Benefits and Challenges of AI/ML in Support of Intelligence and Targeting in Hybrid Military Operations

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ABSTRACT

Intelligence, surveillance and reconnaissance (ISR) and targeting in fast-paced military tactical environment require proper ISR and effect asset allocation to meet mission task demands. Given highly competing tasks, resources available, complexity and constraint diversity, automation and optimization are required to provide operators with suitable decision support deriving best collection/fire plans, and increase the speed, accuracy, and responsiveness of the planning and coordination of the full spectrum of ISR assets and fires/effects. Moreover, AI-enabled target recognition and identification, as well as situation understanding require a mix of AI techniques and consideration/coordination of all operational domains to adequately support decision makers.

In this paper, novel decision support solutions for optimized collection planning/tasking and weapon-target assignment on the one hand, and AI/ML techniques to target classification/recognition and multimodality data fusion on the other are presented respectively. Related challenges are highlighted and are also exposed in the context of hybrid warfare and multi-domain operations.

1.0 INTRODUCTION

Artificial intelligence consists in a set of techniques, including knowledge-based systems, machine learning, computational intelligence, multi-agent systems, and natural language processing, used to emulate/outperform humans in terms of reasoning, learning, planning and acting in complex cyber-physical environments. Artificial intelligence (AI) and machine learning (ML) explosion in the last decade is mainly due to the combination of deep learning algorithms, the availability of large datasets used for training, as well as an increase in computational power and advance of hardware devices. AI/ML has demonstrated significant results, expedited by the use of Deep learning, in two major areas, namely pattern recognition from data sources such as images/videos, text and acoustics, as well as decision making in search of optimal solutions, in particular:

- Machine learning approaches for pattern recognition (e.g. object, event/activity detection/recognition) from imagery or multisensory data, anomaly detection, patterns of life, etc., and natural language processing for information extraction, text analysis, from open source/social media;
- Search for optimal solutions in support of decision making (e.g. resource allocation, path planning) using reinforcement learning and other AI approaches (e.g. evolutionary algorithms).

The military operational environment is evolving and becoming more complex, involving multiple domains and actors and an accelerated tempo, which require advanced automated support at various levels of military processes (planning, situational awareness, decision support). Operations are managed over large physical spaces as well as across several emerging domains (i.e. Cyber, Space and Information). Consequently, modern operations increasingly require collective and coordinated actions across multi-domains, i.e. the traditional physical domains of warfare of air, land, sea with those of information, space, cyberspace, economic and social, involving a heterogeneous set of partners through the planning, coordination and delivery of both kinetic and non-kinetic effects within and across multiple domains.

AI/ML is increasingly used in various military domains and in support of various processes, e.g. Intelligence, Surveillance and Reconnaissance (ISR), Command and control (Observe/Orient/Decide/Act - OODA loop), or Targeting (e.g. Find, Fix, Track, Target, Engage, Assess – F2T2EA processes). In particular, AI/ML techniques provide advanced automated support for ISR data collection from heterogeneous sources, support to the PED (process, exploit, disseminate) process in terms of target detection/recognition/identification, multisensory data fusion and analytics from physics-based multimodality sensors and human-generated sources for intelligence production and situational understanding, as well as dynamic battle management and response. These complex processes which are both data-driven and knowledge-intensive together ask for hybrid AI approaches leveraging machine/deep learning, knowledge representation, logic/symbolic reasoning, combined with other approaches for low- to high- level information processing (situation understanding, higher-level fusion) as well as decision making support. In this context, AI-enabled solutions for data processing and decision support must be flexible, and adaptable to a dynamic environment, enabling an integrated "Sensor-Decider-Shooter" solution and appropriate human-machine teaming.

More precisely, in the context of our research, ISR and targeting processes benefit from AI technologies for optimized resource planning and tasking from a variety of multi-domain assets (i.e. collector/sensor tasking in support of ISR, and effector tasking in support of targeting). Moreover, AI-enabled sensors are capable of target detection and tracking at the tactical edge, and are complemented with multi-sensor data fusion and data analytics over time at a higher level (using appropriate computing architectures, such as fog/cloud computing).

