Detecting and tracking hypersonic glide vehicles: a cybersecurity-engineering analysis of academic literature

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Abstract: Hypersonic vehicles are vehicles travelling faster than Mach 5 (five times the speed of sound). Hypersonic technologies have existed since the end of the 1950s, but recent developments of defence applications have led to their resurgence. Hypersonic weapons can be hypersonic (powered) cruise missiles or hypersonic glide vehicles (HGVs). The near-space trajectories of HGV, combined with their superior manoeuvrability, enable HGVs to evade existing space and terrestrial sensors used to track ballistic missiles, posing an immediate threat to today's radar networks and making HGVs well-suited for intercontinental (> 5500 km) targets. Securing HGV detection and tracking systems is of great interest to at-risk nations and cybersecurity researchers alike.

However, like hypersonic flight technologies, HGV defence technologies are heavily guarded secrets. The shortage of public-domain information did not stop academia from proposing various detection and tracking schemes, but a reasonable question is: "How credible and useful is current public-domain information, including academic publications, on HGV detection and tracking for academic researchers to base their cybersecurity research on?" To answer this question, we scanned and critically reviewed public-domain literature on HGV detection and tracking. We then identified ambiguities and knowledge gaps in the literature. In this paper, we provide a concise version of our multivocal literature review and an analysis of the identified ambiguities and knowledge gaps in our attempt to answer our earlier question.

Keywords: Hypersonic glide vehicle, Hypersonic and Ballistic Tracking Space Sensor, National Defence Space Architecture, satellite constellation, small target detection, target tracking

1. Introduction

Hypersonic weapons can be classified into two main types (Van Wie, 2021): (i) hypersonic (powered) cruise missiles (HCMs), and (ii) hypersonic boost-glide systems (HGVs). HCMs are multistage vehicles that use solid rocket propulsion to accelerate from launch to a speed enabling a scramjet-powered sustainer stage to take over powering the remainder of the flight. HGVs are also multistage vehicles typically powered by solid rockets, but they are simpler by construction. The launch stage accelerates the glide stage to hypersonic speeds at the edge of space, and the glide stage then glides unpowered to its target. While HCMs are for medium-range (1000-3000 km) targets, HGVs are for intercontinental (> 5500 km) targets.

Detecting the launch of an HGV is already within some governments' capability, but the near-space trajectories of HGVs combined with their superior manoeuvrability enable HGVs to evade existing space and terrestrial sensors designed to track ballistic missiles (Sherman, 2022); see Figure 1. HGVs however emit strong thermal radiation in the infrared (IR) spectrum when hypersonic gliding raises their surface temperature to several thousand Kelvins (Tracy and Wright, 2020). Thus space-borne and persistent electro-optical/infrared (EO/IR) sensing is widely recognised as the alternative to ground-based radars for HGV detection.

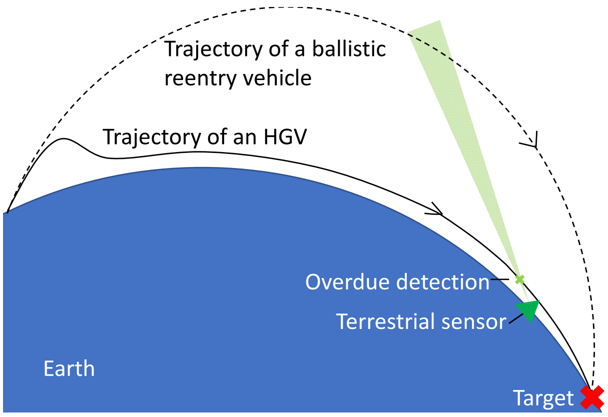

Figure 1: HGV trajectories are not conducive to early detection by terrestrial sensors.

