Machine Learning/Artificial Intelligence for Sensor Data Fusion–Opportunities and Challenges

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Erik Blasch
Air Force Research Laboratory

Chee-Yee Chong
Independent Researcher

Wolfgang Koch
Institute of Electrical and Electronics Engineers

Dave Braines
IBM

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Machine Learning/Artificial Intelligence for Sensor Data Fusion–Opportunities and Challenges

Erik Blasch, Air Force Office of Scientific Research, Arlington, VA 22203 USA
Tien Pham, Army Research Laboratory, Adelphi, MD 20783 USA
Chee-Yee Chong, Independent Consultant, San Jose, CA 94024 USA
Wolfgang Koch, Fraunhofer FKIE, D-53343 Wachtberg, Germany; University of Bonn, 53113 Bonn, Germany
Henry Leung, University of Calgary, Calgary, AB T2N 1N4, Canada
Dave Braines, IBM, Hants SO21 2JN, U.K., Cardiff University, Cardiff CF10 3AT, U.K.
Tarek Abdelzaher, University of Illinois at Urbana-Champaign, Urbana, IL 61801 USA

INTRODUCTION

Machine learning (ML) methods are fundamental to the philosophy of *artificial intelligence* (AI) approaches. With the advent of the computer in the 1960s, both ML and *sensor data fusion* (SDF) took prominence in the engineering community with such developments of the Kalman filter, Bayesian decision trees, expert systems, and probabilistic reasoning [1]. While SDF expanded to multimodal analysis and information fusion in the 1990s [2], trends in the 21st century include big data, uncertainty reduction, user coordination [3], context reasoning [4], and multi-modal analysis, but it is only in the last decade that a radical change in the AI/ML methods surfaced with most notably deep learning (DL) [5], graphical processing units, and reusable software.

AI/ML and data analytics pose both challenges and opportunities for SDF. The challenges arise because they appear to address the same problems as information fusion (see Figure 1); however, SDF seeks methods for situation and impact assessment, while AI/ML focuses on big data analytics supporting object assessment classification. These challenges can also be opportunities as AI/ML spawned new research in deploying *physics-based and human-derived information fusion* (PHIF), learning about context, tracking with graph fusion, coordinating Internet of Things (IoT) security, as well as facilitating dynamic network analysis for multi-domain operations (MDO).

The 2019 panel members (i.e., the authors of this paper) focused on AI/ML issues relating to SDF, illustrating potential approaches and addressing challenges as summarized in Table 1. Each panelist focused on the following questions.

- What is the SDF problem?
- Which part of the SDF problem needs machine learning and why?
- Where are opportunities to bring together AI/ML and SDF?
- When do challenges arise using machine learning for SDF?

Author's current addresses: Erik Blasch, Air Force Office of Scientific Research, Arlington, VA 22203 USA (e-mail: erik.blasch@gmail.com). Tien Pham, Army Research Laboratory, Adelphi, MD 20783 USA (e-mail: tien.pham1.civ@mail.mil). Chee-Yee Chong, Independent Consultant, San Jose, CA 94024 USA (e-mail: chee.y.chong@gmail.com). Wolfgang Koch, Fraunhofer FKIE, D-53343 Wachtberg, Germany, and also University of Bonn, 53113 Bonn, Germany (e-mail: wolfgang.koch@fkie.fraunhofer.de). Henry Leung, University of Calgary, Calgary, AB T2N 1N4, Canada (e-mail: leungh@ucalgary.ca). Dave Braines, IBM United Kingdom Limited, Hants SO21 2JN, U.K., and also Cardiff University, Cardiff CF10 3AT, U.K. (e-mail: dave_braines@uk.ibm.com). Tarek Abdelzaher, University of Illinois at Urbana-Champaign, Urbana, IL 61801 USA (e-mail: zaher@illinois.edu).
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While Table 1 highlights the summary of the discussion, each panelist chose specific issues as related to their experiences in SDF and AI/ML. Figure 2 presents a general intersection of the Data Information Fusion Group (DFIG) model levels (Level 0–6) with AI/ML issues to determine the sentiment of the panelists' opinions. For example, AI/ML supports big data analysis that overlaps all levels of information fusion. Various AI/ML model construction and efficiency methods support the traditional SDF levels. However, there are not many AI/ML methods that support situation and impact assessment or policies for AI/ML which need definitions. Likewise, SDF object assessment benefits from the many approaches of AI/ML, which can enhance or augment SDF user refinement.

In Figure 2, the horizontal bars represent the percentage of topic areas and/or attention devoted to the information fusion community, while the vertical bars are the percentage of discussion from the AI/ML community. For example, "big data" impacts all areas of information fusion, while "policies" are only emerging for object assessment, but not situation assessment. From the rows, the information fusion community highlights the needs for all AI/ML topics in object assessment, while discussions on "mission management" focus on big data which results in data

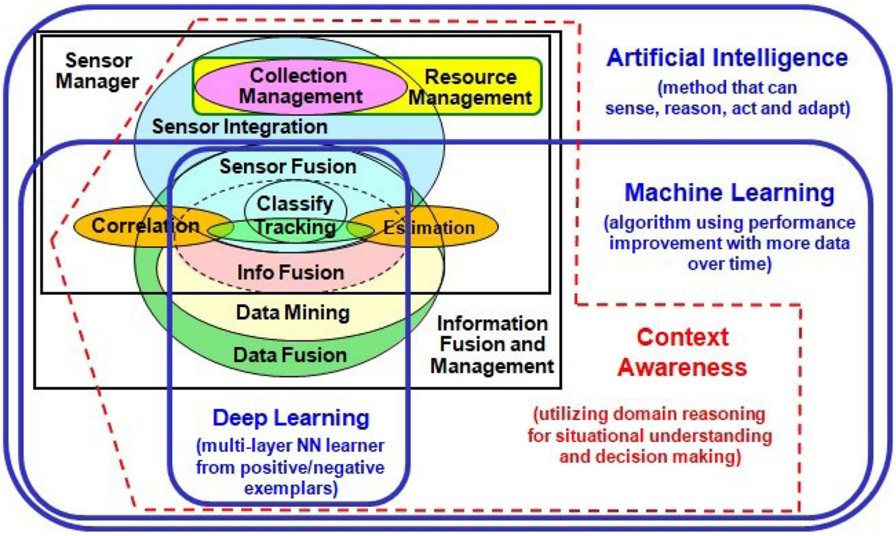

Figure 1.
Artificial intelligence and SDF.

Table 1.

