Fusion Technology and Systems Design Challenges for the Counter-Small UAS Threat

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Abstract

The employment of Small Unmanned Aerial Systems (sUAS) poses an emerging threat to the military and to the civilian infrastructure, and countering these sUAS operations requires addressing challenges that are unique to this problem space. Technologies for addressing these threats, to include Data and Information Fusion technology, are also being challenged. There are several factors that make the challenge of dealing with the threat of sUAS very challenging. One is that the threat envelope for sUAS ranges from manufactured clutter to the delivery of a wide range of lethal weapons. Another is that they are, in the context of currently-deployed technology and technology under development, very difficult to reliably detect, track, and identify even when resolvable by surveillance sensors; many papers use the terms "Low, Small, and Slow (LSS)" to describe this threat category. The LSS category is distinguished from the sUAS category in that, in terms of the usual five-Group UAS categorization, sUAS's fall in the Group 1 and 2 class, and LSS's extend to include Groups 1 to 3[5]. At least two other factors widen their threat envelope for both of these classes: rapidly advancing design and development technologies for sUAS's, e.g., stealthy materials (sUAS's are already a reasonably non-attributable threat), and new methods of propulsion, as well as autonomous operation, and the ability to exploit massing effects via clustering and or swarming.

This paper will provide a systems-engineering overview of the varying impacts of this wide threat envelope on the design, development, and testing of Data Fusion (DF)-centric counter-sUAS (CsUAS) systems. The paper first provides a literature survey of recent and current DF-based R&D across the Levels of Fusion as described in the JDL Data Fusion Reference Model, and across the dimensions of the threat envelope. Importantly, we note the existence of a wide variety of commercial systems that claim DF capabilities although we cannot speak to the specifics of protected DF IP, we draw inferences regarding such capabilities from the claims. We also discuss the systems engineering challenges to be overcome in order to realize the needed DF capabilities with a special focus on test and evaluation. The systems aspects of addressing hybrid designs comprised of purpose-built and commercial system components are also addressed.

1. The sUAS Threat

There are various ways in which the threat from sUAS's can be framed. Importantly, as this is an Unclassified paper, we note that the views here are likely incomplete. Nevertheless, we offer one structured characterization of the various threats that sUAS's can represent, to include swarming, since swarming is closely linked to (but not only limited to) the smaller UAS's. The focus here, for an NSSDF audience, is on military usage of sUAS's but we point out that the extraordinary proliferation of sUAS's [Chavez, 2021] offers non-state actors great new and cheap capability for conducting all types of irregular operations. There is a fairly large number of papers that discuss varying viewpoints of the effects of drones and of drone proliferation, such as [Horowitz, 2016] that, as in other similar papers, describe that the effects vary in different types of conflict, with the effects most impactful in international and domestic terrorism, use by nonstate actors across various environments, and in crisis

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[5] see https://en.wikipedia.org/wiki/U.S._military_UAS_groups for UAS Group designations

operations of various type. One categorization of UAS military missions is offered by [Lehto, 2021] that divides them into kinetic and non-kinetic groupings, as in Table 1. The ability to carry out these missions is a result of the tactical advantages unique to SUASs. These advantages derive from three basic properties of sUAS's: size, speed, and swarm. Each of these properties provides a benefit in armed conflict. Related to the special case of swarming, there is an issue, framed in Lanchester's Laws [MacKay, 2006], that shows that the advantage of numbers of threat platforms outweighs the benefits of quality in defensive capability according to a power law relationship. This remains widely applicable to sUAS due to their low cost of acquisitions and ease of swarming abilities, and directly implies a significant advantage to adversarial options. There are many papers that offer views on UAS threats, as these threats span a wide international space; one NATO view is in [Evangelos, 2021].