Perhaps the best-known example of a space-borne persistent infrared sensor is the Hypersonic and Ballistic Tracking Space Sensor (HBTSS) envisioned by the U.S.' Missile Defense Agency (MDA) and Space Development Agency (SDA). HBTSS satellites sit in low-Earth orbits (LEOs) with a medium field of view and form a part of the Next-Generation Overhead Persistent Infrared (Next-Gen OPIR) multilayered satellite constellation (Strout, 2019). The Next-Gen OPIR constellation is designed to augment and eventually replace the U.S. Air Force's Space-Based Infrared System constellation, a legacy satellite-based early warning missile defence system (Munoz, 2021). As a vehicle passes from one HBTSS' "field of regard" to another's, tracking information is transmitted by the former to the latter in real time. Integration with terrestrial sensors and high-speed data sharing – potentially through optical links – enable continuous tracking of long-range missiles from launch to impact; this is known as *cradle-to-grave* or *birth-to-death* tracking. The U.S.' blueprint for enabling this level of tracking is called the National Defence Space Architecture (NDSA).

Securing an HGV detection and tracking system, within or without the NDSA context, poses not only significant cyber-engineering challenges, but also important scientific problems. The sensitive nature of these problems means researchers investigating these problems must cope with a dearth of critical information on HGV-related technologies. There is nevertheless a steady production of academic literature on HGV detection and tracking. To assess the credibility and usefulness of this literature for analysing the attack surface and security posture of an HGV detection and tracking system, we ask this question:

"How credible and useful is current public-domain information, including academic publications, on HGV detection and tracking for academic researchers to base their cybersecurity research on – what are the ambiguities and knowledge gaps?"

This paper represents our first attempt at answering the question above, and we are potentially the first to critically explore this topic. Hence, **our contribution** through this paper is unprecedented multidisciplinary insight on the viability of cybersecurity research in the context of HGV detection and tracking relying only on public-domain information.

In what follows, we will discuss in Sec. 2 the aspects of the NDSA that are relevant to HGV detection and tracking; in Secs. 3-4 the two main sensing modes; in Sec. 5 aerodynamic modelling as a prerequisite for tracking; and in Sec. 6 tracking algorithms. Each of Secs. 3-6 contains a subsection discussing ambiguities and knowledge gaps in the literature. Sec. 7 summarises our findings and provides a concluding note on our future directions.

2. National Defense Space Architecture (NDSA)

As a blueprint for a proliferated mega-constellation from LEOs to geosynchronous orbits (GEOs), the NDSA consists of seven logical layers (SDA, 2021). Going bottom-up,

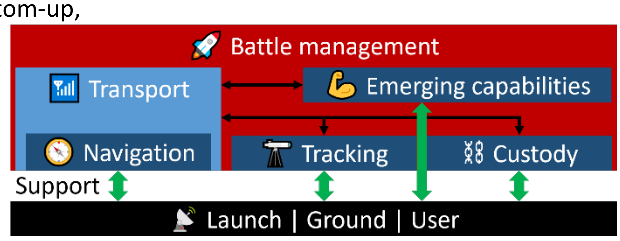

Figure 2: The seven logical layers of NDSA.

- **The Support Layer** provides a common, resilient ground support infrastructure necessary to underpin the space-based capabilities of the other layers to disseminate, process and leverage data.
- **The Transport Layer** provides a low-latency communication backbone, in the form of a mesh network of hundreds of satellites, connected through optical links. Network connectivity extends to existing tactical data links.
- **The Navigation Layer** provides positioning, navigation and timing (PNT) services. By sitting inside the Transport Layer (see Figure 2), the Navigation Layer enables the satellite mesh network to beam PNT signals down as navigation messages to warfighters over existing tactical data links.
- **The Tracking Layer** supports space-based sensing and data fusion across sensors and orbital regimes, and thereby provides from LEOs global indications, tracking, and targeting of missile threats, including HGVs.
- **The Custody Layer** maintains "target custody" and provides the ability to detect and track time-sensitive mobile targets on the Earth's surface (ground and sea) from LEOs. It is focused on deriving weapons-quality geolocations and tracks.
- **The Emerging Capabilities Layer** supports new mission concepts in areas such as space situational awareness and environmental monitoring.
- **The Battle Management Layer** provides automated space-based battle management through command control, mission processing, tasking, and information dissemination to support time-sensitive kill chain closures.

