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Use of Terrain and Obstacle Databases to Support UAS Detect-and-Avoid in Complex Urban Environments

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Abstract

Recent developments in detect-and-avoid (DAA) technologies have focused on onboard sensing and cooperative surveillance, yet their performance is tightly coupled to the underlying representation of terrain and obstacles used to constrain trajectory planning and interpret sensor outputs. This paper investigates the use of high-resolution terrain and obstacle databases as integral components of DAA architectures for small and medium UAS navigating complex urban environments. The study considers static man-made structures, vegetation, moving ground traffic proxies, and topological information such as road corridors and building facades, and examines how their representation influences conflict prediction, sensor fusion, and maneuver generation. A modeling framework is developed in which terrain and obstacle databases support probabilistic occupancy prediction, occlusion-aware surveillance, risk-based separation buffers, and constraint-aware trajectory optimization. The approach is analyzed with respect to map resolution, latency, integrity risk, and robustness to registration errors between geolocation, navigation, and database coordinates. Simulation experiments in canonical downtown scenarios are used to evaluate detectability of cooperative and non-cooperative intruders, feasibility of safe maneuvers within regulatory altitude layers, and sensitivity to degraded database quality. The results highlight the conditions under which terrain and obstacle information significantly influences achievable safety margins and operational efficiency for urban UAS DAA, and identify modeling choices that are compatible with scalable implementation.

1. Introduction

Urban airspace is characterized by dense vertical structures, constrained corridors between buildings, heterogeneous electromagnetic and optical propagation conditions, and strong coupling between ground operations and low-altitude air operations [1]. The introduction of uncrewed aircraft systems at altitudes comparable to building heights introduces nontrivial interactions between obstacle fields, surveillance architectures, and detect-and-avoid functions intended to manage conflicts with cooperative and non-cooperative traffic. In such environments, conventional DAA concepts that assume relatively open airspace or slowly varying terrain are not sufficient to represent occlusion effects, near-field collision geometries, and stringent containment surfaces associated with people and infrastructure on the ground. As UAS operations scale in density and complexity, the use of rich terrain and obstacle databases is expected to become an important element for ensuring that sensing, prediction, and maneuver decisions remain consistent with the true three-dimensional structure of the environment.

Detect-and-avoid systems in complex urban settings must support several tightly coupled capabilities. They must discriminate between feasible and infeasible escape trajectories in the

presence of tall structures, maintain adequate separation to buildings and other fixed obstacles, and incorporate occlusion-induced uncertainty in surveillance data. They must integrate cooperative surveillance sources, such as transponder-based tracks, with non-cooperative sensing modalities, such as radar or optical systems, whose performance depends on line-of-sight and clutter conditions governed by urban geometry [2]. They must maintain consistency with regulatory altitude bounds, ground risk constraints, and geo-fenced no-fly regions that may be embedded within the same database used to encode building volumes and terrain. The database, therefore, is not merely a static background map, but an active component that shapes both probabilistic reasoning and control actions.

The central theme considered here is the explicit use of terrain and obstacle databases as structured priors for UAS DAA algorithms in dense urban environments. The focus is not on proposing a single prescriptive architecture, but on examining how database representation, quality, and integration mechanisms influence conflict detection, risk estimation, and maneuver generation. The discussion considers high-resolution digital surface models, semantic layers differentiating building types and road networks, and dynamic overlays that approximate frequently occupied ground regions. These data support the construction of occupancy models, occlusion-aware sensing fields, and constraint sets for trajectory optimization [3]. Particular attention is given to quantifying how database errors, discretization choices, and latency propagate into the probability of violation of separation minima or airspace constraints.

This paper develops a mathematical modeling framework that links environment representation to DAA performance for representative classes of UAS and urban geometries. State-space models, probabilistic detection functions, and constrained optimization formulations are used to assess how terrain and obstacle information can be incorporated consistently into prediction and control. Simulation-based analysis is used illustratively to explore parameter sensitivities, with an emphasis on neutral evaluation of benefits and limitations rather than prescriptive conclusions. The resulting discussion aims to clarify how terrain and obstacle databases can be systematically exploited to support detect-and-avoid capabilities in complex urban environments without overstating their role relative to other architectural elements.

Table 1. Terrain and Obstacle Database Layers

Layer	Type	Content	Usage
Base Elevation	Surface	Ground height	Altitude reference
Building Footprints	Polygon	Plan shapes	Structural bounds
Building Heights	Attribute	Vertical extent	Clearance margins
Roof Structures	Feature	Local geometry	Vertical constraints
Façade Planes	Surface	Wall segments	Line-of-sight checks
Overhangs	Volume	Cantilever shapes	Corridor tightening
Bridges	Volume	Elevated links	Underflight limits
Vegetation Blocks	Volume	Tree masses	Sensor occlusion
Utility Masts	Point	Tall elements	Local avoidance
Geo-fences	Region	Restricted zones	Prohibited volumes
Preferred Corridors	Path	Recommended tracks	Route structuring
Ground Risk Map	Raster	Relative exposure	Maneuver weighting
Data Currency	Metadata	Update tag	Integrity logic
Source Provenance	Metadata	Origin record	Quality tagging
Coordinate Frame	Metadata	Reference system	Registration alignment