While conventional warfare focuses on physical sensors/effectors and kinetic effects to reach a mission objectives, hybrid and multi-domain operations, consider additional domains such as space, cyber and information environments, for which AI/ML has great potential as well when managed carefully and coordinated with the conventional ones.

In this paper, novel decision support solutions for optimized collection planning/tasking and weapon-target assignment on the one hand, and AI/ML techniques to target classification/recognition and multimodality data fusion on the other are presented respectively. Related challenges are highlighted, and also exposed in the context of hybrid warfare, blending conventional warfare, irregular warfare and cyber warfare.

The paper is organized as follows. In the next sections, we present research work in support of ISR and targeting that makes use of AI/ML techniques, in terms of knowledge representation and reasoning in support of resource-task pairing/matchmaking, multi-objective optimization in the search of optimal collection/effects solutions. Also, AI/ML-based classification and fusion techniques for automatic target recognition are presented, in support of enhanced situational awareness and targeting. We then describe AI/ML techniques benefits and challenges for subsequent extensions of this work for multi-domain and hybrid operations, and for AI operationalization and user acceptance in the military context.

2.0 SENSOR AND EFFECTOR TASKING FOR INTELLIGENCE AND TARGETING

Intelligence, surveillance and reconnaissance (ISR) and joint fire operations in fast-paced military tactical environment require proper collectors and effectors allocation to meet mission task demand. Given highly competing tasks and resources, and multiple objectives under a diversity of constraints (cost, risk, or communication), automation and optimization are required to provide operators with suitable decision support in order to derive best collection/fire plans.

Optimal military resource management for ISR and targeting, i.e. the search of optimal solutions for ISR assets collection planning/tasking or weapon-target assignment, can leverage several AI/ML techniques. This includes knowledge-based, ontology-driven reasoning for sensor/weapon – target matchmaking which can accommodate any resource type (kinetic and non-kinetic), as well as multi-objective optimization, using genetic algorithms or reinforcement learning together with simulation, for optimal sensor/effector planning, tasking and scheduling.

To this end, novel solutions and decision aid prototypes for sensor and effector tasking are being developed, recommending warfighters the best collectors/effectors to be employed in support of ISR and targeting tasks. Figure 1 illustrates the holistic framework linking sensors and effectors management with battlespace management. ISR on the left manages ISR assets for optimized collection automation through the Total ISR Assets Visibility (TIAV) prototype, while joint fires is supported through the Total Fire Asset Visibility (TFAV) prototype, both realizing resource–target matchmaking (sensor/weapon – target pairing) and optimization, making use of modelling and simulation tools.

Figure 1: Linking sensors and effectors and C2

Our proposed solution makes use of various techniques, comprising knowledge-based, ontology-driven reasoning for sensor/weapon – target matchmaking which can accommodate any resource type (kinetic and non-kinetic), as well as multi-objective optimization using genetic algorithms, together with simulation for near-optimal sensor/effector planning, tasking and scheduling. The problem, matchmaking and optimization building blocks are presented below together with the automated solutions. More details about the unified Total ISR and Fire Asset Visibility (TIFAV) framework are provided in [1].

2.1 Problem and Framework

On the ISR side, given a set of weighted collection requirements/task requests, the basic collection tasking problem consists to allocate collection assets or agents (e.g. manned/unmanned autonomous systems,) to tasks in order to optimize single or multiple objectives (e.g. collection value, service level, uncertainty reduction, energy consumption, cost) over a predetermined time horizon. Problem input and/or characteristics include a set of collection assets and supporting resources (e.g. base stations), some collection tasking objective(s), and a set of constraints. Constraints may relate to missions, tasks, operations, collectors, supporting resources, communications (intermittent contact, ad hoc networking), capacity (energy, storage, bandwidth), temporal aspects (task time-windows, setup, deadlines, duty cycle), resource/information/communication -bounded reasoning, itinerary and cost considerations. Collection task requirements emerge from priority intelligence requirements derived from commander's critical information requirements, and prior situation knowledge, e.g., Intelligence Preparation of the Battlefield, ISR picture.