While a holistic approach to securing HGV detection and tracking is analysing all seven layers of the NDSA and their interactions, the focus here is the Tracking Layer, the outputs of which are used by *glide phase interceptors* to close the sensor-to-shooter loop or kill chain. To support beyond-line-of-sight targeting of HGVs by the interceptors, the Tracking Layer needs to generate tracking data of "fire control quality" (Sherman, 2022).

For HGV detection, two sensing modes are of concern: EO/IR sensing and radio detection and ranging (radar), which are discussed in Sec. 3 and Sec. 4 respectively.

For HGV tracking, stochastic estimation/filtering techniques are relevant. These techniques however require a kinematic model of the target. This model typically takes the form of a discrete-time state equation, which allows the target's coordinates and velocity at the next time interval to be predicted based on the measurement/observation at the current time interval. The superior manoeuvrability of HGVs rules out the use of state equations based on simplified kinematic models such as the constant velocity model, the constant acceleration model, the constant turning model and the Singer model (Singer, 1970). The kinematic models used for target tracking do not need to be as detailed as those used for guidance and control, but they do need to take *hypersonic aerodynamics* into account. Following this logic, Sec. 5 discusses aerodynamics modelling before tracking algorithms are discussed in Sec. 6.

3. EO/IR sensing

Detecting HGVs by EO/IR sensing from GEOs is challenging because HGVs appear to be one order of magnitude dimmer than the usual targets (Strout, 2019). Moving sensors from GEOs to LEOs helps, but the associated *signal-to-clutter ratios* (see Definition 1) are still lower than that the typical values for ground-based radars (Sherman, 2022).

Definition 1: *Signal-to-clutter ratio* (SCR) is the ratio of the power of the desired signal to the power of the clutter, typically expressed in decibels.

Note: The term "clutter" originates in the radar literature. A radar receives returns from many sources. Besides reflections from the target(s), the returns include backscatter from the environment and non-targets; these undesired returns are called "clutter" (Greco et al., 2014).

An HGV may not only appear dim but also small in infrared images, to the degree that it may occupy 0.1% or less of the image area (Dai et al., 2021). Methods for detecting dim and small targets in images can be found in the research area of *small target detection*.

3.1 Small target detection

HGVs not only appear small, with a low SCR, in infrared images, but also move at high speed. A fast-changing image background rules out efficient sequential detection algorithms such as matched filtering (which dates back to the 1980s) and necessitates detection to be performed on every image frame. Among the algorithms that use handcrafted features, Chen et al.'s (2014) local contrast method (LCM) and its derivatives were popular. Among the algorithms that use deep features, the first batch of results are widely attributed to Liu et al. (2018), who used a five-layer perceptron.

In recent years, algorithms based on the U-Net architecture (Ronneberger et al., 2015) have gained dominance. the U-Net architecture consists of contracting/down-sampling/encoder layers connected via a bottleneck for high-frequency noise filtering to expansive/up-sampling/decoder layers. Initially proposed for medical image segmentation, the architecture is now widely used in remote sensing, including small target detection.

The deep residual network (ResNet, see He et al., 2016) and feature pyramid network (Lin et al., 2017) are widely used as building blocks. ResNet uses shortcut/skip connection (i.e., connections between network layers that skip one or more layers) with identity mapping to solve the problem of vanishing/exploding gradients. Feature pyramid networks provide features at multiple scales, so that low-level features containing fine details of the target as well as high-level edge/shape features can be simultaneously extracted.

Cross-layer feature fusion (CLFF) refers to the combination of features at different levels for context extraction. This is important for highlighting the features of dim and small targets in deep layers and subsequent accurate segmentation of the target, and is done differently in different detection algorithms. Table 1 compares some recently proposed deep neural networks. Table 1 excludes solutions that analyse multiple frames at a time because they do not work in real time, and solutions (e.g., Wu et al., 2022) not evaluated on a public dataset.

Table 1: Comparing select deep neural networks for small target detection. Datasets SIRST and IRSTD-1k are from Dai et al. (2021) and Zhang et al. (2022) respectively. P_d = % probability of detection. F_a = % false alarm rate. nIoU = % normalised intersection over union.