Table 2. Key Uncertainty Sources Relevant to Database-Supported DAA

Source	Domain	Effect on DAA
Navigation Bias	State Estimation	Shifts relative clearances
Navigation Drift	State Estimation	Enlarges safety margins
Database Registration Error	Mapping	Misplaced obstacles
Obstacle Omission	Mapping	Missing structures
Height Approximation	Mapping	Ambiguous vertical limits
Temporal Staleness	Mapping	Outdated geometry
Sensor Calibration Error	Sensing	Distorted tracks
Occlusion Modeling Error	Sensing	Misestimated coverage
Intruder Motion Model Error	Prediction	Uncertain encounters
Communication Delay	Networking	Late situational updates
Packet Loss	Networking	Incomplete track sets
Processing Latency	Computing	Delayed maneuvering
Model Simplification	Algorithms	Overly coarse constraints
Operational Procedure Deviation	Human/System	Inconsistent behavior

Table 3. Database-Enabled Functions within DAA Architecture

Function	Input from Database	Internal Use	Outcome
Free-Space Extraction	Obstacle volumes	Feasible region build	Path constraints
Clearance Estimation	Building geometry	Distance evaluation	Safety margins
Occlusion Assessment	Façade layout	Visibility check	Sensor planning
Corridor Identification	Street canyons	Route graph creation	Structured routing
Ground Risk Weighting	Risk raster	Cost field shaping	Maneuver preference
Geo-fence Enforcement	Restricted zones	Hard constraint set	Access prevention
Integrity Monitoring	Metadata tags	Quality checks	Margin adaptation
Multi-Platform Consistency	Common schema	Shared interpretation	Compatible behavior
Fallback Region Marking	Sparse coverage	Conservative flags	Degraded mode selection
Trajectory Screening	Distance fields	Feasibility filter	Candidate pruning

2. System-Level Requirements

Urban deployment of uncrewed aircraft systems introduces layered and intersecting constraints that directly shape detect-and-avoid architectures and their dependence on terrain and obstacle databases [4]. These constraints originate from regulatory altitude stratifications, micro-scale variations in ground risk, heterogeneous communication infrastructures, and the spatial concentration of critical infrastructure and pedestrian flows. In contrast to comparatively homogeneous low-density environments, the urban context presents short-range geometry dominated by tall structures and narrow canyons combined with rapidly changing occlusion patterns. Detect-and-avoid logic must therefore operate on spatial and temporal scales at which small deviations in position, attitude, or timing can alter line-of-sight, accessible escape paths, and admissible separation margins. In this setting, terrain and obstacle databases serve as structural priors for reasoning about where conflicts can form, where detection is plausible, and where feasible maneuvers exist within the mechanical limits of the UAS platform.

A system-level requirement is the maintenance of separation not only from airborne intruders

Table 4. Representative Urban Scenario Types for Analysis

Scenario	Dominant Features	DAA Considerations
Dense Core Block	Tall close buildings	Narrow vertical channels
Wide Avenue Canyon	Long aligned facades	Extended occlusion lanes
Mixed Mid-Rise Zone	Varied heights	Irregular corridors
Rooftop Vertiport Approach	Elevated pads	Short final segments
Waterfront Edge	Open on one side	Asymmetric escape paths
Industrial Cluster	Large structures	Broad shadows
Transit Hub Vicinity	Concentrated activity	Ground risk sensitivity
Park Corridor	Open ground area	Reduced occlusion
Construction District	Frequent changes	Database volatility
Perimeter Transition	Urban to open	Mixed constraint regimes

Table 5. Sensing Modalities and Database Interactions

Modality	Dependence on Geometry	Database Contribution	Typical Limitation
Onboard Radar	Line-of-sight surfaces	Occlusion masks	Clutter near facades
Optical Camera	Direct visibility	Shadow prediction	Illumination sensitivity
LiDAR	Surface returns	Structural priors	Multipath reflections
Acoustic	Built environment shape	Channel cues	Ambient noise
Cooperative Beacon	Building layout	Shadow assessment	Infrastructure reliance
Network Surveillance	Site geometry	Coverage planning	Connectivity gaps
Altimeter	Terrain profile	Reference surface	Local anomalies

but also from static obstacles and implicitly protected ground regions. The effective constraint set is the intersection of volume-based no-entry regions and path-dependent risk criteria [5]. Let the admissible state space for the ownship be denoted by a subset of the full state space that excludes database-defined obstacles, regulated exclusion zones, and kinematically unreachable configurations. Conceptually, one can define a mapping from the full state vector to a reduced feasibility indicator, where a state is admissible if its position lies within free space, its altitude respects local rules, and its velocity and turn rates are compatible with available maneuver corridors. Although this mapping is deterministic with respect to the database content, its operational meaning is probabilistic once navigation errors, database uncertainties, and unmodeled dynamics are introduced.

Detect-and-avoid design in this context must accommodate high-density operations where multiple UAS share constrained volumes with limited vertical separation and recurrent crossings near building edges, roof-top vertiports, and approach paths. The system must support conflict detection and resolution among aircraft with varying equipage levels, while acknowledging that some actors may rely heavily on onboard sensing and others on procedural route structures. Terrain and obstacle databases therefore contribute both to individual vehicle reasoning and to any higher-level coordination mechanisms that define preferred routes, buffer layers, or structured corridors [6]. An implicit requirement is consistency: given a shared database specification, independently implemented DAA systems should infer compatible free-space structures and separation conditions, reducing the likelihood of conflicting interpretations of the same environment.