Summary of the Panel Ideas and Issues of AI/ML and Information Fusion

	SDF Problem	Use of ML	Challenges of ML	New Research
Abdelzaher	Physics-based and human-derived IF	Big data analysis of edge-sensing	Unlabeled data	Coordination of DL through multiple AI/ML networks
Blasch	User augmentation	High-dimensional learning	Heterogeneous analysis	Model-based methods to address the unknown
Baines	Contextual support	Interpretable Analysis	Determining the various users	Explainable results
Chong	Data Association	Training from Data	Relevant Models	Context-based AI
Koch	Perceiving and action	Data processing for object assessment	Combining data and models for situation assessment	Need common terms for ethical, social, and usable deployment
Leung	Image fusion	Change Detection	Real-time labeling	Joint multimodal image data fusion
Pham	Multi-domain coordination	Rapidly learn, adapt, and reason to act	Inference in sparse and congested areas	Learning at the edge

management and not on "mission management" policies of AI/ML. Finally, the green colors represent a good overlap of AI and SDF; while blue is somewhat, and red did not have an intersection in the panel discussions. The area on the upper right of Figure 2 shows that future research is needed in AI/ML algorithms to support situation and impact assessment as well as process refinement. The rest of the article presents key discussions from the panelists.

HISTORY OF INFORMATION FUSION AND AI/ML

Chee Chong highlighted the basis of control theory since the 1940s that spawned interest in SDF techniques. In the 1980s, few companies were doing information fusion as there was a lack of computer processing methods. The 2000s saw industrial companies exploring big data computing as the power to process massive amounts of data existed (see Table 2). The challenge with many current AI approaches is that companies are trying to package products without doing the research, testing and evaluation of the results, or determining the ethical and social implications of the developments [6].

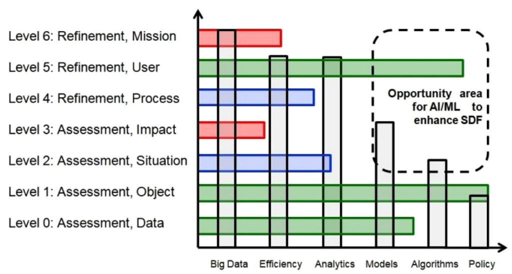

Figure 2.
Intersection of AI/ML issues with that of sensor-data fusion.

EXAMPLE: TARGET TRACKING

The SDF community has existed for 40 years with its roots in the 1980s. The dawn of information fusion began with data fusion with such groups as Garvey at SRII doing AI, Reid at Lockheed working *multiple hypothesis tracking*, Bar-shalom at Systems Control developing the *joint probabilistic data association filter*, and Chong at Advanced

Table 2.

Changes in Computation Power

Performance	1980	2019
Machine	Vax 11/750 Minicomputer	IPhone XS
Speed	3 MHz	2.49 GHz
Operations	120K FLOPS	409 GFLOPS
Memory	2 MB RAM	4 GB RAM
Communications	1200 baud dialup Modem	1 GB network

Figure 3.
Machine learning of adult faces as tracked over time.

Information and Decision Systems exploring distributed fusion [2]. The development of information fusion over the decades saw continual development. The 1970s utilized expert systems for the *single integrated air picture* (SIAP). The SIAP concept developed a hypothesis tree structure that incorporated a rule-based and a signal understanding system. For example, using a hierarchy of rules ingested acoustic signals from hydrophones and inferred signal rules to perform symbolic transformation over different types of processing to detect and locate vessels [7].

Since the 1980s, there have been revolutionary advances in computing and communication, commercial applications in sensor and data fusion, as well as an interest from government and private investment. Over 100 companies claim to do AI that includes elements of ML and SDF. An example from the 1980s sought intelligence computing methods for such mobile systems as the *autonomous land vehicle* (ALV). The ALV road demo in 1985 deployed a sensitive video system to detect road edges at noon and not shadows at night [8]. Further experiments revealed limitations to environmental changes such as mud along the road. Hence, the AI industry (hardware and software) became a bust in the 1980s.

The integration of AI and SDF became apparent in the 1990s. Model-based reasoning by probabilistic graphical models became popular that supported a (1) rigorous representation of uncertainty and inference from evidence, (2) model-based learning from data affording explainable results, and (3) extensions to handle logical relationships.

The general discussion on AI centers on the history with a variety of representations. One example is the three phases of development [9]. The first phase was expert systems where researchers sought to mimic human experts for speech and signals understanding. The second phase utilized probabilistic reasoning with models to do statistical analysis for object and situation recognition. The current phase the third phase, includes advances in neural networks with DL for video tracking and natural language processing. Both the first and second phases constitute the first wave of AI for model-based development with handcrafted (or labeled) knowledge. The third phase supports a second wave of AI that includes statistical learning by learning functions from data. The contemporary AI/ML approaches are riding the third wave for contextual adaptation.

CHALLENGES AND OPPORTUNITIES

Successful implementation requires good models that are manageable for object recognition and speech recognition, but are still difficult for problems such as force structure analysis and intent assessment. As computers become more powerful and massive amounts of data are available, NNs support many low-level functions where modeling is difficult and training is easy. While some results show promise for detecting similar faces over time, the results from AI methods still do not complete transfer learning as easily as humans. Contextual information and metadata (as shown in Figure 3 in tracking a person at the annual fusion conference) are still required to disambiguate the likely results that show similarities that a computer determines, yet humans can easily discern the differences for data association.

Future issues for the coordination of AI/ML and SDF include:

- Development of contextual models;
- Coordination of AI/ML for transfer learning from one situation to the next;
- First-principles understanding for estimation and explainability; and
- Distributed architectures for multi-sensor and multi-algorithmic coordination.

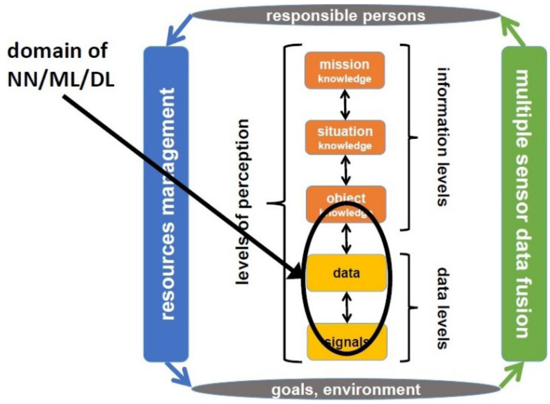

Figure 4.
AI/ML integration for SDF.

PRAGMATIC DEPLOYMENT ISSUES FOR AI/ML

Wolfgang Koch highlights that the tenets of AI should benefit society. For example, the wheel was not seen in nature, but has profoundly changed human society. Hence, artificially intelligent and technically autonomous systems assist pragmatic perception and action. The AI and SDF communities have many things in common as humans need to perceive and act; however, AI comprises much more than the recent progress in NNs and DL.

Using the fusion community DFIG model, then there are two types of issues: (1) *data-driven*: low-level data fusion for object assessment and (2) *model-based*: understand causality for higher level data fusion of situation assessment [10]. NN/DL utilizes signals and data to form a model, but the model does not completely explain the situation context as shown in Figure 4.