Reference	Name and main components	Notable original results
Dai et al., 2021	ALCNet: ResNet-20 as backbone in a feature pyramid network architecture, that uses local contrast to highlight the features of the target in high-level layers, and bottom-up local attention modulation for CLFF.	SIRST: nIoU = 72.8.
Tong et al., 2021	EAAU-Net: Like ALCNet except bottom-up attention modulation is asymmetric and uses (i) fully connected layers instead of point-wise convolution layers, and (ii) global averaging pooling for aggregating global contextual information. Furthermore, channel shuffle fusion of channel attention and spatial attention enables information flow between feature groups.	SIRST: nIoU = 74.5.
Zuo et al., 2022	AFFPN: ResNet-20 as the backbone in a feature pyramid network architecture, that uses atrous/dilated spatial pyramid pooling for CLFF, and attention fusion to enable information flow between feature groups.	SIRST: nIoU = 75.9.
Zhang et al., 2022	ISNet: U-Net network incorporating (i) edge features extraction by solving second-order finite difference equations, (ii) bottleneck convolution for low-pass filtering, (iii) deformable convolution across rows and columns for CLFF.	SIRST: $P_d = 99.2$, $F_a = 4.9$, nIoU = 78.1. IRSTD-1k: $P_d = 95.6$, $F_a = 15.4$, nIoU = 64.8.

Comparing computational complexities has not been a popular practice, but using Dai et al.'s (2021) open-source ALCNet code, we found 20-25 frames per second of processing rate is achievable on an NVIDIA RTX 3060 GPU. This is consistent with Zuo et al.'s (2022) report. Discounting the figure by an order of magnitude, small target detection should be realisable on space-borne IR sensors at several frames per second.

Once a target is detected, tracking can be done by repeating detection or by well-established object tracking techniques in the field of computer vision. Note the problem of IR-based tracking by space-borne sensors is distinctly different from IR-based tracking by hypersonic missile interceptors, which appears to have been accomplished in the 1990s (Oron et al., 1997).

3.2 Ambiguities and knowledge gaps

Ultraviolet (UV) emission from the shock layer of an HGV in near space present distinct spectral features in the 200-300 nm region when measured from any angle (Niu et al., 2016). This suggests multispectral IR/UV sensing provides a more robust detection mechanism than using IR alone (Labbé and Ghanmi, 2022), but multispectral small target detection work has yet to be done.

Dai et al. (2021) supplied code, which we have used to reproduce their accuracy results for ALCNet to within 5% of their original figures, but most other authors have not helped with this aspect of reproducible research. Fortunately, sample code for most of the deep learning building blocks can be found in the public domain, and the soundness of the algorithms proposed to date suggests enough is known about the algorithmic building blocks of an IR sensing-based HGV detection algorithm.

Dai et al. (2021) and Zhang et al. (2022) supplied training datasets, but neither appears to contain images of a fast-moving target. It seems unlikely a public dataset would contain images of an HGV, but this does not rule out the need for images of a fast-moving, dim and small target for model validation.

Given the important yet sensitive nature of an HGV dataset, an underexplored aspect is the *backdoor attack*. Classified by MITRE under the attack technique of "backdoor ML model" (MITRE, 2022), a backdoor attack attempts to embed a stealthy and persistent artifact into a machine learning model, such that the model performs normally on benign test samples, but produces the attacker's desired output when activated by an attacker-implanted trigger in adversarial samples (Li et al., 2022). Backdoor attack can happen in any stage of the training process and is most commonly conducted by poisoning training samples. Poisoning attacks pose realistic and immediate threats to the development of small target detection and warrant close investigations.

4. Radar-based sensing

While EO/IR sensing provides only bearing information, radars have the desirable feature of providing range/distance information as well. Radars can be deployed both on the Earth's surface (ground, sea) and in space (Meng et al., 2020; Sherman, 2022; Bian et al., 2020).

Radar works by (i) bouncing modulated radiofrequency (RF) electromagnetic waves off a potential target, (ii) collecting through a high-gain RF receiver the reflected energy (called "echo") backscattered by the target in the same chosen direction, and (iii) extracting from the received signals information such as range and velocity of the target.

