提出了一种将无人机系统(UAS)集成到非隔离空域的统一的合作与非合作感知与避免(SAA)方法。本文综述了国内外合作与非合作SAA的传感器/系统技术，提出了一种参考系统结构。基于布尔决策逻辑(BDL)执行传感器/系统的自动选择，包括被动和主动前视传感器(FLS)、交通冲突避免系统(TCAS)和自动相关监视广播(ADS-B)系统，以支持所有飞行阶段的可信自主操作。采用BDL允许基于导航和跟踪传感器/系统的当前错误估计动态地重新配置SAA体系结构。该方法的重要性在通信、导航和监视/空中交通管理和航空电子设备(CNS+A)方面进行了讨论，重点讨论了航空电子设备和ATM认证要求。此外，还描述了SAA统一方法(SUM)中用于计算入侵者/障碍物周围空域总体不确定度体积的数学模型。在提出的方法中，影响主机UAS平台和入侵者传感器测量的导航和跟踪错误被转换成统一的范围和方位不确定性描述符。仿真案例研究用于评估统一方法在典型UAS主机平台和一些入侵者平台上的性能。结果证实了提出的统一方法的有效性，为SAA系统的认证提供了一个途径，该系统通常使用一套非合作传感器和/或合作系统。

S. Ramasamy, R. Sabatini and A. Gardi, "Cooperative and Non-Cooperative Sense-and-Avoid in the CNS+A Context: A Unified Methodology." Proceedings of IEEE International Conference on Unmanned Aircraft Systems (ICUAS 2016). Washington DC (USA), June 2016. Print ISBN: 978-1-4673-9333-1

# Cooperative and Non-Cooperative Sense-and-Avoid in the CNS+A Context: A Unified Methodology

Subramanian Ramasamy, Roberto Sabatini and Alessandro Gardi

School of Aerospace, Mechanical and Manufacturing Engineering
RMIT University, Melbourne, VIC 3000, Australia
roberto.sabatini@rmit.edu.au

***Abstract*—A unified approach to cooperative and non-cooperative Sense-and-Avoid (SAA) is presented that addresses the technical and regulatory challenges of Unmanned Aircraft Systems (UAS) integration into non-segregated airspace. In this paper, state-of-the-art sensor/system technologies for cooperative and non-cooperative SAA are reviewed and a reference system architecture is presented. Automated selection of sensors/systems including passive and active Forward Looking Sensors (FLS), Traffic Collision Avoidance System (TCAS) and Automatic Dependent Surveillance – Broadcast (ADS-B) system is performed based on Boolean Decision Logics (BDL) to support trusted autonomous operations during all flight phases. The BDL adoption allows for a dynamic reconfiguration of the SAA architecture, based on the current error estimates of navigation and tracking sensors/systems. The significance of this approach is discussed in the Communication, Navigation and Surveillance/Air Traffic Management and Avionics (CNS+A) context, with a focus on avionics and ATM certification requirements. Additionally, the mathematical models employed in the SAA Unified Method (SUM) to compute the overall uncertainty volume in the airspace surrounding an intruder/obstacle are described. In the presented methodology, navigation and tracking errors affecting the host UAS platform and intruder sensor measurements are translated to unified range and bearing uncertainty descriptors. Simulation case studies are presented to evaluate the performance of the unified approach on a representative UAS host platform and a number of intruder platforms. The results confirm the validity of the proposed unified methodology providing a pathway for certification of SAA systems that typically employ a suite of non-cooperative sensors and/or cooperative systems.**

***Keywords*—*Unmanned Aircraft Systems; Unmanned Aerial Vehicle; Trusted Autonomy; Unified Approach; Cooperative Systems; Non-Cooperative Sensors; Sense-and-Avoid; CNS+A framework.***

## I. Introduction

One of the key challenges encountered by the aviation community for integration of Unmanned Aircraft Systems (UAS) into non-segregated airspace is the provision of a certifiable Sense-and-Avoid (SAA) capability [1]. SAA can be defined as the automatic detection of possible conflicts by the Unmanned Aerial Vehicle (UAV) and the resolution of any existing collision threats by accomplishing safe avoidance manoeuvres.

The maturity of SAA techniques and enabling technologies is considered very limited when viewed in the perspective of civil airworthiness regulations for manned aircraft, raising concerns to certification authorities and airspace users [2]. One of the key technology enablers is the implementation of a unified methodology to non-cooperative and cooperative SAA that will provide UAV the capability to perform equally or even exceed the performance of the see-and-avoid ability of a manned aircraft pilot. Such an approach is considered essential in the evolving Communication, Navigation and Surveillance/Air Traffic Management (CNS/ATM) and avionics (CNS+A) framework.