From a modeling perspective, the operational context can be abstracted as a hybrid environ-

Table 6. Design Dimensions Influencing Database-Supported DAA

Dimension	Example Options	Architectural Impact
Vehicle Class	Multirotor, Fixed-wing	Turn radius and climb profile
Navigation Grade	Basic, Enhanced	Required obstacle margins
Database Resolution	Coarse, Fine	Corridor fidelity
Update Mechanism	Periodic, Event-driven	Temporal consistency
Computation Platform	Onboard, Hybrid	Query strategy
Coordination Concept	Decentralized, Managed	Route encoding
Risk Policy	Conservative, Balanced	Buffer selection
Semantic Detail	Minimal, Rich	Ground risk integration
Validation Approach	Internal, Independent	Assurance level

Table 7. Illustrative Constraints Derived from Terrain and Obstacle Databases

Constraint Type	Basis Element	Enforcement Mechanism	Effect
Minimum Lateral Offset	Building footprint	Distance threshold	Wall clearance
Minimum Vertical Offset	Highest local structure	Altitude threshold	Roof clearance
Corridor Adherence	Preferred paths	Path-following bounds	Structured flow
No-Fly Volume	Geo-fenced region	Hard spatial exclusion	Area denial
Visibility Zone Preference	Occlusion map	Cost adjustment	Safer sensing
Ground Risk Avoidance	Risk raster	Weighted penalties	Exposure reduction
Degraded Data Mode	Low integrity tags	Margin inflation	Conservative behavior
Shared Schema Use	Standardized model	Common processing	Harmonized outputs

ment in which the ownship evolves within a continuous state space partitioned by database-defined surfaces. Within each partition, dynamics and sensing performance are relatively smooth, while transitions between partitions correspond to entering or exiting shadowed regions, altering altitude layers, or crossing over building clusters. To support detect-and-avoid, system-level specifications must ensure that across these transitions, the UAS retains sufficient maneuver authority and sensing capability to either maintain separation or execute an avoidance maneuver that remains within feasible partitions. This requirement implicitly defines minimum look-ahead times, maximum allowable delays in database access, and tolerable navigation and registration error levels as functions of local obstacle density and route geometry.

Risk metrics for urban UAS operations must capture the possibility of rapid escalation from benign proximity to buildings or intruders to constrained escape conditions in which only a small subset of trajectories remains collision-free [7]. While detailed formulations may vary, one representative construct is a spatial risk density defined over the free-space volume, which increases near obstacle surfaces, in areas of limited line-of-sight, and in regions with high predicted intruder density. The terrain and obstacle database provides the structural basis to compute or approximate such densities. Detect-and-avoid performance requirements can then be expressed as bounds on accumulated risk along an executed trajectory, or as constraints that prohibit entering regions where the combination of maneuverability, sensing, and obstacle geometry yields insufficient residual margin to recover from new conflicts. This shifts part of the DAA burden from purely reactive collision avoidance to proactive shaping of trajectories toward structurally safer volumes.

System-level constraints also reflect the coupling between communication and geometry. Many UAS concepts for urban airspace incorporate network-based surveillance and strategic deconfliction services that depend on reliable connectivity [8]. Urban canyons, however, are characterized by spatially heterogeneous signal propagation affected by building layouts. A terrain and obstacle database with suitable electromagnetic annotations can be used to identify volumes where communication links are more fragile. In such regions, detect-and-avoid logic may need to rely more heavily on onboard sensing and locally stored database information, with reduced dependence on external updates. The operational requirement that safety should not degrade sharply in connectivity-poor volumes leads to integration strategies in which databases support both geometric avoidance and robustness against partial loss of external information sources.

The interplay between vehicle performance envelopes and obstacle fields is another critical aspect. Multirotor UAS with low forward speeds and high agility may exploit tight lateral clearances, while fixed-wing platforms require larger turning radii and more generous climb or descent distances. Terrain and obstacle databases enable precomputation of platform-specific reachable sets that respect these limitations in the presence of buildings and elevation changes [9]. At the system level, one may require that for any admissible position within an approved operating volume, there exists at least one collision-free maneuver that respects performance limits and maintains required separation margins over a specified horizon. Verifying such a property is challenging in arbitrary urban geometries, but database-driven approximations can identify regions where this requirement is not met, informing route design, local restrictions, or additional equipage requirements for operations in those areas.

A further requirement arises from the need to manage interactions between DAA maneuvers and ground risk constraints. Urban environments contain spatially varying ground population densities, transportation corridors, and sensitive facilities. Even when an avoidance maneuver is geometrically feasible relative to buildings and intruders, it may increase exposure to ground risk beyond acceptable levels. Terrain and obstacle databases can be augmented with ground risk layers that approximate expected occupancy or criticality of underlying regions [10]. Detect-and-avoid logic can then be formulated to prefer maneuvers that simultaneously preserve airborne separation and avoid concentrating over higher-risk ground zones, within the capabilities of the platform. In dense cores where both obstacles and ground risk are high, these combined requirements significantly narrow the set of acceptable maneuvers, reinforcing the importance of accurate and coherent database-supported constraints.

Safety assurance considerations imply that system-level requirements should be stated in terms of quantifiable margins that explicitly include contributions from terrain and obstacle database uncertainties. For example, minimum vertical and horizontal separation from obstacles may be specified as functions of navigation error distributions and worst-case database inaccuracies. Simple scalar margins can be represented by short conditions such as a minimum distance constraint or an altitude offset above the maximum recorded obstacle height in a local neighborhood. In practice, such margins may depend on local gradient of building heights, variability in data sources, and the presence of transient structures not captured in the database [11]. Requirements that fail to incorporate these dependencies risk either understating or overstating the protective role of database-based information in detect-and-avoid operations.