Compared to thermal sensing, electromagnetic sensing is not any less challenging, because an HGV flying at hypersonic speed in near space has ionised gas molecules (i.e., plasma) enveloping the vehicle – this is called a "plasma sheath". This inhomogeneous plasma sheath absorbs, reflects, and scatters electromagnetic waves, resulting in two immediate problems: (i) communication waves from within the HGV experiences blackout, (ii) scattered radar echoes become attenuated and irregular (Bian et al., 2020; Ma et al., 2021). The latter is relevant here as the backscattered radar cross section (RCS, see Definition 2) of an HGV becomes hard to predict. The relations between each of these variables – radar frequency, radar altitude, HGV altitude, HGV speed – and dynamic RCS are discernible (Bian et al., 2020), but knowledge of these relations has yet to lead to a robust HGV detection scheme.

Definition 2: The backscattered / monostatic / target radar cross section (RCS, see Mahafza and Elsherbeni, 2004) of a target R distance away from a radar is

$$\sigma = 4\pi R^2 \lim_{R\to\infty}\left(P_{Dr}(R)/P_{Di}(R)\right),$$

where P_{Dr} is the power density of the scattered waves at the receiving antenna, and P_{Di} is the power density of the waves incident on the target. Dynamic RCS is an extension of backscattered RCS that accounts for relative motion between the radar and target.

The plasma frequency lies in the range of either 0.1-100 GHz (Ma et al., 2021) or 0.284-28 GHz (Musselman and Chastain, 2020). Two solutions have been proposed:

1. Increase radar frequency to THz or at least the Ka band (26-40 GHz) to improve radar penetration of the plasma sheath. However, THz technologies are still in infancy and Ka-band radars are close-range radars.
2. Decrease radar frequency to the high frequency (HF) band (3-30 MHz) to detect the plasma sheath of an HGV instead. Beyond-line-of-sight detection becomes possible as skywave over-the-horizon radars bounce HF-band signals off the ionosphere to potential targets and collects reflections back from the targets through the same propagation path.

Interestingly, inverse synthetic aperture radar remains effective in the X band (8-12 GHz, see Xie et al., 2022). For circumventing the plasma sheath problem, the common radar bands of L, C and Ku are not as useful.

In terms of real-world implementation, most existing space observation radars have a low resolution (Bian et al., 2020). Pulse compression is commonly assumed for the coherent processing (signal-to-noise ratio maximisation) of echo signals (Xu and Liao, 2014), but pulse compression can be challenging to implement due to the high bandwidth requirement. Long-range radars like the Long-Range Discrimination Radar (MDA, 2022) are too bulky, heavy, and energy-intensive to be space-borne.

4.1 Ambiguities and knowledge gaps

In the literature, there is little mention of concrete plans for space-bound deployment of long-range radars. Both the plasma sheath problem and space-based radar technologies present challenges and uncertainties. Assuming terrestrial long-range radars and over-the-horizon radars are the way forward, data fusion across space-based and ground-based sensing regimes warrants concrete exploration.

5. Aerodynamics modelling

Following the justification in Sec. 2, this section discusses physics-based mathematical modelling of hypersonic aerodynamics. Most HGV tracking algorithms in the literature are based on different variations of the aerodynamic model in Eq. (1), expressed in the velocity-turn-climb (VTC) coordinate system (also known as semi-speed / half-velocity / trajectory / flight-path coordinate system).

$$\dot{r} = v \sin\theta, \tag{1a}$$

$$\dot{\theta} = \frac{v\cos\gamma\sin\psi}{r\cos\phi}, \tag{1b}$$

$$\dot{\phi} = \frac{v\cos\gamma\cos\psi}{r}, \tag{1c}$$

$$\dot{v} = -a_D - g\sin\gamma, \tag{1d}$$

$$\dot{\gamma} = \frac{1}{v}\left\{a_L\cos\sigma + \left(\frac{v^2}{r} - g\right)\cos\gamma\right\}, \tag{1e}$$

$$\dot{\psi} = \frac{1}{v}\left\{\frac{a_L\sin\sigma}{\cos\gamma} + \frac{v^2}{r}\cos\gamma\sin\psi\tan\phi\right\}. \tag{1f}$$

In Eq. (1), r is the radial distance of the HGV from the Earth's centre; θ and ϕ measure the longitude and latitude of the HGV; v is the HGV's speed; γ is the flight-path angle; ψ is the velocity heading angle; σ is the bank angle; g is the gravitational acceleration; a_D and a_L are the magnitudes of the drag and lift accelerations.