Similarly, in support of joint fires, targeting is the process of selecting and prioritizing targets and matching the appropriate response to them to achieve desired effects, considering operational requirements and capabilities REF [2]. In both contexts, the problem is to determine feasible resource-target matchmaking (pairing) and to recommend optimal solutions considering objectives and constraints over a time horizon. The workflow is as follows:

- It takes as input the considered target and tactical task (e.g. track for an ISR task, or neutralize for a targeting task), terrain, weather and mission-related information, as well as the collector/effector domain model and knowledge base of available resources.

- The resource-target matchmaking applies a series of filters to determine matching resources (feasible options);

- These matching resources are considered for optimization input;

- The optimization and simulation engines generate path planning for mobile resources; generate Collection (resp. Fire) Opportunities, and generate Collection (resp. Fire) Plans considering various objective function values, plans that are simulated and visualized.

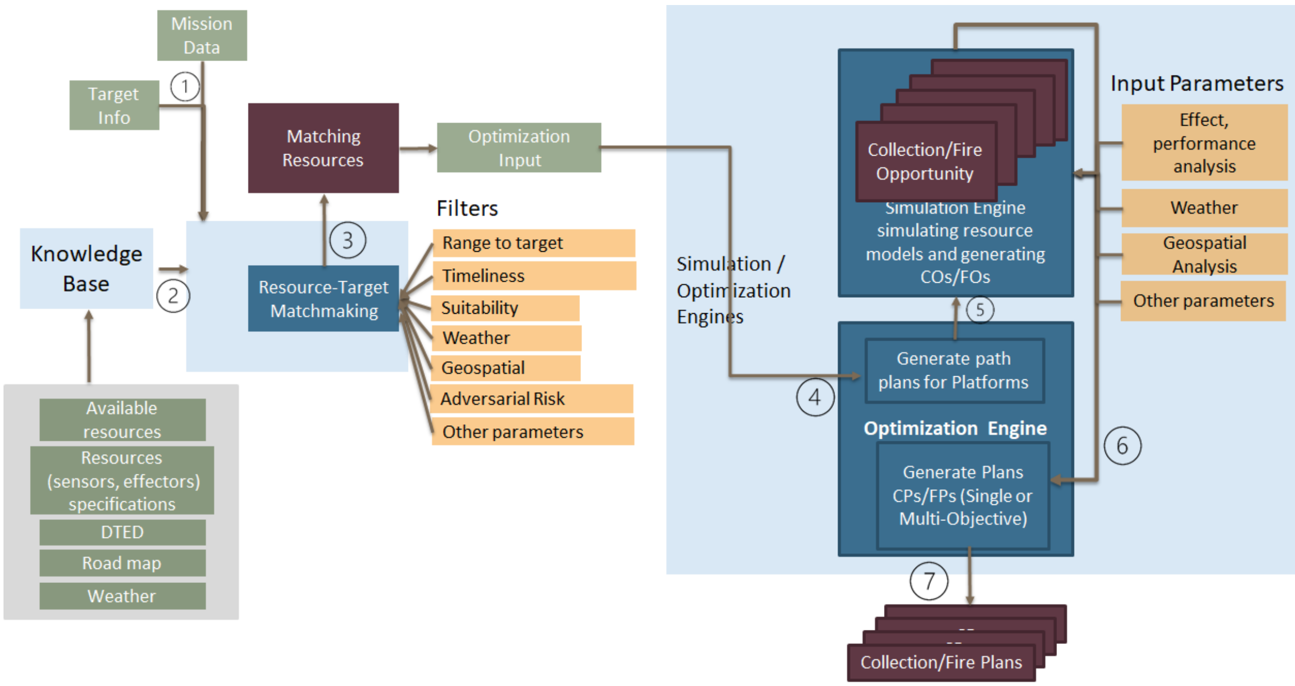

Figure 2: Generic Resource-Target Matchmaking, simulation and optimization framework

2.2 Resource-Target Matchmaking

The matchmaking process determines assets (mobile or fixed) that can satisfy the required ISR/call-for-fire tasks through a series of analyses considering various dimensions (called Multi-Dimensional Filtering) such as suitability, reachability, mission's time of day and weather, timeliness, terrain, and vulnerabilities to adversaries, in order to generate feasible collection/fire opportunities.