Urban operations also impose temporal coherence requirements on environment representation. Since buildings and infrastructure evolve, and temporary installations appear and disappear, a terrain and obstacle database cannot be assumed static over long horizons. System-level requirements therefore include policies for update frequency, validation procedures, and

fallback behavior during intervals where updates are incomplete or inconsistent. The detect-and-avoid system must remain stable under such variations, avoiding abrupt changes in maneuver behavior due to minor database revisions while being sensitive enough to incorporate significant new obstacles or regulatory changes. This balance motivates formulations where database inputs are treated as stochastic but bounded components, and where conservative envelopes are derived in a manner that is robust to modest temporal discrepancies yet responsive to large-scale changes. [12]

Interoperability across multiple UAS operators and manufacturers in the same urban volume requires consistent interpretation of terrain and obstacle data products. From a system perspective, this implies that minimum content, resolution, and error characterization standards for databases should exist so that detect-and-avoid algorithms implemented by different stakeholders do not diverge excessively when exposed to identical environmental structures. While the specific algorithms may vary, their underlying assumptions about obstacle positions, heights, and no-fly volumes should be compatible to prevent structurally conflicting avoidance behaviors. The system-level requirements thus extend beyond single-vehicle safety to collective behavior shaped by a common, database-informed understanding of the environment.

Finally, the operational context necessitates careful treatment of edge cases where database support is weak or ambiguous, such as underground structures that do not affect flight, partially transparent canopies, or complex roof geometries whose impact on safety depends on altitude, vehicle size, and navigation accuracy. Detect-and-avoid logic cannot rely solely on high-level semantic labels to resolve such cases; instead, it must reconcile geometric information, platform characteristics, and sensing capabilities in a consistent manner [13]. Terrain and obstacle databases are one input to this reconciliation, but they interact with estimation, control, and procedural layers. System-level requirements for urban UAS DAA should therefore be framed to recognize that database-supported reasoning is necessary to navigate highly structured environments while incomplete on its own, and that robust performance relies on integrated treatment of environmental data, onboard sensing, and coordinated airspace management.

3. Background and Problem Formulation

Urban DAA for UAS involves the interaction of three principal elements: the ownship vehicle with its guidance, navigation, and control system; the traffic and obstacle environment, including cooperative aircraft, non-cooperative aerial objects, and static or quasi-static structures; and an information architecture composed of onboard sensors, communication links, and terrain or obstacle databases. The formulation considered here assumes a UAS equipped with a navigation solution referenced to a global coordinate frame, one or more surveillance sensors, and access to a terrain and obstacle database aligned to the same frame within a bounded registration error.

Let the ownship state at discrete time index k be denoted by

$$x_k = \begin{bmatrix} p_k \\ [14]v_k \end{bmatrix},$$

where $p_k \in \mathbb{R}^3$ is position and $v_k \in \mathbb{R}^3$ is velocity, defined in an earth-fixed frame. The evolution of the state is described abstractly by

$$x_{k+1} = f(x_k, u_k, w_k),$$

where u_k is the control input and w_k represents process disturbances capturing wind and modeling residuals. This representation is intentionally generic, permitting either point-mass kinematics or higher-fidelity models.

Intruder aircraft or airborne objects are modeled by states $z_k^{(i)}$ for intruder index i, with

$$z_{k+1}^{(i)} = g^{(i)}(z_k^{(i)}, \eta_k^{(i)}),$$

where $\eta_k^{(i)}$ represents uncertainties in intruder motion or tracking. The environment is further characterized by a set of static obstacles, primarily buildings, encoded by a database that defines for each spatial location whether it lies inside or outside an obstacle volume. Denote by $\mathcal{O}$ the union of all obstacle volumes and by $\mathcal{F}$ the free space where ownship may nominally fly, subject to regulatory altitude and geofencing constraints. For any point $r \in \mathbb{R}^3$, the signed distance to the nearest obstacle surface is

$$d_{\mathcal{O}}(r),$$

with negative values indicating points inside obstacles. [15]

The DAA problem in this context is to generate control inputs u_k such that the induced trajectory of the ownship maintains a suitable margin with respect to both dynamic conflicts and static obstacles, while remaining in feasible airspace and respecting performance limits. For a given planning horizon of length N, a feasible trajectory sequence $\{x_k\}_{k=0}^{N}$ must satisfy

$$x_k \in \mathcal{X}_{\text{adm}},$$

for all k, where $\mathcal{X}_{\text{adm}}$ encodes bounds on altitude, speed, and separation from obstacles and protected zones. Potential losses of separation or collisions are treated probabilistically to account for state estimation uncertainty, intruder motion uncertainty, and database errors. Let

$$P_{\text{loss}}(k)$$

denote the probability that at step k the ownship violates a separation criterion with at least one intruder or obstacle, as defined by a suitable metric. The DAA objective is then to ensure that $P_{\text{loss}}(k)$ remains below an acceptable risk threshold while also achieving mission objectives such as transit time or energy constraints.

In complex urban environments, the calculation of $P_{\text{loss}}(k)$ and the construction of $\mathcal{X}_{\text{adm}}$ depend explicitly on the underlying terrain and obstacle database. Occlusion effects caused by buildings, clutter-induced degradation of sensors, and narrow feasible corridors between structures directly influence detection probabilities, conflict geometry, and available avoidance maneuvers. The problem formulation considered in the remainder of this paper is therefore organized around explicitly integrating database features into these probabilistic and control-theoretic constructs.