The successive steps are integration of UAVs into the commercial airspace and then into the aerodrome areas, as identified in the Aviation System Block Upgrades (ASBU) by the International Civil Aviation Organization (ICAO) [3]. Some recommendations towards addressing operational and certification issues for civil UAS were provided by the Joint Aviation Authorities (JAA) CNS/ATM Steering Group [4, 5]. Additionally, a number of special groups and committees such as ASTM F38, EUROCAE WG-73, ICAO UASSG and RTCA SC-228 are working on requirements, design, performance, quality acceptance tests and certification of UAS and its supporting systems including avionics, communication links and ground control station elements [4-6]. Current advances in state-of-the-art avionics technologies (sensors and multi-sensor data fusion software) have led to a number of innovative non-cooperative and cooperative SAA solutions [7]. Such techniques have been predominantly developed either for non-cooperative or cooperative scenarios. A number of global and regional programs are investigating such implementations. In 2009, the European Defense Agency commenced a project named Mid Air Collision Avoidance System (MIDCAS) to develop an experimental SAA system based on electro-optical, infrared and radar sensors [8]. Another such development was the establishment of the SAA Science and Research Panel (SARP) in the year 2011 by the Office of the Under Secretary of Defense (OUSD) for acquisition, technology, and logistics in order to provide solutions for collision

This is the author pre-publication version. This paper does not include the changes arising from the revision, formatting and publishing process. The final paper that should be used for referencing is:

S. Ramasamy, R. Sabatini and A. Gardi, "Cooperative and Non-Cooperative Sense-and-Avoid in the CNS+A Context: A Unified Methodology." Proceedings of IEEE International Conference on Unmanned Aircraft Systems (ICUAS 2016). Washington DC (USA), June 2016. Print ISBN: 978-1-4673-9333-1

avoidance [9]. Although these projects are addressing the requirements of SAA systems, a solid mathematical framework that can be used by the certification authorities is yet to be developed.

This paper addresses the SAA problem by providing a cohesive approach that will support the certification process. In the CNS+A framework, the on board Flight Management System (FMS) for manned and unmanned aircraft acts as the main automated guidance service provider. In order to satisfy the Required Surveillance Performance (RSP) as a subset of the Required Total System Performance (RTSP), the FMS has to provide efficient separation maintenance as well as collision avoidance mechanisms. In a typical operational scenario, the host aircraft would have to maintain the required horizontal and vertical separation with other traffic and also have to sense in advance and avoid any potential conflicts. The host aircraft and other traffic might have be equipped with a different set of non-cooperative sensors and cooperative systems as shown in Fig. 1. The separation between aircraft is envisaged to include time as one of the control variables leading to the introduction of 4-Dimensional Trajectories (4DT) in the CNS+A context. Additionally, the SAA system has to be capable of avoiding ground obstacles including small natural and man-made obstacles such as poles, power line cables, trees and mountains.

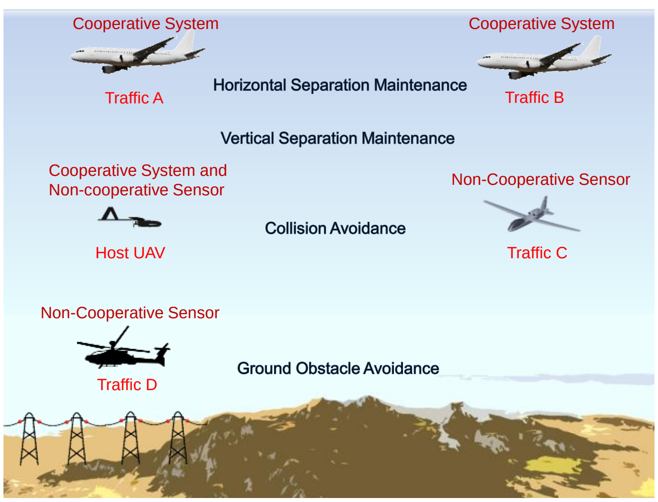


Fig. 1. 4D separation and collision avoidance tasks.

## II. SAA Sensor and Systems

The requirements for designing and developing an effective SAA system can be inferred from the current regulations in place for see-and-avoid [10-12]. In case of see-and-avoid, the main roles and responsibilities of pilots are stated in FAA AC 90-48C and FAR 91.113 and they are described in terms of regulations on maintaining vigilance, regardless of whether the operation is conducted under Instrument Flight Rules (IFR) or Visual Flight Rules (VFR). One of the fundamental limitations for certification authorities to fully certify SAA is to evaluate the ability of the current and future UAS to be able to replicate the human see-and-avoid capability, at a comparable or superior level upon replacing the on-board pilot. This is applicable both for the Ground Control Station (GCS) remote pilot and UAV platform when operated in a fully autonomous mode. The currently available SAA technologies do not completely meet the targeted levels of safety with the practical Size, Weight and Power (SWaP) criteria of UAV platforms for Line-Of-Sight (LOS) and Beyond Line-Of-Sight (BLOS) operations. The proposed detection range and Field of View (FOV) have to be adequate to ensure separation from intruders to prevent a probable mid-air collision. In case of cooperative scenarios, Automatic Dependent Surveillance–Broadcast (ADS-B) systems, Portable Collision Avoidance System (PCAS), FLight AlaRM (FLARM) and different classes of Traffic Collision Avoidance System (TCAS) are employed for sensing and tracking intruders [13]. In recent years, a number of manned and unmanned aircraft are equipped with ADS-B transponders to locate, identify and communicate with neighbouring traffic. ADS-B, although might currently have lower levels of integrity, plays a crucial role, specifically for SAA, in order to support collision avoidance as well as separation maintenance. There have been studies performed on achieving SAA using a cooperative approach with ADS-B, superseding traditional practices using only non-cooperative sensors such as vision based sensors [14].