The matchmaking process uses a knowledge-based reasoning approach, it leverages a comprehensive ISR domain ontology and associated knowledge base [3], extending the ISR ontology from the SAM project [4] and related domain models. Moreover, the TFAV matchmaking counterpart leverages domain models characterizing effectors (weapons, ammunitions, etc.).

First, assets must have the suitable sensing capability to collect relevant data for the task (e.g. detection, classification, identification, and tracking). This can be reflected by the National Imagery Interpretability Rating Scale (NIIRS) for imagery sensors. The reachability analysis determines if the target is within the operating range of platforms/sensors, considering the ability of the platform to move to a position where it can contribute to service the request. The timeliness filter determines collectors that can provide information on time, i.e. collect and report observations based on specified Latest time information of value. An appropriate path plan and collection time are assessed based on platforms characteristics to satisfy the task timeliness. Terrain data and elevation determine if collectors have full/partial line of sight to the target. Moreover, time of day and weather conditions impact platform/sensor performance, which is taken into account to identify suitable assets. Finally, adversarial risk analysis filters out platforms that may be affected by adversarial capabilities on their way toward the target area, and therefore should not be considered suitable to the task.

Similarly, the Effector-Target matchmaking process leverages a rich effector model and associated knowledge base. First, assets must have the suitable effect capability to handle the targeted task (e.g. destroy, suppress, neutralize). This is achieved through the effector employment filter. Reachability analysis verifies if the target is within the operating range of effectors. The timeliness filter determines effectors that can provide the desired effect on the task. An appropriate path plan and related effect time requirements are assessed according to platforms characteristics to satisfy task timeliness. Terrain data and elevation analysis finds out if effectors can engage the target. Finally, engagement feasibility analysis filters suitable platforms whose performance or behavior can meet task time, fire control measure as well environmental constraint requirements, and presenting minimal/acceptable performance degradation or risk facing adversarial capabilities on their way toward the target area or during execution.

In addition to knowledge models derived from expert domain knowledge and automated reasoning, simulation using representative platforms/sensors/effectors models and terrain data supports the matchmaking process to derive collection/fire opportunities, which feed optimization to generate collection/fire plans.

Based on this approach, an estimation (prediction model) of the quality of collection/effect should be proposed for different types of tasks (e.g. probability of detection, for a detection task) to better inform the choice of sensors/collectors to address specific needs. Such quality of collection/effect estimations typically derive from expert knowledge (use of rules), simulations, or neural network learning approaches. Potential use of AI/ML for quality of collection/effect estimates for feasible sensor-task or effector-task pairs based on previous resource-task pairing recommendations are to be investigated beyond Monte Carlo simulation.

2.3 Multi-Objective Optimization

The proposed optimization approach harnesses a new compact agent graph representation and a novel approximate open-loop with feedback decision model formulation (for allocating asynchronously n effectors to service m tasks/targets), to optimize collection/effector tasking subject to a variety of task and resource capacity constraints over a receding time horizon. This aims at maximizing collection/effect value and recommend the best collection/fire options given multiple competing ISR requests and effect (call for fire) tasks. Episodic decision-making is conditioned by incoming requests, cumulative collection value, ongoing resource commitments, remaining resource capacity and plan execution feedback from the previous stage.

The underlying optimization module implementation utilizes graph-based genetic algorithms to find near-optimal solutions quickly [5].