4. Terrain and Obstacle Database Representation

The terrain and obstacle database is assumed to provide a volumetric description of the urban environment at resolutions compatible with UAS navigation accuracy and DAA planning horizons. A common representation is a digital surface model discretized on a regular grid, augmented by vector primitives for building footprints, heights, and roof structures [16]. Let

$\mathcal{G}$ denote a three-dimensional grid with cells indexed by j, each associated with a volume V_j. Each cell is assigned an occupancy indicator, where

$$o_j \in \{0, 1\},$$

distinguishes nominally free space and obstacle space. For applications requiring probabilistic modeling of uncertainties in building heights or shapes, the binary indicator can be generalized to a probability of occupancy,

$$p_j \in [0, 1].$$

The database is subject to errors from source data, temporal changes, and misalignment with the navigation frame. Let the registration error between the database frame and the true earth-fixed frame be modeled as a random vector Δr with distribution characterized by mean zero and covariance matrix [17]

$$\Sigma_{\text{reg}}.$$

For any world point r, the corresponding database query effectively evaluates occupancy at $r + \Delta r$, which induces uncertainty in obstacle boundaries. An approximate probability that location r is free can then be expressed as

$$p_{\text{free}}(r) = 1 - \sum_j p_j \, \phi_j(r),$$

where $\phi_j(r)$ is a localized influence function nonzero only for cells whose volumes intersect a neighborhood of r under the distribution of Δr. The specific choice of ϕ_j depends on interpolation and error models, but this structure illustrates how database uncertainty maps into spatial occupancy probabilities. [18]

Building facades and roof edges introduce sharp discontinuities that are important for line-of-sight reasoning. To capture these, an additional geometric layer stores outward normal vectors and surface classifications. For an obstacle surface point s with unit normal n_s, the half-space

$$H_s = \{r : (r - s)^\top n_s \le 0\}$$

can be used locally to approximate forbidden regions. By aggregating such half-spaces over all relevant surfaces, one obtains polygonal or polyhedral approximations useful for optimization-based guidance. [19]

Latency and temporal inconsistency arise when the database does not reflect transient obstacles such as cranes, temporary structures, or partially constructed buildings. To represent this, a temporal validity interval is associated with each obstacle element. If the age of the data at location r exceeds a threshold, the corresponding occupancy probability can be relaxed toward an uninformative prior,

$$p_j^\star = \gamma p_j + (1 - \gamma)\bar{p},$$

where $\gamma \in [0, 1]$ depends on data age and $\bar{p}$ is a baseline occupancy probability. This blending acknowledges that database-supported guarantees degrade as information becomes stale, and DAA logic must adjust separation buffers accordingly. [20]

In urban DAA, the database may also encode geo-fenced regions, protected ground areas, and preferred corridors aligned with road networks or river channels. These elements can be represented as subsets of $\mathcal{F}$ with distinct risk weights or constraints, offering a structured way to discourage flight over sensitive zones without introducing discrete mode switches in the guidance architecture. The combination of volumetric occupancy, surface geometry, temporal metadata, and semantic labels forms the information substrate from which DAA algorithms in subsequent sections derive their constraints and priors.

5. Probabilistic Sensing and Detection Modeling

Detect-and-avoid performance in urban environments is significantly conditioned by how buildings and terrain modulate sensor fields of view, clutter returns, and signal attenuation. The terrain and obstacle database enables explicit modeling of these effects in a probabilistic sensing framework that informs both track-level fusion and maneuver decisions.

Consider an onboard sensor delivering measurements y_k related to intruder states $z_k^{(i)}$ and ownship state x_k. In a simplified notation, the measurement model is written as

$$y_k = h(x_k, z_k^{(i)}) + v_k, [21]$$

where v_k denotes measurement noise. The probability of detecting intruder i at time k can be expressed as

$$P_{\mathrm{D}}^{(i)}(k) = \Psi(\theta_k^{(i)}, r_k^{(i)}, \chi_k^{(i)}),$$

where $\theta_k^{(i)}$ represents relative geometry, $r_k^{(i)}$ the range, and $\chi_k^{(i)}$ encodes environment-dependent factors derived from the database, such as line-of-sight, expected clutter, and multipath intensity.

Line-of-sight evaluation relies directly on the obstacle database. For a candidate intruder position q and ownship position p, the segment connecting p and q is intersected with the obstacle set $\mathcal{O}$. A binary indicator

$$\ell(p, q) \in \{0, 1\}$$

marks whether this segment is obstacle-free. In practice, due to registration and map errors, $\ell(p, q)$ is replaced by a probability of line-of-sight, [22]

$$P_{\mathrm{LoS}}(p, q) = \Phi(p, q, \Sigma_{\mathrm{reg}}),$$

where Φ integrates the probability that no obstacle cell intersects the segment under perturbations consistent with Σ_{reg}. The detection probability can be decomposed as

$$P_{\mathrm{D}}^{(i)}(k) = P_{\mathrm{LoS}}(p_k, q_k^{(i)})\, \Lambda(r_k^{(i)}, \chi_k^{(i)}),$$

with Λ capturing sensor-specific range and clutter dependencies.

For cooperative surveillance sources, database information still plays a role. Transponder-based systems assume that signals propagate through channels that may be shadowed or reflected by buildings. A simplified effective detection probability for cooperative targets can incorporate building-induced attenuation via a factor

$$\alpha_{\mathrm{env}}(p_k, q_k^{(i)}),$$

derived from the density and height of obstacles along relevant paths [23]. The database thereby influences both non-cooperative and cooperative sensing channels, impacting the overall probability that an intruder is tracked sufficiently early for avoidance.

Sensor fusion algorithms, such as Bayesian trackers, can include database-influenced detection probabilities in their update rules. Let

$$w_k^{(i)}$$

denote the weight or existence probability of a hypothesized track for intruder i. Upon a missed detection event, the track update may incorporate the probability that the missed

detection is attributable to occlusion rather than absence. This leads to an update of the form

$$w_{k+1}^{(i)} = w_k^{(i)} \left(1 - P_{\mathrm{D}}^{(i)}(k)\right) [24] + \xi_k^{(i)},$$

where $\xi_k^{(i)}$ accounts for new measurements or track management logic. Because $P_{\mathrm{D}}^{(i)}(k)$ depends on the terrain and obstacle database, occlusion-rich regions reduce the evidential weight of missed detections, resulting in more persistent uncertainty about unseen intruders behind buildings. This persistence then feeds directly into conservative maneuvering, as trajectories passing through occluded volumes must be evaluated under elevated uncertainty about potential conflicts.