Figure 4 represents the DFIG fusion levels (see Figure 2) in a manner that highlights AI (ML, DL, NNs), impacting the core of SDF for assessment. The surrounding elements include contextual influences (goals, environment) feeding the sensor opportunities that are selected by the operator (i.e., Level 5 user refinement), to manage the resources (i.e., Level 4 process refinement).

The challenge of data-driven and model-based AI fusion methods is "serious use." For example, models need to adhere to predictable and reproducible properties much as the derivation of first-principle physics models. The construction of AI models needs to be insensitive to various "unknowns," robust to noise, and free from attack. The AI systems require adaptation to operational conditions, graceful performance degradation, and methods of explainability. The final aspect for AI adoption is certification such as adherence to and compliance with a "code of conduct."

The critical questions are *what* and *why* of incorporating AI/ML into data fusion systems as described in Table 3. Data-driven methods can process vast amounts of data with dedicated advances in hardware from which there is a growing market. Data-driven methods with the appropriate metadata can discern where and when (e.g., object assessment), but lack the ability to derive the why and for whom (e.g., threat and impact assessment)—which is an unsolved research challenge of *explainable AI* (xAI) [11]. There are opportunities to resolve explainability by combing AI/ML with SDF. To a large extent, the fusion community has leveraged sensor management as a method that predicts future states and then collects data to rule out unlikely events through multiple hypothesis methods for situation explainability.

Table 3.

Data-Driven Versus Model-Based Techniques Concerns	
Data driven: (DL methods).	**Model based**: (Bayes Reasoning methods)
• *Boosting*: vast data and hardware • *Training*: gather enough data samples • *Deception*: adversarial examples • *Context*: learn along with data • *Correlation*: "Tell me why?"	• *Estimation*: "uncertain" logical reasoning • *Testing*: systematic algorithm design • *Action*: probable cause-effect chains • *Context*: utilize expert knowledge • *Association*: "Tell me how?"

The power of DL is in the big data analysis towards ever finer parameter estimation of salient variables. Using Bayesian DL affords measures of reliability, proven probabilistic methods, integration of context, scalability, sparse data analysis, and robust systems engineering. Examples of the benefits of AI/ML and SDF include *sequential Monte Carlo* methods for *long short-term memory* prediction in target tracking [12]. Likewise, the ability to predict behavior adds "induction" into "deductive" probabilistic inference.

One of the challenges for both AI/ML and SDF is *context*. Context is an element of a situation from which dynamic systems have to learn context while training and in many cases for the unknown. Thus, there is a need for human-support to infer the situation. A critical question relates to the infamous philosophical qualia question [13], which is the level of consciousness attended to by a user. For example, the Qualia Exploitation of Sensor Technology seeks to improve the decision quality of a set of agents (human or machine) with three assumptions [14]:

- **Assumption 1:** Fundamental units of conscious cognition are situations.
- **Assumption 2:** Decision quality is dominated by the appropriate level of situational awareness.
- **Assumption 3:** Cohesive narratives are reported products of information fusion systems.

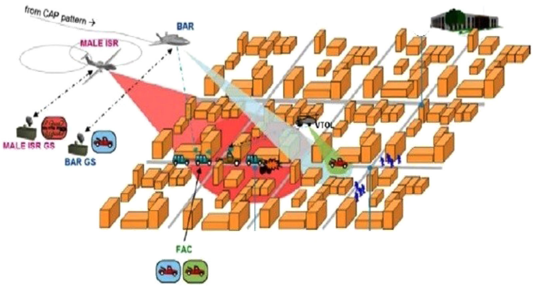

Figure 5.
Urban surveillance.

Thus, there is a required representation as to impute meaning for control. The basis of the integration of low-level analysis for AI/ML towards SDF situation awareness can leverage both advances in AI/ML as well as constructs from SDF.

EXAMPLE: URBAN SURVEILLANCE

An emerging challenge is for urban surveillance (see Figure 5). Unmanned autonomous vehicles (UAVs) have many opportunities for urban traffic control, wildfire monitoring, and target tracking. Figure 5 presents a scenario where a potential lethal engagement could be taken by the forward air controller in response to a detonation from an Improvised explosive device near a convoy. Three unmanned aerial systems (UAS) are available with ground station (GS) support. A medium altitude long endurance intelligence surveillance and reconnaissance (ISR) monitors the situation. The vertical takeoff and landing provides local support. Finally, the Barracuda Unmanned Combat Aerial Vehicle leaves a circular air patrol for engagement with the moving cars.

If surveillance is combined with action, there could potentially be lethal engagement decisions. Thus, there needs to be a responsible use of AI systems, such as *Rules of Engagement* (ROE) of a mission-specific, legally binding frame of action. ROE-compliance by design enables responsible action connecting human command and machine control. For example, one of the most promoted uses of SDF is for autonomous cars that combine imagery and radar technology. Toward certifiable autonomous cars, a *Road Traffic Act* should be a mission-specific, legally binding frame of action. The same issues arise for situations in many AI-based systems coordinated with SDF including: transportation logistics, consumer robots, finance bots, and smart cities. Table 4 presents the challenges of the scenario.

CHALLENGES AND OPPORTUNITIES

SDF includes both object and situation assessment. SDF can leverage AI/ML for object assessment for big data processing, object learning, and joint multimodal learning while there are many challenges that still remain for both AI/ML and SDF for operational use, including the ethical, social, and usable methods in complex scenarios.

The usable technology must come with ROE and documentation. Ethics still remain an important aspect of any technology which should include technical design principles for responsible action—especially with interdiction actions. Humans abide by lethal ROE, while machines require anti-lethal concerns. Laws need to govern the deployment of such systems. The social implications of AI/ML and SDF need a common language (not improper) of expectations such that there is not an overpromise of capability, reliability, and sustainability.

Table 4.

Considerations of AI/ML in SDF Platforms

Considerations and Scenarios	Urban Surveillance	Autonomous Cars
Discrimination	engagement without surveillance gaps.	driving without surveillance gaps.
Adjudication	challenging environments: multisensor drones in urban environment: UAV-to-pedestrians	challenging environments: multiple sensors from machines: car-to-car
Decision	pre-engagement collateral damage prediction	pre-engagement congestion prediction
Pre-caution	priority of the threatening diagnosis	priority of the inauspicious driver, pedestrian prognosis
Imputation	relevance of directed user command	relevance of meaningful human control
Proportionality	selection of appropriate weapons	selection of appropriate options
Legal security	transparent option documentation	transparent option regulations

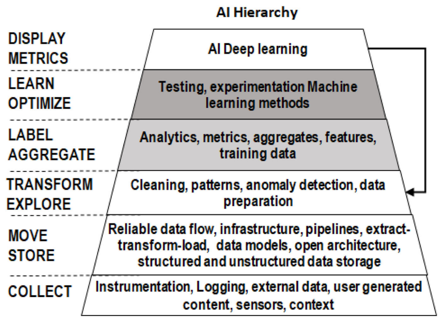

Figure 6.
AI/ML data hierarchy of needs.