While the benefit of a learning approach and optimization in large solution spaces is obvious, challenges still remain in distributed settings, in a closed-loop environment, using a holistic approach (vs a myopic one) to learn optimal solutions. The decision model is specifically designed to embrace generalized ISR/effect task and asset diversity, e.g. extending basic anticipated ‘destroy’ task to include ‘neutralize’, ‘suppress’ and other type of tasks for kinetic and non-kinetic effects. Decision modeling could easily comprise multiple platforms (lethal, non-lethal, cyber) subject to a diversity of resource capacity constraints as well.

Research efforts are underway to refine concepts and processes in the context of multi-domain operations or hybrid warfare, considering cyberspace and information operations. In particular, targeting in multi-domain operations focuses on fires in all five warfighting domains synchronized in time and space to achieve complimentary effects. We will next discuss the applicability of targeting methods in the context of multi-domain and hybrid operations as well as the use of artificial intelligence and appropriate techniques.

2.4 Considerations for Hybrid and Multi-Domain Operations

Joint Fires is intended to integrate all types of fires as efficiently and effectively as possible in order to produce the desired effect(s), which means integrate kinetic and non-kinetic fires to achieve desired lethal and nonlethal effects on targets. Moreover, multi-domain operations encompass fires in all five warfighting domains (air, land, sea, space, cyber) synchronized in time and space to achieve complimentary effects.

We thus need to carefully analyse the applicability of proposed targeting methods in the context of multi-domain or hybrid operations, for target development, capabilities analysis, force allocation, and combat assessment, as well as the use of artificial intelligence and appropriate techniques.

The inclusion of non-munition capabilities for targeting comprises the electromagnetic spectrum (ability to create lethal or nonlethal effects on targets through electromagnetic energy i.e. Electronic Attack), cyber (ability to create effects through the employment of cyberspace capabilities to achieve objectives), and the information space relates to the ability to create effects on humans and automated systems using information related capabilities.

In particular, developing targets in the electromagnetic spectrum (EMS) and cyberspace and the ability to deliver non-kinetic effects via computer networks operations, electronic warfare, information warfare, etc. requires more specialized techniques and tools than lethal targeting, and go beyond physical destruction thinking to include influencing behavior and actions.

Our proposed model can be extended to cover cyber threats. In the context of non-lethal effects (e.g. cyber domain), weapon-target pairing or weaponeering analysis, the process of determining the quantity of a specific type of lethal or non-lethal means required to create a specific effect on a given target, still requires to determine how to achieve the desired effect, e.g. the cyber probability of damage, the appropriate effectors and assessment of their effectiveness and effects. Cyber targeting may require considering various targets (routers on different networks, firewalls, servers, user accounts, etc.) to achieve cyber effects using appropriate cyber weapons while considering collateral damages in cyber operations.

As an example, Maathuis et al [6] propose an AI model based on fuzzy logic in order to estimate and classify the effects of cyber operations, and targeting decisions based on proportionality assessment in cyber operations. This approach is appropriate to develop a decision model in the case of uncertain, incomplete, conflicting information. A set of rules are defined to automatically derive targeting decisions. This is aligned with our approach for effector-task/effect matchmaking combined with optimization to derive optimal solutions.

3.0 AI-ENABLED TARGET RECOGNITION

Command and control, intelligence, or targeting processes comprise target detection, recognition and identification in support of tactical picture compilation and situational awareness, to take appropriate action. In particular, the weapon-target assignment process relies on information about targets of interest and desired effects on them to meet objectives.

Techniques for automatic target recognition/identification and multi-sensor data fusion have been developed for decades [7], [8]. Those comprise kinematic and ML approaches for low-level data fusion, as well as various AI techniques for higher-level fusion, in particular:

- Level 1 – Object assessment: kinematic and ML/DL approaches (e.g. Convolutional Neural Networks), probabilistic reasoning/Bayesian networks.

- Level 2 – Situation assessment (relations between objects): ML (e.g. Recurrent Neural Network, Long Short-Term Memory), logic/symbolic approaches.
- Level 3 – Threat and impact assessment (predictions of likely adversary courses of action and their potential impact): logic, knowledge-based, model-based approaches, Bayesian networks.
- Level 4 – Process refinement (resource management): search/optimization approaches using genetic algorithms [5],[9],[10], or reinforcement learning [11] that learn actions with most rewards.
- Level 5 – User refinement: AI/ML-based contextual reasoning/adaptation.