By explicitly encoding occlusion structure, the database enables spatially resolved detection probability fields around the ownship. These fields define regions of comparatively reliable surveillance and regions where detection is weak or intermittent. DAA algorithms can exploit this information by favoring motion through well-observed volumes when alternative paths are available, or by inflating risk bounds when flying through areas that the database predicts as heavily occluded by buildings or infrastructure.

6. Conflict Prediction and Risk-Based Avoidance Using Databases

Conflict prediction in urban environments extends beyond assessing the relative motion of two aircraft in open space. Static obstacles, narrow corridors, and multiple intruder hypotheses must be integrated into a coherent risk framework [25]. The terrain and obstacle database is central to this integration, as it defines feasible volumes for both the ownship and potential intruders and influences the uncertainties associated with their trajectories.

Define a protected region around the ownship state x_k by a set

$$\mathcal{P}(x_k),$$

characterizing minimum separation requirements with respect to intruders and obstacles. A loss of separation event at time k occurs if any intruder or obstacle state enters this region. Let the random state of intruder i be distributed according to a density

$$\pi_k^{(i)}(z),$$

conditioned on all past measurements and database-informed detection models [26]. The probability of loss of separation with intruder i is then

$$P_{\mathrm{int}}^{(i)}(k) = \int \mathbf{1}\big(z \in \mathcal{C}(x_k)\big)\, \pi_k^{(i)}(z)\, \mathrm{d}z,$$

where $\mathcal{C}(x_k)$ denotes states of the intruder that violate the protected region around x_k. The database influences $\pi_k^{(i)}$ through occlusion-dependent detection probabilities and any constraints on intruder motion that reflect likely flight corridors between structures.

Obstacle-induced collision risk is treated similarly by modeling uncertainty in ownship position and obstacle surfaces. Let the ownship position at time k be a random variable with density

$$\rho_k(r),$$

accounting for navigation errors. The probability of collision with static obstacles can be approximated as [27]

$$P_{\mathrm{obs}}(k) = \int \mathbf{1}\big(r \in \mathcal{O}\big)\, \rho_k(r)\, \mathrm{d}r,$$

with $\mathcal{O}$ derived from the database and inflated to account for registration and model errors. This inflation can be implemented by morphological growth of obstacle volumes or by convolving occupancy probabilities with the navigation error distribution, resulting in effective enlarged obstacles.

DAA maneuver generation seeks control sequences that maintain the total risk

$$P_{\text{tot}}(k) = P_{\text{obs}}(k) + \sum_i P_{\text{int}}^{(i)}(k)$$

below a specified bound, while remaining dynamically feasible and consistent with mission constraints. In an urban environment, satisfaction of these risk bounds often requires exploiting fine-grained database information [28]. For example, when an intruder is approaching laterally at similar altitude, buildings between the vehicles may provide shielding, effectively reducing collision risk along certain headings. Conversely, occluded intersections between corridors may hide non-cooperative traffic and require additional margins.

Risk-based avoidance can be formulated as an optimization problem over a finite horizon of length N. For candidate controls $u_0, \ldots, u_{N-1}$, with induced trajectory $x_0, \ldots, x_N$, define a cumulative cost

$$J = \sum_{k=0}^{N-1} \left(\ell(x_k, u_k) + \lambda[29] P_{\text{tot}}(k) \right),$$

where ℓ penalizes deviations from nominal mission objectives and λ weights risk contributions. Constraints enforcing maximum acceptable instantaneous risk can be expressed as

$$P_{\text{tot}}(k) \le \bar{p},$$

for each k, where $\bar{p}$ is a designer-specified bound. The role of the database is embedded in the evaluation of $P_{\text{obs}}(k)$, $P_{\text{int}}^{(i)}(k)$, and thus $P_{\text{tot}}(k)$. High-resolution obstacle structures inform where small deviations in trajectory may significantly alter risk, enabling avoidance maneuvers that are locally efficient yet remain within constraints.

To remain computationally tractable, these risk terms are often approximated using conservative surrogates. For instance, one may replace integrals with bounds based on distance to nearest obstacle and covariance norms [30]. Let $d_{\mathcal{O}}(p_k)$ denote signed distance from the ownship mean position to the nearest obstacle and let σ_k be a scalar measure of navigation uncertainty. A simple surrogate condition can be written as

$$d_{\mathcal{O}}(p_k) \ge \beta \sigma_k,$$

where β is chosen to achieve a desired bound on $P_{\text{obs}}(k)$ under Gaussian assumptions. Although such surrogates simplify computation, their conservatism depends on the database representation of obstacles and on the validity of the underlying uncertainty models.

7. Trajectory Optimization and Guidance Architecture

Integrating terrain and obstacle databases into DAA requires a trajectory optimization and guidance architecture that can incorporate spatial constraints, risk surrogates, and dynamic feasibility in a unified manner. A common approach is to employ receding-horizon optimization, where at each decision step the UAS computes a finite-horizon trajectory that minimizes a cost function subject to constraints derived from both dynamics and database information.

Consider a discrete-time planning horizon of N steps. Let the candidate trajectory be $\{x_k\}_{k=0}^{N}$ with associated control sequence $\{u_k\}_{k=0}^{N-1}$. The optimization problem can be formulated as [31]

$$\min_{\{u_k\}} \sum_{k=0}^{N-1} \ell(x_k, u_k)$$

subject to

$$x_{k+1} = f(x_k, u_k),$$
$$x_k \in \mathcal{X}_{\text{dyn}},$$
$$x_k \in \mathcal{X}_{\text{safe}}(\mathcal{D}),$$

for all k, where $\mathcal{X}_{\text{dyn}}$ encodes dynamic and performance limits, and $\mathcal{X}_{\text{safe}}(\mathcal{D})$ is the database-induced safe set. The safe set is constructed so that if $x_k \in \mathcal{X}_{\text{safe}}(\mathcal{D})$ for all k, then the probability of violating separation constraints with respect to database obstacles and modeled intruders remains within specified bounds.