Future issues for the coordination of AI/ML and SDF include:

- Common terminology for systems of systems integration;
- Ethical standards for ROE;
- Mathematical representations to combine AI/ML object assessment with SDF situation assessment; and
- Coordination of data- and model-driven approaches for xAI/ML.

MACHINE–HUMAN AI/ML DATA FUSION CONCERNS

Erik Blasch presented emerging issues for the coordination of AI with SDF including: data preparation for learning, joint learning and estimation, and user coordination [15]. While SDF systems typically work with low-dimensional data for estimation (e.g., target tracking), new methods of AI/ML seek high-dimensional analysis (e.g., multi-intelligence graphical methods). The merging of AI/ML with SDF requires mathematical rigor to support the joint analysis which relies on SDF methods of data association, uncertainty reduction, and prediction. Finally, as AI is learning patterns, there is a need to incorporate physics-based first principle models to provide structure, explainability, and repeatability.

EXAMPLE: DATA PROCESSING

The SDF problem can leverage AI/ML coordinated with SDF for: (1) knowledge reasoning and understanding, (2) information fusion enhancement, (3) object recognition and tracking, (4) combining data with models, and (5) deep multimodal fusion strategies to support the user**.** To realize these benefits, a human–machine coordination can manage heterogeneous and uncertain knowledge sources, detect duplicate or incomplete concepts, and support explainability. One example is the AI data hierarchy of needs, shown in Figure 6 [16].

CHALLENGES AND OPPORTUNITIES

To implement AI/ML systems, the first challenge is data preparation (and aligned with data assessment) involving collecting, moving, transforming, and labeling data before AI/ML systems conduct analytics (see Figure 6).

The second challenge, as shown in Figure 7, is testing AI/ML with SDF systems. With the ability to process big data (volume, velocity, veracity, variety, value), the collaboration policies between SDF and AI/ML need to be understood through evaluation that considers operational deployment needs such as computation efficiency, adversarial robustness, and system maintainability. Methods of robust evaluation for verification and validation support consistency, reproducible results, and user expectations.

SDF in MDO affords the ability to observe the scenario from many perspectives, build situation assessment, and learn patterns. Methods have been shown for AI/ML multi-modal sensing and image fusion to support object assessment for filtering, estimation, and prediction [17]. However, AI/ML needs to coordinate with SDF that brings together systems issues for command and control (e.g., process refinement) using dynamic context toward awareness (e.g., user refinement). Together, SDF and AI/ML will provide enhanced capabilities from which policies (e.g., guidelines, mandates, and standards) will dictate the appropriate use of the technology.

With the many advantages of AI/ML and SDF, additional research needed includes:

- Simulated (synthetic-measured) data complemented with data collections for predicting future needs;
- PHIF [18] toward needs-based data processing;
- Contextual awareness to support AI/ML that leverages a priori knowledge;
- Transfer Learning over operating spaces (sensors, environments, targets) for joint data association; and
- Joint AI/ML/SDF architectures to transcend transparency and explainability of learned knowledge.

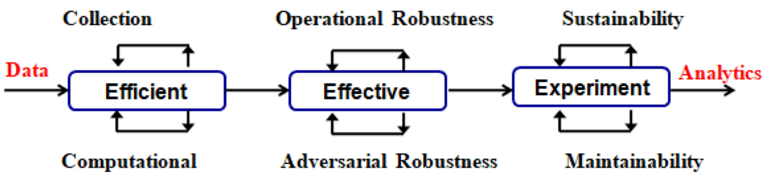

Figure 7.
Testing and evaluation of AI/ML system.

MULTI-IMAGERY FUSION USING AI/ML

Henry Leung presented the contemporary opportunities of AI/ML as a powerful method for big data analytics. For example, AI/ML methods can detect an anomaly in an image, such as a moving object in a static scene, through the use of different sensors. For image fusion, substantial improvements in image processing using AI/ML methods have outperformed standard pixel-level and feature-level statistical histogram processing. The use of different sensors such as *electro-optical and infrared* (EO/IR) imagery affords robustness as detection of features from variations in the scene.

EXAMPLE: ANOMALY DETECTION

Anomalies and noise in the images appear different from the different sensors and hence it is highly unlikely that noise or anomalies in one image are the same as in the other image. With the labeled data, learning supports feature extraction and object detection. One variation is to label and train one modality and then when deployed, use the known imagery to help label the second imagery. For example, with video imagery, 3-D convolution operations are used to form the feature map (extract appearance/motion from frames) corresponding to the location in one input converted to a 1-D set of features. Examples have been shown for the faster *region-based convolutional neural networks* (RCNN) image fusion with convolution features for anomaly detection (AD) [19]. For example, in Figure 8, the accuracy of AI/ML with SDF improves from 82% with optical imagery to 87% with infrared imagery.

CHALLENGES AND OPPORTUNITIES

One of the challenges with the emergence of DL methods is that the features have to be handcrafted. Typically, developers have to label features in all modalities. With the labeled data, the image fusion system can extract spatiotemporal features and perform automatic AD. AI/ML for feature extraction challenges include hand-crafting traditional features (e.g., edge, gradient) specific to each sensor (e.g., EO, IR, radar, etc.), tailored motion features (e.g., optical flow) dependencies of scale and preprocessing; and modality-specific features (e.g., color features does not exist in IR).

ML advances have demonstrated other options such as to increase input resolution, improve signals for better detection, and enhance detection through *superresolution* (SR) [20]. Instead of searching for the nearest patch similarity to a database, ML for SR can learn the mapping of a low-resolution patch to a high-resolution patch, and combining to create

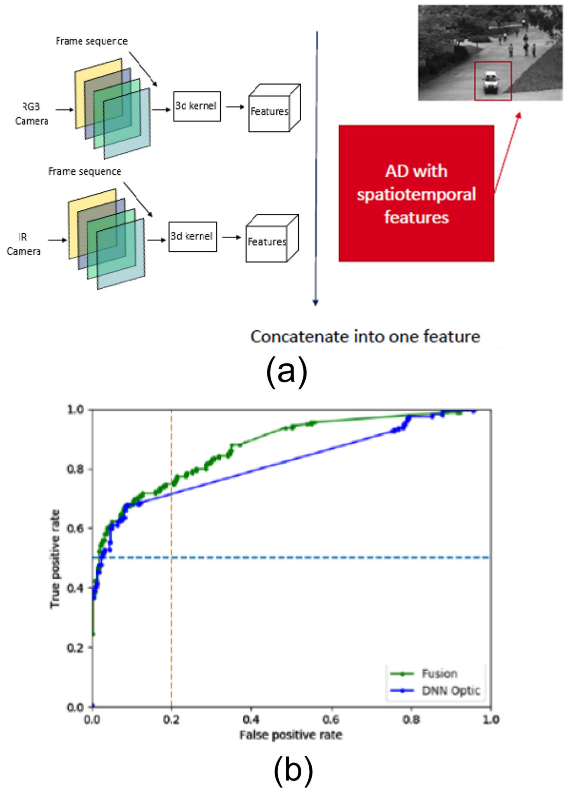

Figure 8.
(a) Multimodal AI/ML data fusion and (b) performance enhancement through fusion (green line) over no fusion (blue line).

a full image. Recent results include a *Generative Adversarial Network* (GAN) with a generator for the features and discriminator as an analysis of the simulated features. An example is for ship detection in synthetic aperture radar in which there is an SR GAN for resolution and RCNN for object classification [21]. Other examples of GANs for SDF include multiple-perspective fusion for radar ATR [22] and multimodal image fusion [23].