Table 1 UAS and sUAS Notional Combat Missions (derived from [Lehto 2021])

Mission Type	**Characteristics**
	Non-Kinetic Type
ISTAR	Signifying the activities related to Intelligence, Surveillance, Target Acquisition and Reconnaissance
Cyber	Can be carried out in either a Passive or Active context, related to cyber surveillance or attack—e.g., disrupting WiFi, LAN's, RF networks, and RF operations of defensive UASs.
	Kinetic
Combat	sUAS armed with a wide variety of air-to-air or air-to-ground weapons
Wingman	Supports Persistent-Close Air Support of hostile aircraft; also useable as a decoy
Assassin/Kamikaze	Used against various possible targets to include defensive UAS, ground defenses, and even people via face recognition technology
Loitering	Used as loitering weapon as part of adversarial weapon inventory

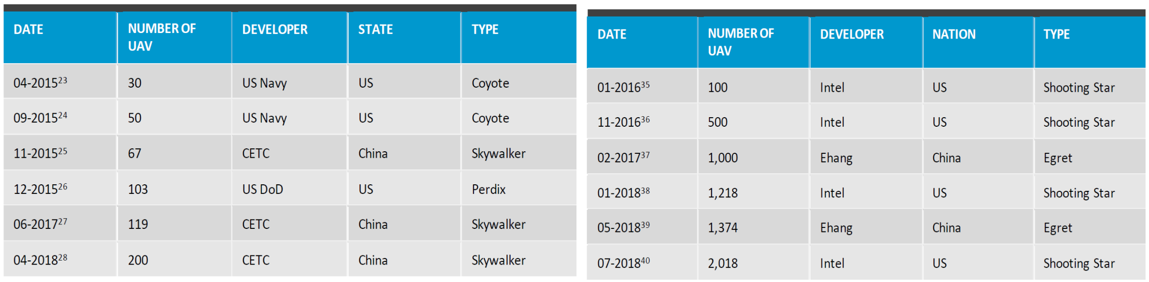
1.1 The Very Special Case of UAS Swarms

Swarming UAS's comprise a special case of the UAS-based threat, and there are wide-ranging views of the effects of employing UAS swarms in different mission contexts, both on the friendly side and adversarial side. Arquilla and Ronfeldt [Arquilla, 2000] proposed that the next evolution of warfare would be the swarm, which would combine the large numbers of individual elements found in decentralized "melee" combat with the mobility and coordination of maneuver warfare. In [Beaudoin, 2011], Beaudoin et al raise the question of how to defend against swarms and asserts that the only defense possible is a counter-swarm (although non-kinematic swarm countermeasures have been developed). A discussion on swarm countermeasures is provided in [Guitton, 2021], addressing both passive (e.g., hardening of high-value assets) and active measures but concluding in regard to active measures that none are adequate in isolation, also raising the notion of defensive swarms. In [Tsatsanifos, 2021] the problem of modeling and control of large-scale adversarial swarm engagements is addressed, and an analysis of a defensive strategy against an adversarial swarm is posed in the context of optimal control, involving different models of swarm dynamics. Even in the swarm versus swarm case, there is the issue of defensive drone-to offensive drone "weapon-target pairing"; this issue is the subject of some papers that look at game theoretic solutions for such problems; in [Montalbano, 2020] and [Cao, 2020], tradeoffs among four heuristic optimization methods are analyzed for this combinatorial problem.

Certainly, it seems China is moving in the direction of a swarm capability as even witnessed in publicly available materials. The picture below (from https://www.dailymail.co.uk/news/article-8843745/China-unveils-terrifying-weaponised-UAS-troop-launched-truck.html) shows a Chinese prototype swarm-launcher employing a 48-tube launching capability termed as suicide UASs in the open literature. In addition, another website (https://www.thedefensepost.com/2021/04/09/china-aircraft-carrier-launches-drone-swarm/) shows a similar but airborne swarm-launcher under development in China as in Fig. 1.

Figure 1 Chinese UAS Swarm Deployment Technologies; Ground (left) and Air (right)

The swarm threat can be expected from any nation-state actor and even non-state actors as supportive technologies evolve. Table 2 shows the evolving capability of swarm sizes for military and civil applications, from [Hambling, 2018] that is a 2018 publication; here we see sizes of about 200 for the military case, accomplished by the Chinese.