Eq. (1) is based on the prevalent simplifications (Li et al., 2015) that (i) the Earth is a nonrotating uniform sphere, and (ii) the HGV's sideslip angle is negligible, leaving attitude and trajectory to be fully described by the angle of attack and bank angle. Furthermore, the commanded/desired acceleration is assumed to be zero (Hough, 2017; Cheng et al., 2020).

Most academic researchers based their model on the Hypersonic Technology Vehicle 2 (HTV-2), a research vehicle in the now completed DARPA Falcon program (Walker et al., 2008), and Common Aero Vehicle (CAV, see Phillips, 2003). We note HGV models are dominated by reentry dynamics (Hough, 2017), and cannot be based on the widely cited hypersonic vehicle models by Shaughnessy et al. (1990) and Parker et al. (2007). However, the absence of flight test data serving as ground truth poses two difficulties: (i) parameter values cannot be estimated from data, (ii) models cannot be validated. Academic researchers have been coping with these difficulties through *parametric modelling*, where a geometric model (Cheng et al., 2020) or aerodynamic model (Liu et al., 2018b) or manoeuvre model (Hu et al., 2021) is parameterised and subjected to simulations for the determination of suitable parameter values. For example,

- Li et al. (2019) applied the oblique shock and Prandtl-Meyer expansion flow theory to express accelerations in VTC coordinates as functions of three parameters: angle of attack, bank angle and mass (the first two of which are in fact variables). The values of these parameters were constrained to fixed ranges, which were in turn discretised into 12 value points, resulting in a total of 12×12×12 possible models. Out of these many possible models, 12 models were selected as the model-set for an interacting multiple model (IMM) filter (see Sec. 6).
- Cheng et al. (2020) sampled the geometrical design space of HTV-2 to determine five possible geometrical configurations. For each of the five configurations, computational fluid dynamics simulations were (likely) used to calculate the values of three parameters, namely lift coefficients, drag coefficients and lift-to-drag ratio, for different angles of attack and Mach numbers.

To generate/simulate HGV trajectories, besides an aerodynamic model, representative values of guidance commands are also needed. Assuming acceleration command is zero (as mentioned earlier), the commanded angle of attack and bank angle still need to be specified based on type of manoeuvre. Different classes of manoeuvres have emerged in the literature, but Li et al.'s (2015) classification seems to cover most cases: (i) equilibrium glide, (ii) longitudinal skip glide, (iii) lateral turning manoeuvre, (iv) lateral weaving manoeuvre.

5.1 Ambiguities and knowledge gaps

Seeing a significant amount of work published in generic open-access journals rather than aeronautics journals raises the question of whether there has been enough expert scrutiny. Even where the methodology is sound, there are difficulties in reproducing the published models. For example,

- In (Feng et al., 2017), lift and drag accelerations should not depend on the Earth's radius.
- In (Li et al., 2019), the analytical expressions for the accelerations in VTC coordinates are missing.
- In (Cheng et al., 2020), some symbols are undefined and multiple parameter values are missing, including three time constants; and the lift and drag coefficients as functions of angle of attack and Mach number.

Missing parameter values and model details hamper reproducible research.

6. HGV tracking

This section discusses two main tracking paradigms: stochastic estimation and machine learning.

Stochastic estimation: Target tracking or trajectory estimation using a state estimation filter is a well-established field, but the hypersonic context is new. The distinct manoeuvre modes of an HGV make the IMM filter a natural algorithmic component and thus feature prominently in Table 2. Distributed bearing-only filtering schemes are a good fit for the NDSA (see Sec. 2). Wang and Li's (2021) in Table 2 is an example of such a scheme.

Table 2: Comparing select filtering schemes for tracking HGVs.