Future issues for the coordination of AI/ML and data fusion include:

- Efficient labeling in multiple modality imagery sources;
- Effectiveness in making machines more autonomous;
- Robustness of replacing handcrafted features with learned features; and
- Scaling for natural detection in complex scenes.

MULTI-SOURCE AI/ML FUSION AT THE EDGE

Tien Pham highlights that AI/ML designs require further testing to move from the laboratory towards a complex multi-domain environment, such as large-scale, cluttered, and contested urban environments. In the future, MDO will require the capacity, capability, and endurance to

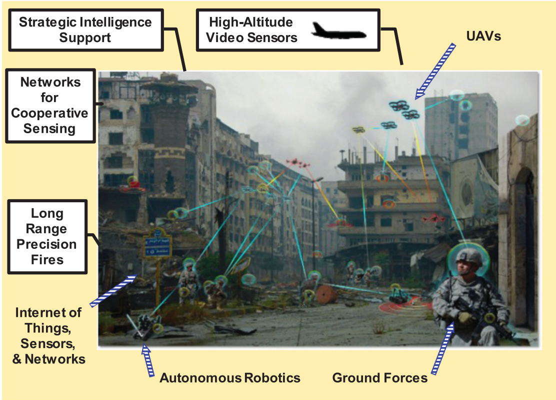

Figure 9.
MDO at the tactical edge.

operate across multiple domains—from a dense urban terrain to space and cyberspace—and in contested environments of the physical domains (space, air, land, ground, and sea) as well as the *electromagnetic spectrum* (EM) cyber and information domains. The goal is to think holistically about the future coordination of data, information, and policies that includes agents as networks (hardware), human (commands), and algorithms (software). Figure 9 shows a complex multi-domain urban protection area with information from air, ground, and cyber networks.

The use of AI/ML can support data collection to conduct distributed intelligence, autonomous maneuver, and strike activities across all domains at the tactical edge [24].

EXAMPLE: AWARENESS

Examples of AI/ML with SDF include data-aware, uncertainty-aware, human-aware, and machine-aware ML. For *data-aware ML*, one recent example is exchanging the final Bayesian-based softmax layer with an evidential reasoning approach to account for uncertainty in the decision and allowing multiple selections, where an *evidential neural network* (ENN) determines when and if a system should make a decision choice [25]. The ENN utilizes the NN output layer interpreted as Dirichlet parameters for training a loss function that balances prediction accuracy against accrual of conflicting evidence. The ENN recognizes its limits due to novel events or significant changes to the environment. Figure 10 provides a demonstration of classifying a digit 1 as 1, 2, or 5 when the image of a 1 is rotated. While it is the same digit, the softmax makes a hard high probability choice of 1 (correct), then 2 and 5 (incorrect), and 1 again. However, using the evidential reasoning approach, the ENN outputs the correct classification when it is known, but when there is high uncertainty (50–140 degree rotations of the image) the classification choice is reported with a low probability.

To support the robust inference, *uncertainty-aware ML* characterizes error based on the similarity of the test sample with the sparse training data. The challenges are formulating quantitative types of uncertainty, learning methods of uncertainty, and isolating and explaining causes of uncertainty. The results seek to mitigate the risk of poor decisions due to unexpected events and/or observations and provide effective teaming with human agents through explanations of uncertainty [26].

The *human-aware ML* incorporates the *human-in-the-loop* (HIL) to evaluate human feedback for improved performance. Utilizing human demonstration, intervention, evaluation, and integration methods [27], HIL reinforcement learning provides improved decision-making in dynamically changing environments, where data availability and computational resources are limited. The methods envision human roles in environments where AI/ML systems learn to appropriately use and react to human input. Multiple sources of human feedback are investigated towards fast, robust, and possibly superhuman task learning, training and adaption by nonexpert users, and learning tasks that are otherwise difficult or impossible to encode [28].

The *machine-aware ML* seeks methods of computational efficiency through hardware design. DL provides

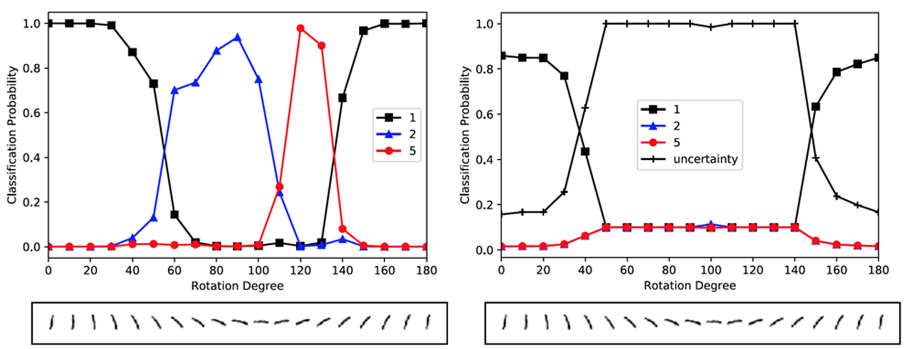

Figure 10.
Discrimination of the rotated digit 1 (at bottom) at different angles between 0 and 180 degrees. Left: Softmax classification probability. Right: ENN classification probability and uncertainty.

intelligent edge-device services for situation understanding in complex high-tempo environments. One common example is that of NN compression through analytical software and low-end embedded hardware processors. To support DL for resource-constrained *Internet of Battle Things* (IoBT) environments, *NN compression* reduces the original trained NN to fit within resource-constrained fielded sensor devices to determine robustness/performance tradeoffs. For example, compression using the *DeepIoT* framework [29], orders of magnitude reduction in time, energy, and memory of *Deep Neural Networks* (DNN) inference results without loss of image recognition accuracy.