Federal Aviation Administration (FAA) regulations are highly prohibitive for UAS operations, expecting non-cooperative sensors to be on board all UAV platforms, but this approach is changing [14]. In this perspective, a number of non-cooperative sensors have been employed for detecting and tracking other traffic in the surrounding airspace. A lightweight radar sensor and a computationally efficient method for determining collision avoidance manoeuvres proves efficient for avoiding any identified collision [15]. Vision-based sensors have been explored for a number of years considering the criticality of these systems in UAS applications. These systems are efficient in detecting real-time collision conflicts at distances that are safe for performing an avoidance manoeuvre. The key issues associated with these sensors are the cost, high computational complexity and the need for high resolution sensors. Nevertheless, several research activities have focused on the development of low-cost vision-based sensors and the development of efficient algorithms to deal with the computational cost drawbacks associated with high-resolution optical sensors. LIDAR has emerged as a promising technology for obstacle detection and tracking. The main advantages of this sensor are the higher levels of accuracy that can be achieved and the narrow FOV that it offers. Furthermore, these systems are typically complemented with other non-cooperative technologies, particularly in the case of SAA applications.

Generally, the FOV has to be equivalent or superior to that of a pilot in the cockpit and it corresponds to a primary

This is the author pre-publication version. This paper does not include the changes arising from the revision, formatting and publishing process. The final paper that should be used for referencing is:

S. Ramasamy, R. Sabatini and A. Gardi, "Cooperative and Non-Cooperative Sense-and-Avoid in the CNS+A Context: A Unified Methodology." Proceedings of IEEE International Conference on Unmanned Aircraft Systems (ICUAS 2016). Washington DC (USA), June 2016. Print ISBN: 978-1-4673-9333-1

FOV of 60˚ vertically/70˚ horizontally and a secondary FOV of 100˚ vertically and 120˚ horizontally. To satisfy this requirement, typically a suite of sensors including optical, thermal, LIDAR, MMW radar, Synthetic Aperture RADAR (SAR) and acoustic sensors are employed. LIDAR has been used for detecting, tracking and avoiding obstacles in low-level flight [12]. The adoption of a multi-sensory approach to SAA (employing passive and active MMW radar, Forward Looking Infra-Red (FLIR), LIDAR and an Electronic Surveillance Module (ESM) for obstacle detection) has resulted in adequate performance especially in low- to medium-dynamics platform applications. Acoustic sensors are specifically used in small UAVs and they provide effective intruder detection a 360º FOV, that can be used for performing quick-reaction avoidance manoeuvres [16]. More recently, cooperative systems including TCAS and ADS-B systems are used in conjunction with a non-cooperative sensor suite [17]. Since a variety of information are available, effective multi-sensor data fusion techniques and novel Human Machine Interface (HMI) designs are required. Such considerations are addressed by researchers in the US Air Force Common Airborne Sense and Avoid (C-ABSAA) program and other programs.

After identification and review of the state-of-the-art SAA technologies, Boolean Decision Logics (BDL) are employed, allowing a dynamic reconfiguration of the SAA architecture, based on the current error estimates of navigation and tracking sensors/systems. This SAA system reference architecture is illustrated in Fig. 2. The architecture allows automated selection of sensors/systems including passive and active Forward Looking Sensors (FLS), TCAS I/II/II or Airborne Collision Avoidance System (ACAS) I/II/III/X and ADS-B system is performed to support trusted autonomous operations during all flight phases.  A SAA approach that is dynamically reconfigurable based on the current performances of sensors/systems and satisfying the total required system performance will support the CNS+A framework. A typical example of selection is to prioritise TCAS data over ADS-B information, given the higher levels of integrity provided by the TCAS. The ground surveillance network information consisting of ATM RADAR tracks and Air Traffic Controller (ATCO) instructions in digital format are uplinked to the UAV platform and shared with the ground control station remote pilot.  Implementations involving Boolean logics are generally hard wired and cannot be reconfigured and this limits the scope of cooperative and non-cooperative SAA unified framework in terms of automatic decision-making capability. Therefore adaptive Boolean decision logics, which are based on real-time monitoring of the SAA sensors/systems performances, are presented in the CNS+A context. A hierarchy for selecting sensors/systems is defined based on their current error estimates. Such implementations are feasible by employing field programmable gate arrays that can provide effective selecting and sorting mechanisms realised by an array of dedicated programmable logic blocks.

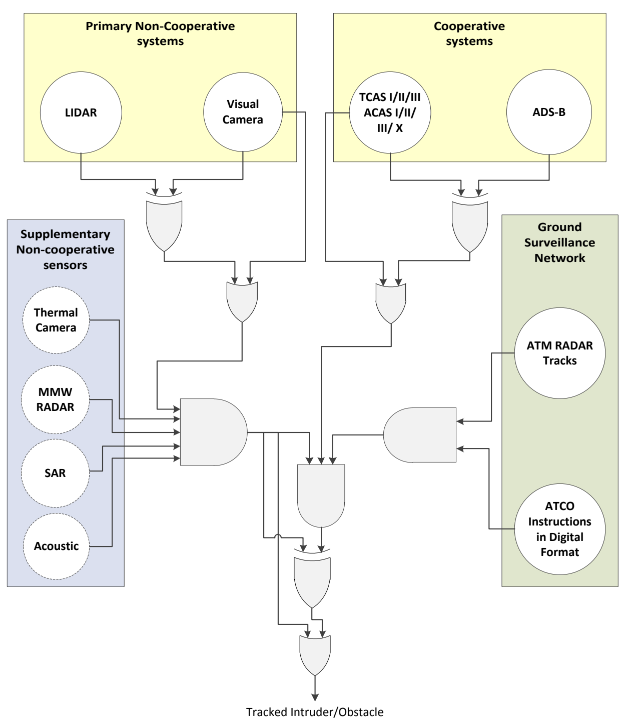


Fig. 2.   Reconfigurable UAS SAA reference architecture.