DATE	NUMBER OF UAV	DEVELOPER	STATE	TYPE
04-2015[23]	30	US Navy	US	Coyote
09-2015[24]	50	US Navy	US	Coyote
11-2015[25]	67	CETC	China	Skywalker
12-2015[26]	103	US DoD	US	Perdix
06-2017[27]	119	CETC	China	Skywalker
04-2018[28]	200	CETC	China	Skywalker

DATE	NUMBER OF UAV	DEVELOPER	NATION	TYPE
01-2016[35]	100	Intel	US	Shooting Star
11-2016[36]	500	Intel	US	Shooting Star
02-2017[37]	1,000	Ehang	China	Egret
01-2018[38]	1,218	Intel	US	Shooting Star
05-2018[39]	1,374	Ehang	China	Egret
07-2018[40]	2,018	Intel	US	Shooting Star

Table. 2 2018 Era Evolution of Military and Civil Swarm Sizes [Hambling, 2018]

To give some perspective to the evolution of UAS swarm size capabilities (admittedly these are single-purpose type displays), Intel set the first swarm record in late 2015 with 100 drones; in 2018 Intel launched a swarm of 2066 UAS's—in September 2020 Geoscan of Russia launched a swarm of 2198 UAS's—in September 2020 a Chinese company set a record of 3051 UAS's, to be broken soon after by Genesis in March 2021 with a display of 3281 UAS's—and most recently the largest swarm size was again broken at a size of 5200 UAS's to celebrate China's 100th year of communism (see https://dronedj.com/2021/07/02/world-record-5200-drones-light-show/). Implications of all this on the military side are unclear, but in any case, these sizes are impressive and the foundational swarm technologies are clearly advancing.

2. The Role of Data Fusion Technology

In contemplating requirements for DF technologies, we follow Bowman's [Bowman, 2004] ideas on systems engineering of DF capability in asking what the Roles for DF capability are in the context of friendly missions. On the friendly side, defensive operations fall into the category of the Defensive Counter-Air (DCA) mission (and possibly others but we focus on this for this paper), that has a Passive side bounded by Detection and Warning and an Active side involving Destroying, Nullifying, or Reducing the effectiveness of hostile air threats. Tactics for these will be dependent on what is being defended, e.g., whether the DCA system is part of an area defense operation or defending a high-value asset. What DF needs to do is linked to both the methods of defense in the context of countermeasure support but also to Tactics, Techniques, and Procedures (TTP's) that friendly forces will employ. Following the swarm discussion above, one interesting question regarding DF requirements is whether, in the case of an adversarial swarm, all targets need to tracked and identified at the individual level or as an extended or grouped target. We find papers on both sides of this issue in the literature. Further, the DCA mission and system context in the case of sUAS's is more specifically in the context of Short-Range Air Defense or SHORAD type systems, since the overall range context for sUAS's will be relatively low; this is not the case for the larger LSS class threats Thus, managing mission-level response time will be a critical factor in friendly defensive mission management operations. It is also important to understand whether the SHORAD systems are part of a larger air defense system and thus a "layer" in the overall air defense system architecture. Because issues regarding doctrine, TTP's, rules of engagement (ROE) and other non-technical factors have not yet been fully developed, our paper develops notional remarks on the Roles for DF. We follow the basic capabilities of the various Levels of DF in that discussion.

3 Fusion Technology in the UAS/sUAS Problem Space

To provide a survey of DF technologies in open-source literature as applied to the Cuas/CsUAS problem, we organize our findings by the Levels in the Joint Directors of Laboratories (JDL) Data Fusion Reference Model (see [Hall, 1997] for an elaboration of the JDL Data Fusion Reference Architecture). There are some papers that also provide surveys of counter-UAS technology assessments, such as in [Wang, 2020] and [Herrera, 2017], as well as a book [Joint Air Power Competence Centre, 2020], but these works do not restrict themselves to the small UAS domain nor do they focus on the fusion technology aspect.

3.1 JDL Level 0: Signal Processing and Detection

Single and multisensory detection processes may span both JDL Level 0 (sometimes labeled as "upstream data fusion"; see [Newman, 2013]) as well as Level 1; this is especially true for the sUAS platform case where the earliest-possible detection is needed since in most cases this problem is framed by short ranges and very limited response times, as previously mentioned. Our team reviewed a number of open-source, recent works in studying the UAS detection problem from a multi sensor standpoint as shown in Table 2 (sensors are Radio Frequency (RF), Acoustic (ACSTC), Radar (RAD), Visual (VIZ) and Infrared (IR)) .