CHALLENGES AND OPPORTUNITIES

AI/ML provides efficiency and effectiveness for SDF awareness methods. There is a need to engage the AI research community to rapidly advance adaptive AI capabilities for autonomous maneuver and learning to support complex MDO. Future goals are to research and develop AI agents (heterogeneous and distributed) that rapidly learn, adapt, reason, and act in contested, austere, and congested environments. The challenges include (1) learning over multidomain deception techniques to new jammers, novel threats, network attacks, and AI manipulations; (2) learning and reasoning in complex environments that include data challenges of small, sparse, dirty, clutter, and deceptive measurements; (3) resource-constrained situations with AI processing at the point of need to balance communications and computations for low *size, weight, and power, time* (SWaPT) available systems, as well as (4) generalizable, explainable, and predictable AI. The community must provide challenging problems with access to the large, unique database for AI and ML research and development that facilitates partnerships and transition opportunities between government, industry, and academia coordination through open and extended research technical alliances.

While awareness-based ML methods incorporate SDF, the future research needs for SDF ML systems (SMS) considerations for a multidomain environment include:

- *Isolated systems*: forward-deployed SMS could become isolated with only organic AI/ML;
- *Contested Scenarios*: SMS must be resilient to adversary attacks;
- *Dynamic, distributed, resource-constrained*: SMS should adaptively and efficiently learn on-the-fly with limited resources;
- *Un-modeled phenomena*: SMS need to respond to new jammers, threats (e.g., drone swarm), network or AI attacks, and multidomain deception techniques; and
- *Comparable performance evaluation*: Common scenarios are needed to research SMS complexity in multidomain environments.

EXPLAINABLE AND INTERPRETABLE AI/ML

Dave Braines discussed how AI/ML and SDF information technology enable distributed analytics and information science for situation awareness, such as web-based ML techniques to improve situation understanding, establish collations of people working together, and design computational methods at the network edge. To enable methods to run at the edge, dynamic, and secure coalition information infrastructures for anticipatory situational understanding are needed and must support interoperability.

There is a need to provide consistent terminology for the various components, to better understand complex and rapidly changing situations given a limited number of personnel and increasingly rich, varied, and distributed datasets. The goal is to improve the entire fusion process from signal to information processing, by synergistically leveraging ML and human insight (integrating reasoning and learning approaches). One key research gap is the ability to verify predictive analytics and exploit the synergies between the user and machine learning and reasoning.

EXAMPLE—EXPLAINABILITY

The goal for *trustable, assisted, and explainable* AI requires user interaction. For *trusted* AI, the goal is to investigate bias, enable two-way information exchange between human and machine agents, and to handle a wide degree of variance. *Assisted* AI encapsulates the primary motivation that the human agents are augmented in their capabilities by the AI, not replaced by it. For example, the common *Cognitive Observe-Orient-Decide-Act* loop has well been utilized as an SDF framework that is inherent in the DFIG model [30], which is updated to show where AI/ML can support models as shown in Figure 11. Insights from Miller [31] from social sciences indicate that xAI methods include *explanations* that are:

- *Short*, as humans typically prefer one or two causes;
- *Contrastive*, to discern plausible outcomes and abnormal causes;
- *Selectable*, without the need for a complete thorough list of causes, even with inconsistency or contradictory data;
- *Social*, where the social context will drive the explanation content, possibly through a sequence; and
- *Truthful*, where explanations match with prior beliefs and are generalizable and probable.

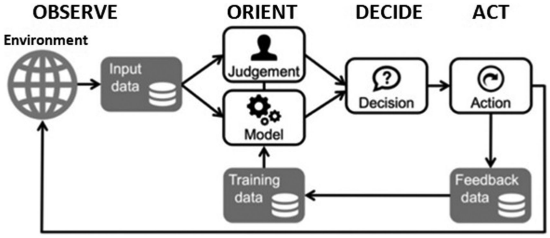

Figure 11.
OODA loop with AI/ML methods.

To develop xAI systems, it is important to explicitly acknowledge that there are many types of users in the AI/ML systems. In [32], Tomsett *et al*. indicate that an ML system's interpretability and explainability should be defined in relation to a specific agent or task. The system's designers should not ask if the system is interpretable, but to whom the explanations are intended to support. The role of the user, as an agent, can be the designer (e.g., creator, subject, or examiner) or customer (e.g., operator, executor, or decision-maker) as shown in Figure 12. For example, the creator of the ML system seeks methods to prove the processing of the data, whilst the operator needs to determine whether the system output is relevant and useful. Higher level collation into a product that is delivered to the executor is often needed. Hence, the type of analysis and explainability of processes and products is dependent on the consumer of the information.

Another example is the focus on *conversational interaction*. The dialog between the human and the machine in a conversational style explores explanations together in the situation narrative. Such interactions in support of SDF could include using text, imagery, graphs, sound, etc. towards an analysis, which aided by AI/ML can provide a robust situation assessment. Key considerations for such interactions in the context of SDF analysis include: agility, flexibility, complexity, consumability, reusability, and technical analytics. As well as being supported by machine agents in the conversational context, the skill, experience, and work domain of the stakeholders involved is also critically important to ensure that the conversation can be meaningful and relevant to the human users.

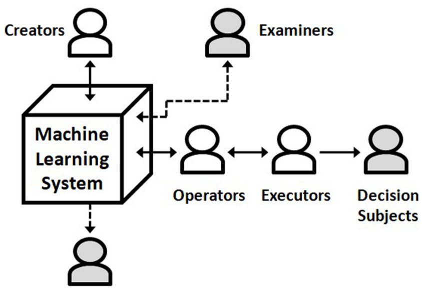

Figure 12.
Producers and consumers of AI/ML and SDF methods, results, and explanations.

CHALLENGES AND OPPORTUNITIES

There are many issues of ML interpretability in adversarial settings with complex spatiotemporal sparse data sets. The objective is to understand the efficacy of ML methods/tools in these settings and the need for SDF techniques able to take account of bias within data sources and learned models. Situation understanding warrants the best approach to handling uncertainty due to bias across the entire fusion process. A third need is for more expressive knowledge representations affording explainability (and therefore interpretability) to data-scientist and nondata scientist users. Hence, every step change in efficacy of such representations over current capabilities helps to bring together the AI/ML and SDF developers with consumers.

The challenges for ML include three key areas: (1) users (e.g., qualified practitioners, domain experts) with a range of available capabilities and skills; (2) data and models (e.g., training data, model maturity, failure models, performance); and (3) the explainability/interpretability (e.g., handling context and change, explainability, trust, expectation mismatch, bias, and flexibility). Addressing these challenges has the potential to provide a rich and rewarding experience for the human users when interacting with the SDF and ML processes, offering the potential for increased trust and efficiency in the hybrid system.

Future issues for the coordination of AI/ML and data fusion include:

- Deriving methods for explanations that meet user needs;
- Coordinating interpretability between SDF, AI/ML, and users as producers and consumers;
- Establishing measurement of trust via social/contextual integration of human and machine agents; and
- Designing interfaces to allow human insight to be gained and added to the system.