Blasch et al [12] recently analyzed the use of AI/ML in the context of Sensor data fusion and propose means to coordinate/combine AI/ML with Sensor Data Fusion as complementary approaches for enhanced results, efficiency and explainability.

3.1 Maritime Surveillance from Airborne Sensors

One of the key challenge in maritime surveillance is the automatic target recognition from airborne platforms exploiting multisensory sources, including aerial images from electro-optical and infrared cameras, radar data, etc., using AI/ML techniques to augment situation understanding and reduce cognitive overload of human analysts/operators.

For that purpose, we investigated the use of Deep Learning and Convolutional Neural Networks (CNN) which provide very good results for object classification, and tested several CNN architectures. In this context, transfer learning is used to leverage a large labelled pre-trained dataset, and fine-tune the model with a maritime vessel dataset targeted for this specific task. Testing of different networks and configurations demonstrated good accuracy results when compared to state-of-the-art in similar conditions [13].

The combination of multi-sensor imagery data (e.g. EO, IR, SAR) through data fusion has an advantage in the increase in performance of automatic target recognition (ATR) systems. To exploit these data sources and reduce classifier results uncertainty, the proposed approach is based on the combination of several deep learning classifiers, using evidential reasoning (Dempster-Shafer theory) to better take into account the uncertainty at the last layer of the classifier. The traditional softmax layer is replaced with more adequate layers to model the uncertainty. Such layers are based on the min-max or ReLu scalings, jointly with additional modeling of the uncertainty. Results obtained from maritime observation videos are compared: the evidential fusion approach provides better classification results than the initial Bayesian classifier [14].

3.2 AI/ML Challenges for Target Recognition and Identification

While automatic target recognition is a mature research topic, challenges still remain, as illustrated by the abundant literature on AI-enabled target detection/recognition/identification in recent years.

Despite the good performance of AI/ML for target classification for well-defined signatures, there are still challenges and need for improvement for accurate target recognition/identification and enhanced situational awareness. More importantly, AI/ML data-driven approaches require the acquisition of sufficient variety and quality of datasets to ensure good representativeness. The lack of labelled data for military targets (either images or acoustic signals) and/or missing classes in the dataset represents a significant deficiency. An interesting approach to augment the datasets is to generate realistic synthetic data using advanced 3D models and simulation techniques. This guarantees the provision of representative and well-balanced labelled datasets for the types of targeted classes to be encountered in the operational environment. The combination of real and synthetic datasets for model training, as well as transfer learning technique provide enhanced classification outputs.

Challenges also exist for small object detection/recognition from aerial imagery (e.g. distinguish drones from birds), and specific techniques (e.g. super-resolution) are required for the processing of small objects. Moreover, multimodal data fusion combining various sources to obtain accurate estimates should also consider at which level AI/ML is best exploited (pixel, feature, decision level). Also, the need to properly quantify and handle uncertainty in ML requires appropriate techniques to quantify the uncertainty of a classifier's predictions, as proposed in [14],[15].

Considering the variety of sources to be combined for enhanced situational awareness, the concept of hard/soft fusion, i.e. fusion from physics-based multimodality sensors readings and human-generated information emerged. Despite advances in this area, there are still challenges to align heterogeneous data and combine associated uncertainty. While frameworks for hard/soft fusion have been proposed, the exploitation of AI/ML still presents challenges to automatically derive trusted intelligence and situation understanding to take informed actions.

4.0 AI CHALLENGES FOR HYBRID AND MULTI-DOMAIN OPERATIONS

AI/ML is anticipated to be a key technology in future conflicts, and the use of AI/ML techniques in the cyber or information domain has significantly increased in the last years. Cyber operations are a central piece of multi-domain operations and hybrid warfare, but the information environment and cyberspace will be more and more subject to attacks. Operational domains are inextricably linked and there remain numerous challenges and uncertainties to be tackled. Some of these challenges are reported below.

