustrated in Figure 7. The advances in intelligent processing include information fusion [121] and cognitive jamming methods [122]. Other methods to support cyber protection include survivability through Markov approaches [123], communication loss [124], frequency-hopping spread spectrum techniques [125], radio interference mitigation [126], and beam-forming approaches [127].

5.4 Information Management (Social Assessment)

Information management includes data access, processing, and storage which is central to "Autonomy in Use". A managed information object (MIO) [128] can be used as a method to organize information such as moving from an activity-based intelligence (ABI) perspective to an object-based production (OBP), as shown in Figure 8. ABI focuses on tracking and ID of objects [129, 130, 131], which requires information management of situation [132] and threat [133, 134, 135] assessment data. Managing the situation/threat collection requires command can control (C2) for resource management [136,137, 138]. Effectively dealing with big data requires resource allocation through SSA sensor management [139, 140, 141], data routing optimization [142, 143], and database methods such as cloud computing [144, 145].

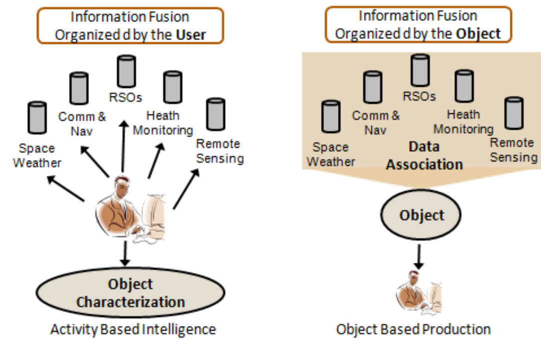

Figure 8–Object-Based production for SSA

5.5 Space Entity Awareness from the Environment

Space weather detection is important to understanding the threat environment for satellites supporting communication, navigation, and remote sensing [146]. Examples include (a) *background emissions*, the categories include solar wind and electromagnetic radiation (radio interference, solar cells function, and x-ray long distance communications and b)*transient space weather* includes radio bursts, x-ray flares, coronal mass ejections, and high energy solar particles. Current SSA efforts focus on the results of weather effecting reliable communications [147].

5.6 Space Object Situation Awareness from Satellite Health Monitoring

Satellite health monitoring (SHM) includes the power and electronics to control the satellite [148]. As data could be transferred as a function of the constraints on the uplink and downlink, there is a need for processing the signals on the satellite. Examples could be steering and processing the raw data before sending the information to the ground. For example, Responses to space weather and other satellites would aid in collision avoidance and maneuvering for health protection. Recent efforts have focused on the power harvesting [149] as well as power control [150]. Responding to various interferences [151] is also needed to maintain robust communications.

5.7 Spectrum Management Cyber Awareness

Along with the satellite health monitoring, recent efforts have focused on dynamic spectrum access for space. Resolving uncertainties of satellite locations, data requirements, and antenna processing are needed to optimize performance. Examples include spectrum awareness [152], waveform selection [153], and reasoning engines to enhance satellite performance [154]. Over the many aspects of the satellite performance, a reasoning strategy using a Bayes' network, or other reasoning engines, can be used to process the large amounts of data to robustly optimize performance. DDDAS methods for spectrum, health, or weather enhancement can determine course of actions (COA) from near real time visualization methods.

5.8 Situation Visualization Knowledge Awareness

The visualization of SSA with big data would afford a team of users to refine the knowledge of the space environment as concerning object, situation and threat assessment [155], ontological classes, (e.g., descriptions of ground areas [156]), and meaningful narratives [157]. Improvements in graphical processors have enabled machine learning and real-time rendering of large amounts of data. Rendering options support the design of a *User Defined Operating Picture* (UDOP) for a user's cognitive observe-orient-decide-act (C-OODA) loop [158]. The ability to plot tracks, discussions, and labels of objects enhances the situation understanding through big data hardware and software processing [159]. Visualizations, as shown in the many examples in the paper, provide benefits to ensure that satellites are operating for reliable communications, navigation, and remote sensing. The benefits of understanding the space environment can help ensure that users are actively engaged with standards on data formats [160] as well as understanding of both the space and atmospheric conditions.

6. CONCLUSIONS

Future constructs of space autonomy require pragmatic concerns for the data that used for autonomy. Data in motion and data at rest also includes data in use. Hence, there is a need for autonomy in use (AIU). AIU includes the historical autonomy at rest (AAR) for context assessment as well as autonomy in motion (AIM) for context management. Context assessment utilizes advances in artificial intelligence and machine learning, while context management includes advances in enterprise control and systems design, both of which are emerging in SSA research. AIU is also inherent in data, sensor, and information fusion designs that support multi-domain unmanned autonomous systems. As SSA includes many dynamic systems, autonomy in change (AIC) determines the data for autonomy in use (AIU) to coordinate the autonomy at rest (AAR) products for autonomy in motion (AIM) performance.

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