This is the author pre-publication version. This paper does not include the changes arising from the revision, formatting and publishing process. The final paper that should be used for referencing is:

S. Ramasamy, R. Sabatini and A. Gardi, "Cooperative and Non-Cooperative Sense-and-Avoid in the CNS+A Context: A Unified Methodology." Proceedings of IEEE International Conference on Unmanned Aircraft Systems (ICUAS 2016). Washington DC (USA), June 2016. Print ISBN: 978-1-4673-9333-1

Fault Tree Analysis (FTA) and Failure Modes Effects and Criticality Analysis (FMECA) are required to identify the probability of failure associated with the sensor and system suite. As a result, the sensor/system, which provides the best state estimate of other traffic, is automatically selected. The presented approach thus provides trusted autonomy and robustness in all flight phases. The method lays foundations for the development of an airworthy SAA capability and a pathway for manned/unmanned aircraft coexistence in all classes of airspace. Thus, instead of implementing hardwired decision logics (given by a pre-defined set of instructions), the dynamically reconfigurable logic ensures that the required levels of integrity are satisfied in all flight phases.

## III. SAA Process

An efficient Flight Management System (FMS) that enhances safety should address effectively both collision avoidance and separation maintenance tasks. In order to implement a common FMS functionality for manned and unmanned aircraft, key SAA tasks including Tracking, Decision-making and Avoidance (TDA) must be addressed considering the sequential steps depicted in Fig. 3.

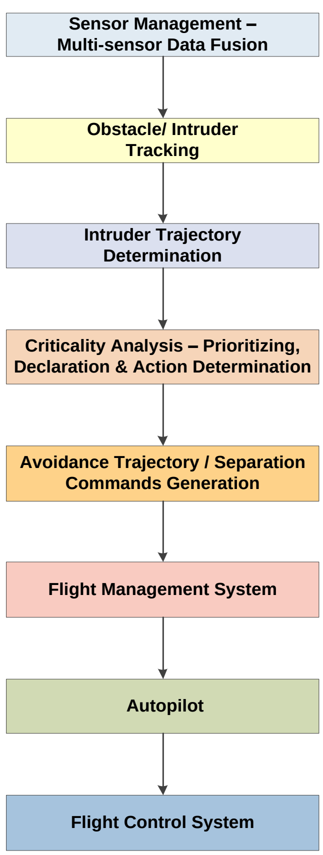


Fig. 3. SAA system process.

The processes that need to be performed are classified as:

- Detection of obstacles (air and ground) and other traffic based on information obtained from multi-sensor data fusion algorithms.
- Tracking the detected obstacles and traffic and predicting other traffic states.
- Prioritising collision risks and declaring flags for conflicts.
- Determining the optimised avoidance trajectory and providing steering commands to the guidance component.
- Execution of avoidance manoeuvres.

The state vector of the tracked obstacles are obtained by employing multi-sensor data fusion algorithms including Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Particle Filter (PF) and other knowledge-based techniques including learning based mechanisms in order to predict the intruder trajectory in a given time horizon. Currently, on-board trajectory re-planning with dynamically updated constraints based on intruder and the host UAV platform dynamics is used to generate obstacle avoidance trajectories [18]. After obtaining the trajectory information, criticality analysis is performed to prioritize (i.e. to determine if a collision risk threshold is exceeded for all tracked intruders) and to determine the steering commands required for executing an avoidance action. If possibility of a collision exists, the SAA system generates and optimises an avoidance trajectory according to a cost function that is based on minimum distance, fuel, time and closure rate criteria with the aid of differential geometry or pseudo-spectral optimisation techniques to generate a smooth and flyable trajectory [19]. The Airborne Separation Assurance Function (ASAF) is implemented as a FMS component (Fig. 4).

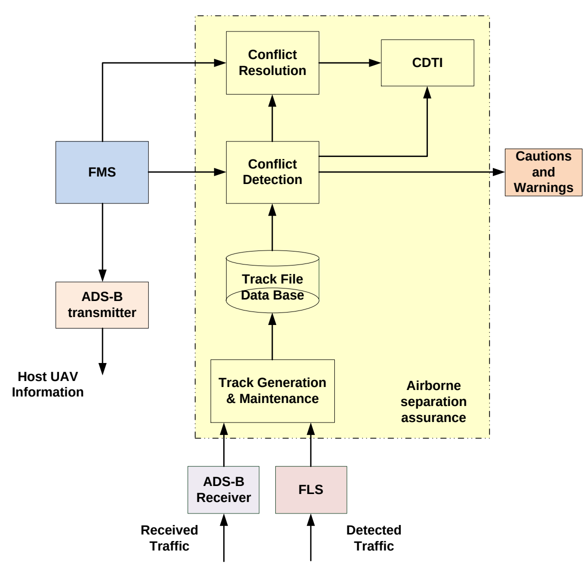


Fig. 4. ASAF system architecture.

The ASAF gradually will transfer from the current ATCO controlled modes to distributed modes. The distributed modes provide robustness in terms of reliability. The FMS thus in addition to providing enhanced path planning, navigation, guidance and aircraft performance, provides automated separation assurance capabilities. The Cockpit Display of Traffic Information (CDTI) is used for displaying traffic information. In the CNS+A context, the ASAF equipage required is summarised in Table I.