AI/ML FUSION OF INTERNET BATTLE OF THINGS

Tarek Abdelzaher focused on SDF and AI/ML to support the IBoT as a contemporary approach to MDO edge analysis. The trends that drive the research include (1) machine intelligence redefining future multidomain networks, (2) MDO coordination with fusion needs, and (3) doctrine changes that empower automated response. For example, future operations will feature tighter integration across heterogeneous assets in multiple domains. The doctrine

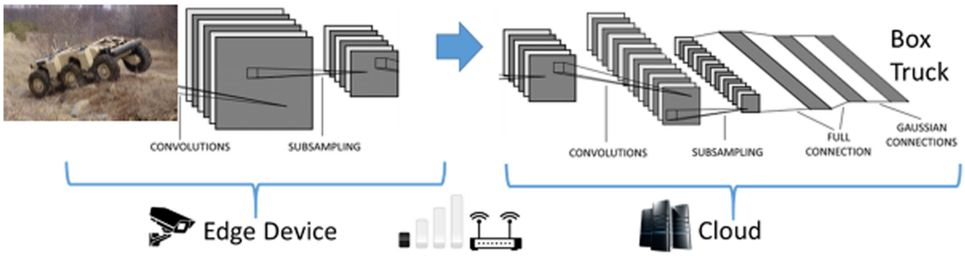

Figure 13.
AI/ML and SDF integration of edge and cloud information.

changes include command by intent, command by plan, and command by control. Each command approach requires data, sensor, information, and intelligence fusion for heterogeneous coordinated asset control to empower local initiative within the commander's mission intent [33].

EXAMPLE: EDGE ANALYTICS

AI/ML integration of data from the surveillance sources as well as edge devices helps to determine the situation. The targeting/decision options are: detect objects, disable communication, discern behavior, dissuade harmful results, and determine situational actions. In a complex battlefield, integrating data-centric with model-centric ML SDF combines strategic surveillance with tactical human sensor knowledge. Leveraging of the models of the underlying physical phenomena supports explainable solutions for situation knowledge. Figure 13 demonstrates how an edge device with cameras and wireless connections in a DL approach can serve to provide data to another DL layer to integrate cloud data towards a labeled decision. Figure 13 leverages the traditional CNN by first processing the distributed edge devices and then aligns the results for the traditional three layers of the CNN: convolution (to learn features), max polling (as dimension reduction), and fully connected layer (for classification).

The basis of information fusion is uncertainty analysis. An AI/ML approach with SDF offers reliable error bounds

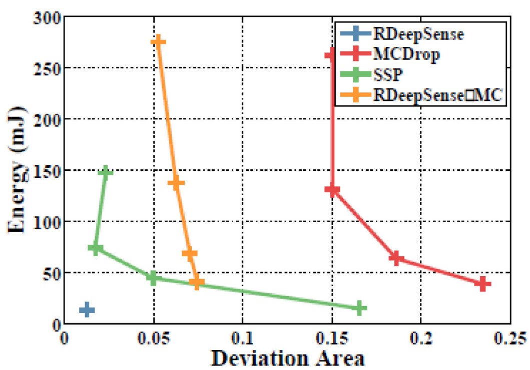

Figure 14.
RDeepSense providing optimal results with minimal energy.

to discriminate the target type. A concern for AI/ML is how to continuously evolve/adapt intelligent fusion components in an ever-changing environment without the benefit of large amounts of labeled data. An example is a GAN that generates model-based data that when combined with collected data allows both machine and human discrimination through a SenseGAN [34] for robust situation analysis. For regression problems, the area between the calibration curve of an algorithm and the optimal calibration curve, called *deviation area*, represents the measurement of uncertainty as the smaller the deviation area is, the better the algorithm estimates the quality of uncertainty. Figure 14 further explores the energy needed, as determined from the number of learning iterations, for IoBT sensing devices towards decision making. The RDeepSense [35,36] provides an efficient and effective method demonstrating the benefits of AI/ML with SDF while increasing object assessment. Compared with the simple and scalable predictive uncertainty estimation algorithm, RDeepSense uses dropout regularization as an implicit ensemble method, which avoids running multiple DL models with Monte Carlo sampling methods such as dropout during model inference on embedded devices.

CHALLENGES AND OPPORTUNITIES

The challenges include the optimal distribution of resources for SDF, training intelligent sensors with little or no labeled data, and uncertainty analysis. For example, there is a concern on how to optimally place AI components in the distributed (likely contested) edge system for maximum fusion speed and efficacy and for minimum communication/emission footprint. The system must automatically distribute prediction and inference computations over heterogeneous device networks with varying connectivity and bandwidth. Such an example is to map a multilayer prediction and inference architecture onto a physical device network as well as jointly optimize all layers to account for device resource limitations, expected network conditions, and stealthy requirements.

The coordination of AI/ML with SDF provides many examples and research opportunities to exploit GANs to generate labeled data samples to train for operational needs. For example, dropout training in DNN and

Bayesian inference in Gaussian processes affords not only the mean estimate but also the variance (using Bayesian inference). AI/ML solutions to fuse data from physics-based (e.g., sensor) and human-derived (e.g., human text, news, social media) sources support social sensing where robust performance results from fusing unreliable data and context [37], and explainable narratives.

Future issues for the coordination of AI/ML and data fusion include:

- Prepare for the big data and big sensor analysis over the IoTs;
- Consider doctrine changes that empower automated response;
- Utilize human knowledge with surveillance information; and
- Enhance generative methods for heterogeneous data learning.

CONCLUSION

The coordination with AI/ML and SDF has many advantages and results indicate promise by leveraging contextual modeling, aligning big data AI/ML processing for SDF object assessment, and providing methods for human–machine teaming. SDF seeks to reduce uncertainty with provable and consistent performance bounds while AI/ML trains a model based on the available data. As with the high-level information fusion challenges [38], the opportunity is to further explore xAI/ML with SDF to generate robustness guarantees of uncertainty estimates.

Some of the common themes of challenges and opportunities from the panel are:

1) AI/ML big data analytics for SDF joint multimodal object assessment;
2) AI/ML results feeding context-aware methods for SDF situation assessment;
3) AI/ML model-based generative approaches for SDF threat assessment;
4) AI/ML reinforcement learning for command and control over complex, congested, and data-starved AI/ML for SDF MDO process refinement;
5) AI/ML supports explainable results towards SDF user refinement; and
6) AI/ML requires ROE for SDF mission refinement policies.

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REFERENCES

[1] J. Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. San Mateo, CA, USA: Morgan Kauffman, 1988.

[2] E. Waltz and J. Llinas, *Multisensor Data Fusion*. Norwood, MA, USA: Artech House, 1990.

[3] E. Blasch, E. Bosse, and D. A. Lambert, *High-Level Information Fusion Management and Systems Design*. Norwood, MA, USA: Artech House, 2012.

[4] L. Snidaro *et al.*, *Context-Enhanced Information Fusion: Boosting Real-World Performance with Domain Knowledge*. Berlin, Germany: Springer, 2016.