Table 2 Overview of Open-Source Literature on UAS Detection

	Sensors					Nature of Results
Paper	RF	ACSTC	RADAR	VIZ	IR	

Laurenzis [2017]		**x**	**x**	**x**		Sensor-specific Detect; MUSIC Algorithm for multi-UAV tracking
[Knoedler, 2020]			**Passive GSM Radar**			Track-Before-Detect Scheme; decent performance for R and Rdot
[Ganti, 2016]		**x**		**x**		Limited single-UAS results
[Aledhari, 2021]	**x**			**x**		Deep NN to process the RF data; Convolutional NN to process image data. Feature fusion for Detection; Pd ~ 75%
[Ezuma, 2019]	**x**					Only RF used for both Detect (~80%|10db) and Classification (various NN methods) at ~80% accuracy
[Muller, 2017]				**x**	**x**	Decent single UAS performance at night; bounding-box vision-based tracking
[Jovanoska, 2018]	**x**		**x**	**x**		Detection and MHT tracking in simulation environment; Pd~ 0.9
[Svanstrom, 2020]		**x**		**x**	**x**	YOLO methods for Viz and IR; Used simple OR logic for "fusion"; detection good, classification F1 about 75%
[Goecks, 2020]				**x**	**x**	Multi-UAS expts; Pd ~ 75%; YOLO methods for detection
[Busset, 2015]		**x**		**x**		Special acoustic camera for detection and tracking; decent performance; experimental
[Hengy, 2017]		**x**	**x**	**x**		MUSIC algorithm for acoustic processing; detection and localization-based field trials

The results reviewed here are based on a sampling of 11 open-source papers that include a range of international efforts. It can be seen that the studies include a wide range of test conditions ranging from single-UAS based works to multi-UAS, to daytime and night-time conditions, and to varying weather conditions. It is encouraging to see that the detection results are pretty good in a qualitative sense, although few papers present well-qualified numerical results; for example, there are no ROC curves presented across this set.

Some remarks about the basic challenges to UAS and sUAS detection (and tracking) are as follows:

- Fairly significant UAS elevation dynamics impacted by ground and natural clutter
- Interplay between short response time requirements and requirement for large steradian scanning; this leads to a sensor-management challenge
- Low speeds pose challenges in terms of Minimum Detection Velocity (MDV) for radar sensors.
- Acceleration capability is impressive and target trackers must work with larger bandwidth and therefore less sensitivity; see [de Almeida, 2013] regarding UAS maneuverability issues, also commented on below related to the Level 1 discussion.
- Applicable RCS models related to radar sensing are Swerling [Swerling, 1960] Types 1 (or 2); scan-to-scan variability is very typical especially for sUAS's that flit around much like insects

We also looked at the literature on Machine Learning (ML)-based approaches to UAS detection. There are a number of papers on this topic but a pretty recent ML-specific survey was conducted by Taha, et al in [Taha, 2019]. That paper: reviewed 14 papers on Radar-based methods, 8 papers on Visualization-based methods, 7 on Acoustic methods and 3 on RF-based methods for UAS detection. Some summary remarks drawn from that paper are:

- The Radar-based papers are of mixed purpose; some are explicitly to detect UAS presence (RCS-based), some to distinguish UASs from birds (kinematics-based), some to detect the presence of multiple UASs, and some attempt to classify UASs (feature-based).
- Many results are pretty positive but generalization to cover more UAS types, wider ranges (many were at close range), different radar sensors, and different signal processing schemes is yet to be realized.
- Most of the works are experimental, basic research that do not offer insight on comparative design alternatives.