TABLE I. SUMMARY OF ASAF EQUIPAGE.

| **Equipage Type** | **Equipage** |
|---|---|
| Communication | Telecommunications datalinks, Controller Pilot Data Link Control (CPDLC), voice communication |
| Navigation | Navigation sensors providing 3D/4D navigation |
| Surveillance | Cooperative systems (TCAS, ACAS, etc.) Non-cooperative sensors (active and passive FLS) |
| Situational Awareness | CDTI Display |
| Autonomous Decision Making | Strategic, tactical and emergency flight planning and re-planning<br>Intelligent conflict detection, resolution and avoidance<br>Weather and terrain avoidance |

The software functional architecture of ASAF is illustrated in Fig. 5.

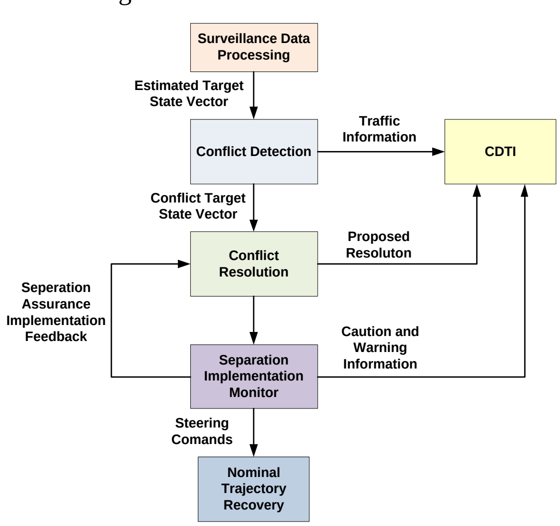


Fig. 5. Airborne separation assurance software functional architecture.

The ASAF software architecture consists of surveillance data processing, conflict detection and resolution, separation implementation and monitoring, nominal trajectory recovery, information processing and representation in a CDTI display.

## IV. TRAJECTORY OPTIMISATION ALGORITHMS

In the context of conflict identification and resolution perspective, trajectory optimisation is characterised by the identification of the most suitable 3D/4D avoidance trajectory from the time of detection to a point where the avoidance trajectory re-joins with the nominal one. In this optimisation problem, dynamics/airspace constraints, user preferences, intruder trajectory, as well as meteorological and traffic conditions are considered. Hence, the adoption of computational algorithms required for trajectory optimisation in achieving SAA represents a substantial evolution from the conventional safe-steering methodologies adopted in current CNS/ATM systems. Current research efforts are addressing practical implementations of advanced multi-model and multi-objective 3D/4D trajectory optimisation algorithms in novel ground-based and airborne CNS+A systems [20]. Both direct and indirect methods are employed for computing an efficient avoidance trajectory. Most computationally efficient trajectory optimisation algorithms adopted for UAS applications belong to the family of direct methods. These solution methods involve the transcription of the infinite-dimensional problem in a finite-dimensional Non-Linear Programming (NLP) problem, hence following the approach termed as "discretise then optimise". Safety-critical applications of trajectory optimisation algorithms are actively investigated for airborne emergency Decision Support Systems (DSS), also known as safety-nets. These safety-critical CNS+A applications impose real-time requirements on the trajectory generation algorithm. Additionally, all generated trajectories must necessarily fulfil each and every set constraint, as the obstacle avoidance and the manoeuvring envelope are formulated as constraints. As a result, these requirements limit considerably the choice of solution methods and multi-objective optimality decision logics. Robust parallelised direct shooting solution methods with a posteriori decision logics are implemented for the generation of safe obstacle avoidance trajectories as part of the research on LIDAR for manned and unmanned aircraft [21, 22]. Direct shooting methods involving the transcription into finite-dimensional NLP problem can be either performed by introducing a control parameterisation based on arbitrarily chosen analytical functions, as in transcription methods, or by adopting a generalised piecewise approximation of both control and state variables based on a polynomial sequence of arbitrary degree, as in collocation methods. In both cases the transcribed dynamical system is integrated along the time interval between an initial and final time $[t_0; t_f]$. The search of the optimal set of discretisation parameters is formulated as a NLP problem, which is solved computationally by exploiting efficient numerical NLP algorithms. In direct transcription methods, a basis of known linearly independent functions $q_k(t)$ with unknown

This is the author pre-publication version. This paper does not include the changes arising from the revision, formatting and publishing process. The final paper that should be used for referencing is:
S. Ramasamy, R. Sabatini and A. Gardi, "Cooperative and Non-Cooperative Sense-and-Avoid in the CNS+A Context: A Unified Methodology." Proceedings of IEEE International Conference on Unmanned Aircraft Systems (ICUAS 2016). Washington DC (USA), June 2016. Print ISBN: 978-1-4673-9333-1

coefficients $a_k$ is adopted as the parameterisation in the general form:

$$\mathbf{z}(t) = \sum_{k=1}^{N} \mathbf{a}_k q_k(t) \quad (1)$$

In the direct shooting and multiple direct shooting, the parameterisation is performed on the controls $u(t)$ only. The dynamic constraints are integrated with traditional numerical methods including Runge-Kutta appraoch, and the Lagrange term is approximated by a quadrature approximation. The parameterisation of the control variables is this expressed as:

$$u(t) = \sum_{k=1}^{N} c_k q_k(t) \quad (2)$$

In case of multiple shooting, the analysed time interval is partitioned into $n_i + 1$ subintervals, and the direct shooting method is applied to each divided subinterval. Parallel implementations of direct shooting methods involve the simultaneous integration of a family of trajectories. The solution is based on different control parametrisation profiles and takes advantage of increasingly common multi-thread/multi-core hardware architectures. The optimal solution is determined a posteriori, both in the case of single objective and multi objective implementations. In the unified approach, the following set of Differential Algebraic Equations (DAE) introducing a variable mass 3-DoF model was employed and are given as:

$$\begin{cases} \dot{v} = \frac{g}{W}\,(T\cos\epsilon - D - W\sin\gamma) \\ \dot{\gamma} = \frac{g}{v\,W}\cdot[(T\sin\epsilon + L)\cos\mu - W\cos\gamma] \\ \dot{\chi} = \frac{g}{v\,W}\cdot\frac{(T\sin\epsilon+L)\sin\mu}{\cos\gamma} \\ \dot{\phi} = \frac{v\cos\gamma\sin\chi+v_{w_\phi}}{R_E+z} \\ \dot{\lambda} = \frac{v\cos\gamma\cos\chi+v_{w_\lambda}}{(R_E+z)\cos\phi} \\ \dot{z} = v\sin\gamma + v_{w_z} \\ \dot{m} = -FF \end{cases} \quad (3)$$

where the UAV state vector consists of the following variables: v is longitudinal velocity (scalar) [m $s^{-1}$]; $\gamma$ is flight path angle (scalar) [rad]; $\chi$ is track angle (scalar) [rad]; $\phi$ is geographic latitude [rad]; $\lambda$ is geographic longitude [rad]; z is flight altitude [m]; $\epsilon$ is thrust angle of attack [rad] and m is aircraft mass [kg]; and the variables forming the control vector are: T is thrust force [N]; N is load factor [ ] and $\mu$ is bank angle [rad]. Other variables and parameters include: D is aerodynamic drag [N]; $v_W$ is wind velocity, in its three scalar components [m s-1]; g is the gravitational acceleration [m $s^{-2}$]; $R_E$ is radius of the Earth [m] and FF is fuel flow [kg $s^{-1}$]. Adopting a multi-phase trajectory optimisation formulation, the selection of the optimal avoidance trajectory in the safe steering phase is typically based on minimising a cost function of the following form [23, 24]:

$$J = w_t \cdot t_{safe} + w_f \cdot m(t_f) - w_d \cdot D(t_f) - w_{id} \cdot \int D(t)dt \quad (4)$$

where $D(t)$ is the slant distance of the host platform along the avoidance trajectory from the avoidance volume associated with other traffic and $t_{safe} = TTT + 2\,AMT$ is the time at which the safe avoidance condition is successfully attained, where TTT is the time-to-threat and AMT is the avoidance manoeuvre time [23]. $m(t)$ is the host platform's mass and $\{w_t, w_d, w_{id}, w_f\}$ are the positive weightings attributed to time, distance, integral distance and fuel respectively. In time-critical avoidance applications (i.e., closing-up obstacles with high relative velocities), appropriate higher weightings are used for the time and distance cost elements. Separation maintenance also has to be achieved in the vicinity of airports. In this case a runway capacity model is considered taking into account the time of separation between host UAV platform and other traffic and is given by:

$$T_{i,j} = \max\left[\frac{r+s_{i,j}}{v_j} - \frac{r}{v_i},\ o_i\right] \text{ when } v_i > v_j \quad (5)$$

$$T_{i,j} = \max\left[\frac{s_{i,j}}{v_j},\ o_i\right] \text{ when } v_i \leq v_j \quad (6)$$

where $T_{i,j}$ is the time of separation, $v_i$ and $v_j$ are the velocities of adjacent aircraft, $s_{i,j}$ is the distance of separation, r is the required separation and o represents the order of the separation required.

## V. SAA Unified Methodology

The presented SAA Unified Method (SUM) calculates the overall uncertainty volume surrounding the intruder tracks or obstacles in the airspace. In this method, both navigation error of the host UAV platform and tracking error of other traffic are combined in order to obtain an overall avoidance volume. Therefore, the navigation and tracking errors are expressed in range and bearing uncertainty descriptors. In order to estimate navigation and tracking errors, sensor error modelling is performed. The variation in the UAV state vector, x is expressed as:

$$\delta\big(x_i(t)\big) = \left[\frac{\delta x}{\delta p}\right]_t . \sigma_{p_j} \quad (7)$$

where p is the position of the UAV and t is the time of measurement. Let R, $\alpha$ and $\epsilon$ be the range, azimuth and elevation obtained from A SAA sensor/system. Let $R_0$, $\alpha_0$ and $\epsilon_0$ be the nominal range, azimuth and elevation values. Consider $\sigma_R$, $\sigma_\alpha$ and $\sigma_\epsilon$ as standard deviations of the error in range, azimuth and elevation respectively. Hence, the error ellipsoids are given as:

$$\frac{(\mathbf{R}-\mathbf{R_0})^2}{\sigma_{\mathbf{R}}{}^2} + \frac{(\alpha-\alpha_0)^2}{\sigma_\alpha{}^2} + \frac{(\epsilon-\epsilon_0)^2}{\sigma_\epsilon{}^2} = 1 \quad (8)$$