[5] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[6] S. Lo Piano, "Ethical principles in machine learning and artificial intelligence: cases from the field and possible ways forward," *Humanities Soc. Sci. Commun.*, vol. 7, 2020, Art. no. 9.

[7] H. P. Nii, E. A. Feigenbaum, J. J. Anton, and A. J. Rockmore, "Signal-to-symbol transformation: HASP/SIAP case study," AI Magazine, 1982.

[8] J. E. Franklin, C. L. Carmody, K. Kellter, T. S. Levitt, and B. L Buteau, "Expert system technology for the military: Selected samples," *IEEE Proc.*, vol. 76, no. 10, pp. 1327–1366, Oct. 1988.

[9] J. Launchbury, "A DARPA perspective on artificial intelligence," 2017.

[10] E. Blasch, S. Ravela, and A. Aved, *Handbook of Dynamic Data Driven Applications Systems*. Berlin, Germany: Springer, 2018.

[11] D. Gunning and D. W. Aha, "DARPA's Explainable Artificial Intelligence Program," *AI Mag.*, pp. 44–58, 2019.

[12] A. Milan, S. H. Rezatofighi, A. Dick, I. Reid, and K. Schindler, "Online multi-target tracking using recurrent neural networks," in *Proc. 31st AAAI Conf. Artif. Intell.*, 2017, pp. 4225–4232.

[13] T. Nagel, "What is it like to be a bat?" *Philos. Rev.*, vol. 83, no. 4, 435–450, Oct. 1974.

[14] E. Blasch, S. K. Rogers, H. Holloway, J. Tierno, E. K. Jones, and R. I. Hammoud, "QuEST for information fusion in multimedia reports," *Int. J. Monit. Surveill. Technol. Res.*, vol. 2, no. 3, pp. 1–30, Sep. 2014.

[15] E. Blasch, I. Kadar, L. L. Grewe, G. Stevenson, U. K. Majumder, and C. - Y. Chong, "Deep learning in AI and information fusion panel discussion," *Proc. SPIE*, vol. 11018, 2019, Art. no. 110180Q.

[16] E. Blasch, J. Sung, T. Nguyen, C. P. Daniel, and A. P. Mason, "Artificial intelligence strategies for security and safety standards," AAAI Fall meeting, 2019.

[17] Y. Zheng, E. Blasch, and Z. Liu, *Multispectral Image Fusion and Colorization*. Bellingham, WA, USA: SPIE Press, 2018.

[18] E. Blasch, A. J. Aved, "Physics-Based and Human-derived Information Fusion Video Activity Analysis," in *Proc. Int. Conf. Inf. Fusion*, 2018, pp. 997–1004.

[19] E. Blasch, U. Majumder, T. Rovito, and A. K. Raz, "Artificial intelligence in use by multimodal image fusion," in *Proc. Int. Conf. Inf. Fusion*, 2019, pp. 1–8.

[20] C. Dong, C. C. Loy, K. He, and X. Tang, "Image super-resolution using deep convolutional networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 38, no. 2, pp. 295–307, Feb. 2016.

[21] K. Wang, G. Zhang, Y. Leng, and H. Leung, "Synthetic aperture radar image generation with deep generative models," *IEEE Geosci. Remote Sens. Lett.*, vol. 16, no. 6, pp. 912–916, Jun. 2019.

[22] U. Majumder, E. Blasch, and D. Garren, *Deep Learning for Radar and Communications Automatic Target Recognition*. Norwood, MA, USA: Artech House, 2020.

[23] R. Zhang, J. Bin, Z. Liu, and E. Blasch, "WGGAN: A wavelet-guided generative adversarial network for thermal image translation," *Generative Adversarial Networks for Image-to-Image Translation*, M. Naved, Ed., Elsevier, 2020.

[24] G. Cerincione and D. Verma, "Federated machine learning for multi-domain operations at the tactical edge," Proc. SPIE, Apr. 2019, Paper 11006.

[25] M. Sensoy, M. Kandemir, and L. Kaplan, "Evidential deep learning to quantify classification uncertainty," in *Proc. Int. Conf. Neural Inf. Process. Syst.*, Dec. 2018, pp. 3183–3193.

[26] E. Blasch, R. Cruise, A. Aved, U. Majumder, and T. Rovito, "Methods of AI for multimodal sensing and action for complex situations," *AI Mag.*, vol. 40, no. 4, pp. 50–65, Winter 2019.

[27] N. Waytonich, V. Geocks, and V. Lawhern, "Cycle of learning for autonomous systems from human interaction," in *Proc. AAAI Fall Symp. Ser.*, Oct. 2018.

[28] G. Warnell, N. Waytowich, V. Lawhern, and P. Stone, "Deep TAMER: Interactive agent shaping in high dimensional state spaces," in *Proc. AAAI Conf. Artif. Intell.*, 2018, vol. 32, pp. 1545–1553, 2018.

[29] S. Yao, Y. Zhao, A. Zhang, L. Su, and T. Abdeizaher, "FastDeepIoT: Towards understanding and optimizing neural network execution time on mobile and embedded devices," in *Proc. ACM Conf. Embedded Networked Sensor Syst.*, Nov. 2018, pp. 278–291.

[30] E. Blasch, R. Breton, P. Valin, and E. Bosse, "User information fusion decision making analysis with the C-OODA model," in *Proc. Int. Conf. Info Fusion*, 2011, pp. 1–8.

[31] T. Miller "Explanation in artificial intelligence: Insights from the social sciences," Artificial Intelligence, 2018.

[32] R. Tomsett, D. Braines, D. Harborne, A. Preece, and S. Chakraborty, "Interpretable to whom? A role-based model for analyzing interpretable machine learning systems," in *Proc. ICML Workshop Hum. Interpretability Mach. Learn.*, 2018, pp. 8–14.

[33] A. Kott, A. Swami, and B. J. West, "The internet of battle things," *Computer*, vol. 49, no. 12, pp. 70–75, Dec. 2016.

[34] S. Yao *et al.*, "SenseGAN: Enabling deep learning for internet of things with a semi-supervised framework," in *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, Sep. 2018.

[35] S. Yao, Y. Zhao, H. Shao, A. Zhang, C. Zhang, S. Li, and T. Abdelzaher, "RDeepSense: Reliable deep mobile computing models with uncertainty estimation," ACM IMWUT, 2018

[36] S. Yao *et al.*, "ApDeepSense: Deep learning uncertainty estimation without the pain for IoT applications," in *Proc. IEEE Int. Conf. Distrib. Comput. Syst.*, 2018, pp. 334–343.

[37] D. Wang, T. Abdelzaher, and L. Kaplan, *Social Sensing: Building Reliable Systems on Unreliable Data*. San Mateo, CA, USA: Morgan Kaufmann, Apr. 2015.

[38] E. Blasch *et al.*, "High level information fusion (hlif): Survey of models, issues, and grand challenges," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 27, no. 9, pp. 4–20, Sep. 2012.