For Visualization-based methods, most of the work was done using learned features, where it is known that deep learning methods are data driven and require huge labeled datasets to generate robust models. This boundary led some to explore transfer learning and also to develop specialized data sets. Another ML approach is to use the smallest NNs with an automatically adaptive architecture that achieve the RMS training accuracy requirements, Bowman [Bowman, 2018]. For the Acoustic methods, they are of course dependent on UAS design and ambient factors, and here too any generalization is very difficult due to the different study conditions. Thus, ML approaches can be used that affordably adapt to each sensor-target environment. Taha reports in [Taha, 2019] that "Proposed acoustic detectors have at most 150m detection range.", so the range boundary with these methods may not be satisfactory for many practical applications. Detecting and classifying RF signals from the UAS controllers is a promising process for detecting UAS's as discussed in various references. These techniques, many of them ML/NN-based, are trained based on the raw data, which is coming from the RF signals when the UAV controller is managed by the control system. A non-trivial issue however, is that there is a wide range of signals for different types of UAS's, requiring robust a priori signature databases to be developed for training; [Al-sad, 2019] provides a good overview of these issues in RF exploitation. Samples of strategies for RF-based detection and classification are shown in [Nguyen, 2016] and [Nguyen, 2018]. RF methods are of course also not applicable for autonomous UAS's, and even command-guided systems do not offer continuous signals.

3.2 JDL Level 1: Tracking and Classification

For JDL Level 1 we reviewed nine papers that were directed to the UAS tracking problem; see Table 3. We noted especially that none of these employ traditional DF multisensory multitarget tracking methods. Another primary remark is that very few addressed the multitarget case; in such cases the number of total targets was small. However, a couple of papers address a large number of targets, one paper addressed the swarming case. We note also that in searching under a "tracking" search term, that many papers address problems of different type; e.g., there are probably more papers on tracking a target *from* a UAS that tracking a UAS from the ground; some papers are navigation-oriented such as to maintain a given swarm configuration. The specific algorithms noted in Table 3 are of wide variation, from traditional Kalman Filtering methods to template and simple measurement fusion techniques.

Only a few studies present organized, parametric-type results, as most of these works are research-level efforts, exploring feasibility of different schemes.

Table 3 Overview of Open-Source Literature on UAS Tracking

Paper	Tracking Problem	Sensing	Estimation Algorithm	Performance
[Xie, 2019]	Single 3D Sim UAS	R, Az, El presumed	• Particle Filter • Linear motion model	Good performance under low and high noise conditions
[Pilté, 2017]	• 1 Real UAS • 3 types	R, Bearing	• Invariant Extended Kalman Filter; UKF • Frenet-Serret frame in 2D	Very limited data but good performance
[Srigrarom, 2020]	1 to few Real 3D UAS	Video from Surveillance UAS	• EKF • No association re multiple targets	Feasibility-based study
[Liang, 2021]	2 Real 3D UAS	MultiCamera; optical flow for 3D location msmts	• Least squares msmt fusion • Crude Data Association scheme	Feasibility-based study
[Chang, 2018]	1 Real 3D UAS	Acoustic array; Improved TDOA	• Simple Kalman Filter	Good quantitative results
[Sun, 2019]	1 Real Small UAS	Monochrome video + Radar	• KCF (Kernelized Correlation Filter) with adaptive thresholding • Focus is improved image location	Good quantitative performance
[Guerlin, 2020]	Sim and Real small swarms	Radar	• Group Target Poisson Multi Bernoulli, PMB, ETPMB compared	High cardinality errors w PMB, ETPMB; GTPMB Tracks swarm as extended tgt bounded by ellipse
[He, 2020]	10 Sim UAS	Radar	• JPDA w Gibbs Sampling	Good performance for study-type results

Some summary remarks on Table 3 and Tracking:

- There is almost no discussion in any of these papers about measurement qualification and the overall issue of Data Association; the [He, 2020] paper naturally includes association as part of a JPDA approach.
- The Guerlin paper poses an interesting approach to whole-swarm tracking, motivated by difficulties in efforts to track individual member UAS's of a swarm.
- No plots of residuals, or other traditional methods of evaluation are presented.

The open-source literature on Classification processing reveals a high bias to the use of Machine Learning-based methods. Note that UAS classification as a binary classification of UAS/non-UAS can be part of the detection process; as a result, searching on Detection or Classification will yield papers on either or both topics. Regarding ML techniques, we show just a few such methods in Table 4 since the survey paper by Taha referenced above [Taha, 2019] also addresses classification and offers a quite-comprehensive overview of ML-based approaches to UAS classification. Another survey paper by Patel [Patel, 2018] provides a survey of radar-based (both active and passive-based methods) methods that expands on various details of signal levels such as RCS and micro-Doppler signatures. That paper also shows the many papers on classification that are ML-based, and reviews some 17 papers that employ a range of methods for UAS classification based on radar data.