In order to develop a unified approach to cooperative and non-cooperative SAA, the error ellipsoids are typically subjected to two transforms: rotation, R and translation, T that is defined as a projection along the LOS vector of the UAV. The inverse transformation applied to one of the two ellipsoids with respect to another, L is thus expressed as:

$$\mathrm{L}^{-1} = \mathrm{R}^{-1}\, \mathrm{T}^{-1} \mathrm{L} \tag{9}$$

The intruder position vector, p translated from host body frame to Earth Centred Earth Fixed (ECEF) reference frame with respect to R is given by:

$$\tilde{\mathrm{p}} = \mathrm{R}\ \mathrm{p} \tag{10}$$

The intruder position vector uncertainty in ECEF frame ($\delta\tilde{\mathrm{p}}$) is expressed as:

$$\delta\tilde{\mathrm{p}} = \Delta_{\mathrm{R}}\ \mathrm{p} + \mathrm{R}\ \delta\mathrm{p} \tag{11}$$

where $\delta\mathrm{p}$ is the error in the position vector of other traffic in the host body frame and $\Delta_{\mathrm{R}}$ is the rotation (angular) error matrix. The rotation matrix in terms of azimuth and elevation angles is given by:

$$\mathrm{R} = \begin{bmatrix} c\epsilon\ c\alpha & s\alpha & -s\epsilon\ c\alpha \\ -c\epsilon\ s\alpha & c\alpha & -s\epsilon\ s\alpha \\ s\epsilon & 0 & c\epsilon \end{bmatrix} \tag{12}$$

where c and s represent cosine and since of azimuth and elevation angles. Therefore the position vector after rotation is expressed as:

$$\begin{bmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{bmatrix} = \begin{bmatrix} c\epsilon\ c\alpha & s\alpha & -s\epsilon\ c\alpha \\ -c\epsilon\ s\alpha & c\alpha & -s\epsilon\ s\alpha \\ s\epsilon & 0 & c\epsilon \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} \tag{13}$$

The angular error matrix is given by:

$$\Delta_{\mathrm{R}} = \begin{bmatrix} -\delta\epsilon\ s\epsilon\ c\alpha - \delta\alpha\ c\epsilon\ s\alpha & \delta\alpha\ c\alpha & -\delta\epsilon\ c\epsilon\ c\alpha + \delta\alpha\ s\epsilon\ s\alpha \\ \delta\epsilon\ s\epsilon\ s\alpha - \delta\alpha\ c\epsilon\ c\alpha & -\delta\alpha\ s\alpha & -\delta\epsilon\ c\epsilon\ s\alpha - \delta\alpha\ s\epsilon\ c\alpha \\ \delta\epsilon\ c\epsilon & 0 & -\delta\epsilon\ s\epsilon \end{bmatrix} \tag{14}$$

and the error in position is expressed as:

$$\begin{bmatrix} \delta\tilde{x} \\ \delta\tilde{y} \\ \delta\tilde{z} \end{bmatrix} = \begin{bmatrix} -\delta\epsilon\ s\epsilon\ c\alpha - \delta\alpha\ c\epsilon\ s\alpha & \delta\alpha\ c\alpha & -\delta\epsilon\ c\epsilon\ c\alpha + \delta\alpha\ s\epsilon\ s\alpha \\ \delta\epsilon\ s\epsilon\ s\alpha - \delta\alpha\ c\epsilon\ c\alpha & -\delta\alpha\ s\alpha & -\delta\epsilon\ c\epsilon\ s\alpha - \delta\alpha\ s\epsilon\ c\alpha \\ \delta\epsilon\ c\epsilon & 0 & -\delta\epsilon\ s\epsilon \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} c\epsilon\ c\alpha & s\alpha & -s\epsilon\ c\alpha \\ -c\epsilon\ s\alpha & c\alpha & -s\epsilon\ s\alpha \\ s\epsilon & 0 & c\epsilon \end{bmatrix} \begin{bmatrix} \delta x \\ \delta y \\ \delta z \end{bmatrix} \tag{15}$$

In a static non-cooperative case, the errors in range, azimuth and elevation are given by:

$$\delta\mathrm{R} = \mathrm{R}_0 + \sigma_{\mathrm{R}} \cdot \sin\psi \tag{16}$$

$$\delta\alpha = \alpha_0 + \sigma_\alpha \cdot \cos\varphi \cdot \cos\psi \tag{17}$$

$$\delta\epsilon = \epsilon_0 + \sigma_\epsilon \cdot \sin\varphi \cdot \cos\psi \tag{18}$$

where $\mathrm{R}_0$, $\alpha_0$, $\epsilon_0$ are the nominal range, azimuth and elevation measurements. $\{\varphi, \psi\}$ are the parameterization factors required for reduced information transfer between air and ground systems. The transformation of $\{\mathrm{R}, \alpha, \epsilon\}$ to $\{x, y, z\}$ is given by:

$$x = \mathrm{R} \cdot \cos\alpha \cdot \cos\epsilon \tag{19}$$

$$y = \mathrm{R} \cdot \sin\alpha \cdot \cos\epsilon \tag{20}$$

$$z = \mathrm{R} \cdot \sin\epsilon \tag{21}$$

Correlation analysis of the measurements provided by the SAA sensors/systems is essential to determine the overall uncertainty volume. As a result uncorrelated, covariant and contravariant cases are possible. As an example, considering ADS-B measurements obtained from the host UAV and other traffic, the dependences of errors in $\{x, y, z\}$ on the correlation between the sensor measurements are given by:

$$\sigma_x{}^2 = (\sigma_{x\_A}{}^2 + \sigma_{x\_O}{}^2 + 2\ \sigma_{x\_A\, x\_O}) \tag{22}$$

$$\sigma_y{}^2 = (\sigma_{y\_A}{}^2 + \sigma_{y\_O}{}^2 + 2\ \sigma_{y\_A\, y\_O}) \tag{23}$$

$$\sigma_z{}^2 = (\sigma_{z\_A}{}^2 + \sigma_{z\_O}{}^2 + 2\ \sigma_{z\_A\, z\_O}) \tag{24}$$

where {x_A, y_A, z_A} is the position of the intruder obtained from ADS-B, {x_O, y_O, z_O} is the position of the host UAV obtained from ADS-B and $\{2\ \sigma_{x\_A\, x\_O}, 2\ \sigma_{y\_A\, z\_O}, 2\ \sigma_{y\_A\, z\_O}\}$ define the correlation between the system measurements. An example of the two combined navigation and tracking error ellipsoids assuming error in range only, and the resulting uncertainty volumes for uncorrelated and correlated (covariant and contravariant) sensor error measurements (3 out of a total of 27 possibilities) are illustrated in Fig. 6 and 7 respectively.