<u>Centralized/distributed processing</u>: Multi-domain and hybrid military operations need automated data processing from multi-sensor multi-intelligence sources at various paces, to support warfighters in the field as well as operational/strategic decision makers. A mix of AI-enabled data processing at the edge, local distributed fusion, and centralized big data analytics on cloud servers have to be designed optimally, exploiting resource management techniques subject to communication constraints and bandwidth limitations in contested environments, for optimal data processing and dissemination. Moreover, ML data-driven approaches require excessive training resources that make them challenging at the edge and require appropriate training techniques.

<u>Adversarial ML</u>: AI and in particular deep reinforcement learning is able to solve complex, dynamic, high-dimensional problems. It is increasingly used for resource allocation, and cyber defence problems, e.g. intrusion detection systems or DRL-based game theory in the context of jamming, spoofing, and malware attacks [16]. Machine learning approaches are not robust in unconstrained domains, so ML-based intrusion detections systems are vulnerable in the face of adversarial perturbation. Adversarial ML may cause vulnerabilities to ML-based approaches, by generating adversarial examples (through evolutionary algorithms or generative adversarial network) which may cause misclassification.

<u>Explainability</u>: the application of machine/deep learning led to the development of highly accurate models but lack model interpretability and inference explainability as it does not explain the situation context. To guarantee AI user acceptance, AI/ML should provide user-tailored explanation, based on learning paradigms as well as explainable models for decision support that require expressive knowledge representations. Research efforts are part of the DARPA Explainable AI Challenge (XAI) efforts [17].

<u>Hybrid AI</u>: considering the problem of sparse training data, the complexity of situation understanding beyond

object detection/classification, and need to provide explainable outputs to decision makers, the combination of various AI techniques, data-based and model-based approaches, or neuro-symbolic approaches combining neural networks with symbolic reasoning and learning are suggested to capitalize on their complementary strengths, including explainability exploiting multimodal sensor feeds in layered approach as proposed by Preece et al [18].

AI operationalization: The construction of AI models needs to be insensitive to various "unknowns," robust to noise, and free from attack. AI systems require adaptation to operational conditions, graceful performance degradation, and explainability methods. AI operationalization for military operations must deliver robust and trustable AI systems, and consequently the TEVV (Testing – Evaluation – Verification – Validation) of AI-enabled systems must guarantee computation efficiency, adversarial robustness, system maintainability, reproducible results, for AI adoption and user trust/acceptance. Modelling & Simulation provides insight into complex systems and support decision-making, simulations should consist major sources of data and scenarios for training and testing AI systems, and the use of AI technologies should be exploited to enhance modeling & simulation. Efforts are also underway to provide standardization of ML lifecycle and certifications.

5.0 CONCLUSION

Representative AI/ML applications for automatic target recognition as well as decision aid in search of optimal solutions for resource allocation have been presented. The proposed TIFAV framework for this problem is flexible enough to be extended in support of hybrid/multi-domain military operations. These research work is aligned with the US DoD Joint All-Domain Command and Control (JADC2) initiative and related efforts, in particular the US Army Convergence project which aims to accelerate the use of AI at multiple stages of the targeting process.

There remain various challenges to address for the design of reliable, robust and trusted AI-enabled systems, their operationalization/deployment and adoption by decision makers and operators. The US National Security Commission on Artificial Intelligence (NSCAI) recently published a final report [19] providing a set of recommendations in this direction, in particular it mentions the need to develop and deploy AI-enabled cyber defences and techniques to counter adversarial information operations.

Moreover, data-driven ML approaches for multi-domain and hybrid operations need excessive training resources, and are vulnerable to adversarial attacks (e.g. in computer vision, or cyber domain). The complexity of the military domain, the consideration of multiple domains and nature of hybrid warfare, the need for real-time situational awareness to quickly respond to imminent threats, and the need to synchronize across domains and to adapt dynamically to changes, ask for enhanced automation through a combination of AI techniques and optimal human-AI teaming that need to be carefully designed.

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