The Taha paper [Taha, 2019] describes the range of ML-based classification-labeling for different applications, ranging from (as mentioned above) UAS/non-UAS, UAS vs Bird, UAS type, Drone Characteristics (such as bearing a payload), and multiple or labeled groups of UAS's. This paper also reviews the classification methods by sensing modality, and ranges over radar, visual, RF, and acoustic sensing and classification techniques. As concluded in the paper, no single sensing modality will be sufficient for UAS classification in most practical applications. The viability of the use of ML methods may hinge on whether learned or handcrafted features can be used for ML algorithm development; this paper asserts: "Collaborative efforts to build publicly available datasets are indispensable to help researchers and developers build robust classification models for drones based on all modalities."

Table 4 Overview of Open-source Literature on UAS Classification Methods

Paper	Classification Problem	Sensing	Classification Approach	Declaration Space	Nature of Results
[Sommer, 2021]	Survey of performance of SOA Classifiers against public data set. 5 types of Quadrotor UAV's	Constrained to EO imagery	• Classifies only data passed by first-stage Detector • 8 SOA ML Classification methods tested	DJI Phantom, DJI Matrice, DJI Inspire and DJI Mavic	Wide range of results shown; best classification accuracies about 85%
[Rahman, 2020]	2 Real Quadrotor, I Hexacopter UAS	MMW Radar; micro-Doppler based	GoogLeNet CNN	DJI Phantom Standard 3, Joyance JT5L-404) and DJI S900	Very good performance based on good data

[Hudson, 2021]	5 Simulated Quadrotor UAS	Radar; using long-windowed, short-time Fourier transform (STFT)	CNN	DJI Mavic Air DJI Mavic Mini 160 2 Parrot Disco DJI Phantom DJI Matrice 300 RTK	Parametric study; wide range of results
[Zhang, 2017]	Real Helicopter, Quadcopter, Hexicopter	Dual-band (K, X) Radar micro-Doppler	SVM; with/without feature concatenation	Unnamed Helicopter, Quadcopter, Hexicopter	Very good performance
[Kilic, 2021]	Public data from 3 Quadrotor UAS	RF Spectral Features	SVM	Drone/No-drone, Drone Type, Drone Characteristics	Good performance in general but RF Feature dependent

3.3 JDL Levels 2 and 3: Situation and Threat Assessment

Developing methods for Situation Assessment (SA) and Threat Assessment (TA) for the newly-evolving category of UAS/sUAS tactical use cases can be expected to be in a very evolutionary state, in part because the conditions of interest will be of wide variation. This is due in part to the potential use of UAS's by both state and non-state actors, the extraordinary range of UAS types and capabilities even within a UAS Group-designated class, the range of mission categories (as in Table 1), and other factors to be determined. So, the notion of a Situation of interest is difficult to form, given this wide range of possibilities. Another factor is the rapid evolution of a Situation in the sUAS cases, since in those cases overall mission timelines will be short; this implies that for Situation estimates to be helpful they need to be early-onset type Situations, of an early warning type. We saw one paper [Loui, 2016] that addressed the idea of ontologies for adversarial plan recognition in the context of active and passive aerial drone threats. The mission focus is related to force protection and protection of high value assets. While the paper is about plan recognition, plan recognition can also be supportive of intent recognition and thus provide the early awareness required in these mission settings. The focus of the ontology suggested here draws from the work of Agre [AGRE, 1996] and for the UAS mission is focused on describing the attack space in relative terms, e.g., which UAS is closest to the target, which UAS's are in range, etc. That ontology is based on the well-known "Belief-Desires-Intentions (BDI)" model used in many studies of behavior. This work is just a very first start to the development of a more rigorous ontology.

While we find no substantive papers on the Level 2 focus on Situations, we find several papers on the general topic (i.e., not UAS-specific) Air Threat recognition. Air target threat assessment refers to comprehensively considering various factors affecting the target threat value, establishing a reasonable indicator system and quantifying it, and then establishing a threat assessment model to evaluate the target threat value. Methods that address this estimation challenge include Bayesian and Fuzzy methods and a range of ML/NN techniques. Table 5 provides an overview of a small sample of papers addressing Threat estimation in a Defensive Counter-air mission context, showing that wide-ranging methods have been explored for this problem, and that the research is basically exploratory and ranges over a wide variety of analytical methods.