One mechanism for including database constraints is through barrier functions. For each obstacle element represented in the database, a scalar function $b(r)$ is defined such that $b(r) > 0$ in free space and $b(r) \to 0$ as r approaches the obstacle boundary. A composite barrier for the ownship position p_k can be written as [32]

$$B(p_k) = \sum_j \phi_j(p_k),$$

where ϕ_j are localized terms derived from obstacle cells or surfaces. The optimization then enforces

$$B(p_k)[33] \geq \varepsilon,$$

for a chosen margin $\varepsilon > 0$. Because the database provides explicit obstacle geometry, the barrier functions can be tuned to reflect realistic clearances in narrow urban canyons, while also absorbing uncertainties from Σ_{reg} and navigation errors.

Conflict with moving intruders can be integrated via predicted trajectories that also make use of database information. For intruder i, let $\hat{z}_k^{(i)}$ denote the predicted mean state over the horizon, obtained from motion models constrained to plausible corridors. A separation function

$$s^{(i)}(x_k)$$

measures distance in position and velocity space between ownship and intruder. The optimization imposes [34]

$$s^{(i)}(x_k) \geq s_{\min},$$

which can be softened with penalties if strict feasibility is not always attainable. Database-informed occlusion can be incorporated by adjusting $s_{\min}$ or by augmenting constraints in regions where uncertainty in intruder presence is higher.

The guidance architecture executes this optimization in a receding-horizon fashion. At each time step, the current state estimate and most recent intruder tracks are used to update constraints and cost terms. Only the first control input from the optimized sequence is applied, and the process repeats. Because database queries and geometric computations can be expensive, practical implementations often precompute summaries such as distance fields, visibility graphs, or constrained corridors. Let

$$\Gamma[35]$$

denote a set of precomputed admissible waypoints or corridor segments embedded in free space with margins derived from the database. The optimization then operates in a reduced space by selecting and connecting elements of Γ, while still evaluating barrier and separation conditions using local database information.

This architecture supports the integration of terrain and obstacle databases without requiring exhaustive three-dimensional search at every step. However, its behavior remains sensitive to database resolution, registration, and completeness. Inconsistent or low-resolution data may cause either overly conservative margins, reducing airspace capacity, or insufficient margins that fail to capture critical obstacles near candidate trajectories. Neutral evaluation of such sensitivities is essential for understanding the robustness of database-supported DAA. [36]

8. Simulation Study and Discussion

To examine the implications of terrain and obstacle database usage for urban DAA, consider simulation scenarios in which a small multirotor or fixed-wing UAS traverses canonical downtown environments represented by high-resolution obstacle databases. Building footprints, heights, and roof structures are modeled at spatial resolutions on the order of a few meters or finer, while intruder traffic follows parametric motion models constrained to corridors aligned with streets or open plazas. The DAA system employs the previously outlined receding-horizon optimizer, barrier-based obstacle avoidance, and probabilistic sensing models influenced by line-of-sight calculations from the database.

In representative scenarios, the ownship is tasked with flying from one corner of a dense urban block to another at a fixed nominal altitude band slightly above median roof height. Non-cooperative intruders traverse orthogonal corridors, occasionally intersecting the ownship's intended route. In the presence of full and correctly registered database information, the DAA system identifies narrow but feasible lateral maneuvers between buildings, exploiting known obstacle geometry to maintain separation while limiting deviations from the nominal path [37]. In corridors where the database reveals strong occlusion, the system increases standoff distances, effectively reshaping the path to remain within volumes of higher detection probability. These behaviors emerge from the joint influence of barrier constraints, occlusion-aware detection probabilities, and risk-weighted cost terms.

When database resolution is degraded, subtle rooftop structures, overhangs, and small obstacles may be omitted or smoothed. In simulations that replace a fine grid with a coarser representation, the optimizer occasionally selects trajectories that pass closer to true obstacle surfaces than intended, because barrier functions are constructed from an incomplete geometry. To mitigate this, inflating obstacles by margins tied to resolution and registration uncertainty recovers conservative behavior but also erodes available free space. Quantitatively, one observes that small changes in inflation parameters can shift the fraction of feasible candidate trajectories by several tens of digit%, indicating a strong sensitivity of available maneuvering corridors to database calibration. [38]

Database misregistration introduces another class of effects. When the database frame is offset relative to the navigation frame by biases comparable to building setbacks, simulations show that trajectories satisfying nominal barrier margins in the database frame may in reality approach obstacles more closely than desired or even intersect them. Incorporating explicit covariance-based inflation, as described earlier, reduces the frequency of such events, but also amplifies conservatism. The trade between safety margin and usable airspace depends on quantifiable bounds on registration errors. In cases where those bounds are not well controlled, reliance on detailed obstacle geometry for precise clearances becomes less appropriate, and

DAA strategies may revert toward more generic altitude and corridor rules.

Occlusion-aware detection modeling using the database affects the timing and nature of avoidance maneuvers. In simulations with strong building-induced shadowing, the probability of early detection of intruders is reduced along certain approach angles [39]. The DAA system responds by initiating maneuvering earlier when entering such regions or by preferring routes that keep the ownship within higher-visibility volumes when alternative paths exist. This does not guarantee improved overall safety in all configurations, but it aligns maneuver decisions with spatial variations in sensing reliability derived from the database. Comparisons with baseline strategies that ignore occlusion show measurable differences in conflict geometry, including shifts in where crossings occur and how residual risks are distributed spatially.