Reference	Tracking filter	Notable aspects
Fan et al., 2017	Hybrid grid multiple model and Cubature Kalman filters	Uses multiple models in the initial tracking stage but single model in the stable tracking stage.
Feng et al., 2017	IMM with updates to Markov transition matrix	Trajectories not based on any aerodynamic model. Instead, acceleration is modelled as a zero-mean stochastic process with sinusoidal autocorrelation.
Li et al., 2019	IMM and unscented Kalman filters	Using 6 models in the model-set achieves the same level of accuracy as using 12.
Cheng et al., 2020	Iterative extended Kalman filter	As accurate as but more efficient than unscented Kalman filter.
Wang and Li, 2021	Distributed information-weighted consensus filtering incorporating cubature point calculation rules from cubature Kalman filter	Can work with IR sensors because it uses only bearing measurements, but requires multiple sensors. Cubature rules facilitate efficient nonlinear estimation.

Machine learning: Viewed as a time series, a trajectory can be estimated using multivariate time series forecasting methods. Due to their feature extraction capabilities, recurrent neural networks (with or without gated recurrent units), long short-term memory (LSTM), and transformer models have become popular methods. Common strategies include the following:

- Trajectory prediction is divided into two parts: linear and nonlinear. For example, Xie et al. (2021) applied a recurrent neural network with bidirectional gated recurrent units to the nonlinear part, and a single-layer perceptron to the linear part. Zhang et al. (2022) applied the seq2seq architecture to the nonlinear part and also a single-layer perceptron to the linear part.
- Use the convolution operator to extract spatial features and LSTM for extracting temporal features; see (Zeng et al., 2021) and (Zhang et al., 2022).

6.1 Ambiguities and knowledge gaps

In general, papers that focussed on tracking used a simplified model, but without ground-truth data, the impact of these simplifications is unclear. Following Wang and Li (2021), the natural next step is distributed tracking using bearing-only measurements, that is resilient to false data injection attacks, where rogue sensors feed false data to its network neighbours. The relevant research lies in the area of secure/resilient distributed estimation/filtering, which is a maturing area, but not in the hypersonic context.

For the evaluation of tracking filters, values for process noise, measurement noise and the initial error covariance matrix – when they are provided at all – generally require more rigorous justification and investigation. For example, these values are missing in (Cheng et al., 2020) and not justified in (Wang and Li, 2021).

For the evaluation of machine learning methods, absence of ground-truth data means whichever model is used to generate the training and test trajectories is taken for granted. Radar measurements should be modelled.

Since stochastic estimation is a mathematically rigorous and more established field, comparing machine learning methods with tracking filters serve clear scientific interests.

7. Conclusion and future directions

The intrinsic ability of the Tracking Layer (see Sec. 2) to maximise *precision* and *recall* is clearly important, but our main concern here is security, as a disruption to the kill chain can have disastrous consequences. More than security, *resilience* accounts for the inevitability of an attack by detecting, containing and resolving any security breach (Thompson et al., 2016).

Resilience requires intercepting insider adversaries who understand and can infiltrate the system. Hence, defenders also need to understand the system beyond its ICT functions, including the information flows across cyber-physical boundaries (e.g., sensing and tracking). Motivated by this need, this paper presents a highly compressed review and analysis of the latest advances in HGV detection and tracking.

Based on our review, we conclude that (i) small target detection is sound and promising, (ii) bearing-only multispectral sensing necessitates distributed detection and tracking by a satellite constellation, (iii) data fusion across space-borne multispectral sensors and terrestrial radars is necessary. Uncertainties encountered include: (i) the applicability of space-borne radars; (ii) the adequacy of existing hypersonic flight models for tracking scheme development; (iii) the merits of machine learning methods over estimation filters for tracking.

The preceding observation explains the priorities of the NDSA, and motivates as future work (i) a threat assessment of the Tracking Layer assuming the existence of aforementioned components and accordingly (ii) a security plan. A fertile ground for cybersecurity research is the feasibility of backdoor learning (see Sec. 3.2), i.e., the feasibility of releasing a rigged dataset so that small target detection algorithms trained on it malfunction in pre-planned scenarios. Another promising direction is attack-resilient distributed tracking using bearing-only measurements (see Sec. 6.1).

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