Table 5 Overview of Open-source Literature on Threat Assessment Methods

Paper	Context/Focus	Threat Assessment Method Employed	Results/Remarks
[Yue, 2019]	Threat assessment for conventional aircraft and missiles	Variety of optimization-based techniques employing Threat features	Complex analysis of tradeoffs of alternative optimization methods; assert the performance of "Moth Flame" techniques
[Krenc, 2019]	Swarm-based Threat recognition	Contextual exploitation using a Polymorphic model approach	Exploratory study
[Sander, 2018]	Drone Classification	Hybrid single UAS classification; not Threat	Modeling approach; Combines knowledge-based (High-Level Fusion) with sensor-based classification
[Luo, 2021]	UAS Threat estimation	Analytic Hierarchy Process (AHP) plus Entropic aspects	Small simulation results show advantages and issues of this approach
[Unver, 2019]	Multi-aircraft Threat Recognition	Analytic Network Process (expansion of AHP) based on Capability, Intent, Proximity approach	Simulation results good; shows benefits of including interaction effects omitted in AHP

3.4 JDL Level 4: Adaptation in Fusion Processing

There is very little literature on Level 4 Process Refinement for the CUAS/CsUAS application. We found two papers that are relevant regarding discrete adaptive operations and one that argues for an adaptive architecture. Table 6 summarizes the discrete adaptation papers and remarks on the adaptive architecture paper follow below.

Table 6 Adaptive Processing and Sensing for Counter sUAS

Paper	Application Context	Adaptive Focus	Adaptive Details	Notion of Results
[Xie, 2020]	2 Types of Real UAS; varying weather/observation conditions	Multisensor adaptive spatiotemporal detection with multiple EO sensors	Adaptive real-time switching of spatial and temporal features sets for detection	Very good performance in comparison to several alternative methods
[Laurenzis, 2018]	1 to 7 sUAS flying reconnaissance mission	Runtime augmentation of static sensor network with a mobile sensing unit	Topography optimization for mobile sensing deployment	Good but exploratory results

This situation, i.e., the limited number of papers, seems quite sensible, since the range of sensors and sensor combinations necessary to provide Level 1 to Level 3 estimation capability is a topic clearly under considerable research and discussion. Individual sensor effectiveness needs to be assessed, along with the effectiveness of nominated set-wise sensor groupings, and this research is underway at present with mixed results as demonstrated in this paper. Virtually all papers considering the sensing issue suggest that multisensory techniques will need to be employed but which combinations, and therefor what type of data fusion is needed, are currently open questions.

Summary

It is expected that Dr. Alex Kott, Chief Scientist of the Army Research Lab, will be providing a Keynote talk at this conference on the topic related to the 2020 Karabakh War and its science and technology implications. If that war is studied, it will be seen that the Azerbaijanians claimed that the use of TB2 drones acquired from Turkey accounted for destruction of $1B in equipment of the Armenian forces (see https://www.youtube.com/watch?v=S_X_9oWLmfU) and were a major factor in its success. We have drawn remarks from several sources to try and gauge the current nature of UAS threats and in particular sUAS threats but it is clear that trying to get a reliable situation picture is difficult. For the sUAS threat, most threat analyses are concerned about how the threat picture is evolving, more so than its state at the moment. The same can be said for the state of all technologies directed toward defending against the sUAS threat, including Data Fusion technologies; most are in development and are to the moment directed to the current state of design of sUAS's, and often (but not exclusively) studying the sUAS in isolated, not ensemble scenarios, and almost no Data Fusion R&D exists for the swarming case. As sUAS's primarily gain their tactical strength through grouping and swarming, this R&D gap is a significant shortfall in needed research. Further, if it is argued that the heart of Data Fusion methods is based on methods of Data Association, then the state of CsUAS Data Fusion technologies can be said to be in their infancy, as we see very little in the way of formal methods being applied to the association function. Coupled with the asserted need for multisensor systems, this is a significant shortfall in R&D; together with our other remarks, this implies a long road to go toward achieving robust capability against these threats.

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