Overall, the simulations indicate that terrain and obstacle databases can materially influence DAA behavior in urban environments, primarily through shaping feasible maneuver spaces, modifying effective detection probabilities, and enabling structured risk surrogates. At the same time, performance is sensitive to database fidelity, latency, and alignment, suggesting that cautious treatment of database uncertainties is necessary to avoid overconfidence in map-derived clearances.

9. Implementation Considerations and Limitations

Implementing database-supported DAA for UAS in complex urban environments introduces multiple practical considerations extending beyond idealized modeling [40]. These considerations pertain to computation, communication, certification, and the inherent limitations of static or quasi-static databases in representing a dynamic urban landscape.

From a computational perspective, integrating high-resolution obstacle data into real-time optimization requires efficient data structures and query mechanisms. Volumetric grids and polygonal meshes must be indexed to allow rapid determination of line-of-sight, distance to nearest obstacle, and construction of local barrier functions. Precomputation of signed distance fields or multi-resolution representations can reduce online computational load, but their memory footprint and update mechanisms must be managed carefully for small UAS platforms with constrained resources. Real-time guarantees become more challenging as the complexity of the environment increases, and worst-case query times must remain compatible with DAA response requirements.

Communication architectures influence how terrain and obstacle information is provisioned and updated [41]. Some implementations may rely on ground-based or network-provided databases, which introduces latency, coverage gaps, and potential inconsistencies between onboard caches and authoritative sources. These factors complicate assurance of database integrity and raise questions about how DAA systems should respond when database updates are partial, delayed, or unavailable. Conservative fallbacks, such as inflating obstacles or reverting to simpler altitude rules, can mitigate abrupt degradation, but they also reduce operational flexibility.

Validation and certification aspects are nontrivial. Demonstrating that a database-supported DAA system meets risk targets requires evidence about both algorithm performance and database quality. This includes characterizing error distributions in obstacle positions and heights, quantifying the likelihood of missing significant structures, and establishing that registration errors are bounded within margins used for inflation and barrier construction [42]. Because urban environments evolve, continuous or periodic verification mechanisms are needed to ensure that the assumptions underpinning DAA constraints remain valid over time.

The lack of universal standards for urban obstacle databases complicates uniform assurance.

Static databases have limited capacity to represent dynamic obstacles such as cranes, temporary construction platforms, or mobile infrastructure. While some of these can be integrated through higher-frequency updates or dedicated reporting mechanisms, many remain unmodeled or only coarsely approximated. As a result, DAA systems cannot rely solely on terrain and obstacle databases for obstacle avoidance. Onboard sensing retains a critical role in detecting unmodeled objects, and the integration framework must gracefully combine database-derived priors with sensor-based evidence [43]. In regions with substantial ongoing construction, the reliability of database-supported margins may be reduced, necessitating adaptive adjustments to clearance policies.

Another limitation arises from the assumptions made in probabilistic modeling. Representations that approximate navigation errors as Gaussian, treat registration errors as spatially homogeneous, or assume independence between obstacle uncertainties and sensor noise may not hold uniformly in complex urban environments. Multipath effects, spatially correlated positioning biases, and systematic omissions in source data can introduce structured deviations that are not captured by simple covariance inflation. This may lead to either underestimation or overestimation of risk in specific geometric configurations. Addressing this requires more sophisticated uncertainty models, but these models further complicate computation and validation. [44]

Finally, reliance on detailed obstacle databases can raise interoperability and resilience issues. Different operators may use databases with varying resolution, update cycles, and semantic richness, leading to heterogeneous interpretations of the same physical environment. Discrepancies in how margins and constraints are derived from these databases can result in inconsistent behavior among vehicles sharing the same airspace. Ensuring acceptable levels of safety in such a context may require harmonized minimum specifications for database content and processing, as well as mechanisms for detecting and handling inconsistencies.

10. Conclusion

Terrain and obstacle databases offer structured information that can be integrated into detect-and-avoid systems for uncrewed aircraft operating in complex urban environments. When incorporated into probabilistic sensing models, conflict prediction logic, and trajectory optimization frameworks, such databases contribute to defining feasible corridors, representing occlusion patterns, and constructing risk-based constraints that reflect the three-dimensional geometry of buildings and infrastructure [45]. The mathematical formulations considered in this paper illustrate how occupancy probabilities, barrier functions, and risk surrogates can be derived from database content and used within receding-horizon guidance architectures to influence avoidance maneuvers and separation margins.

At the same time, the analysis underscores that the benefits of using terrain and obstacle databases are conditional on the fidelity, timeliness, and alignment of the underlying data. Errors in building representations, temporal discrepancies due to urban development, and registration offsets between navigation and database frames can propagate into the same constructs that DAA systems use to make decisions. Conservative treatments, such as inflating obstacles and adjusting detection models, can reduce the likelihood of overconfidence but also tend to reduce available maneuvering space and may limit operational efficiency in constrained airspace.

The discussion presented here emphasizes that database-supported DAA should be viewed

as part of an integrated architecture that also relies on onboard sensing, cooperative surveillance, and higher-level airspace management constructs. Terrain and obstacle information is a useful input to detect-and-avoid functions, particularly for representing static structures and occlusion effects, but it does not obviate the need for robust sensing and conservative design choices. Continued work on uncertainty characterization, standardization of database specifications, and empirical evaluation across diverse urban settings can help clarify appropriate roles and integration strategies for terrain and obstacle databases in the support of UAS detect-and-avoid capabilities [46].

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