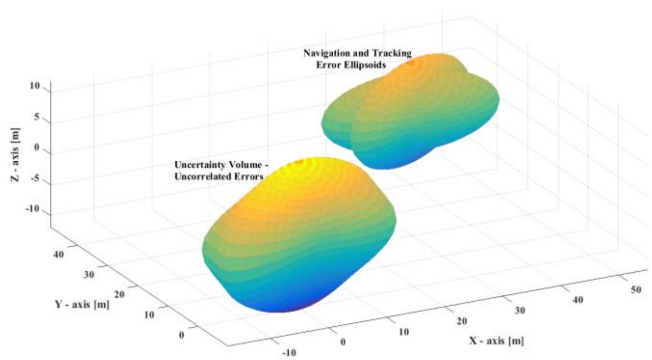


Fig. 6. Uncertainty volume obtained from range only uncorrelated errors.

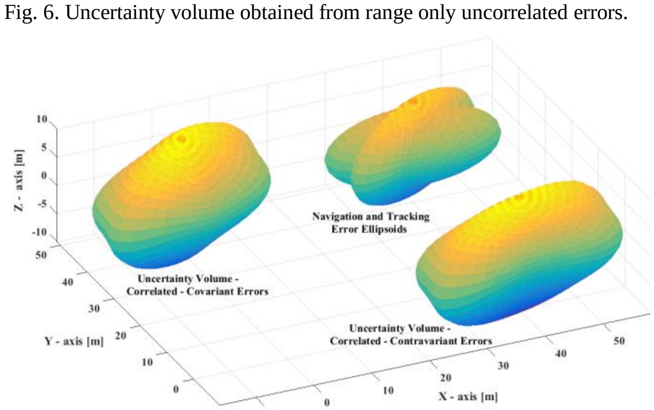


Fig. 7. Uncertainty volumes obtained from range only correlated errors.

This is the author pre-publication version. This paper does not include the changes arising from the revision, formatting and publishing process. The final paper that should be used for referencing is:

S. Ramasamy, R. Sabatini and A. Gardi, "Cooperative and Non-Cooperative Sense-and-Avoid in the CNS+A Context: A Unified Methodology." Proceedings of IEEE International Conference on Unmanned Aircraft Systems (ICUAS 2016). Washington DC (USA), June 2016. Print ISBN: 978-1-4673-9333-1

In the dynamic case, the uncertainty volume is obtained based on a confidence region governed by the errors in {x, y, z} given by:

$$\sigma_x{}^2 = (\sigma_{x0}{}^2 + \sigma_{v_x \cdot t}{}^2 + 2\,\sigma_{x0\, v_x \cdot t}) \tag{25}$$

$$\sigma_y{}^2 = (\sigma_{y0}{}^2 + \sigma_{v_y \cdot t}{}^2 + 2\,\sigma_{y0\, v_y \cdot t}) \tag{26}$$

$$\sigma_z{}^2 = (\sigma_{z0}{}^2 + \sigma_{v_z \cdot t}{}^2 + 2\,\sigma_{z0\, v_z \cdot t}) \tag{27}$$

When an error in elevation and azimuth is present, the resultant volume obtained at the estimated range is illustrated in Fig. 8. In a dynamic case, there exist a variation of uncertainty volume in every time epoch due to errors in range and bearing, and relative dynamics between the platforms.

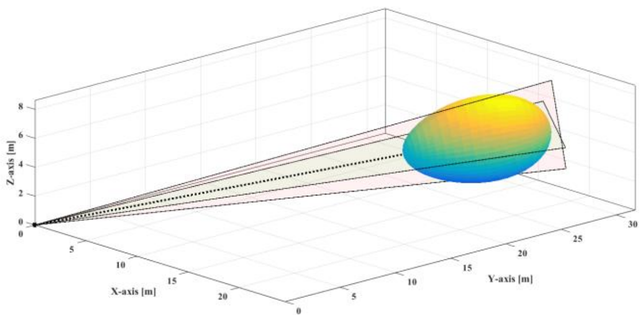


Fig. 8. Uncertainty volume obtained as a result of bearing errors at the estimated range.

## VI. Simulation Case Studies

Simulation case studies were performed using the AEROSONDE UAV as the host platform. In all the cases, the host UAV was presumed to be equipped with both non-cooperative sensors (vision-based camera and LIDAR) and cooperative system (ADS-B). Other traffic including manned and unmanned aircraft platforms (AEROSONDE UAV and Airbus A320 aircraft) were considered in the simulation case studies. In the first case, it is assumed that no cooperative systems are on board the intruder (AEROSONDE UAV). The uncertainty volume is generated in real-time after evaluating the risk of collision at the collision point (Fig. 9). An avoidance trajectory is generated (based on the platform dynamics) to maintain the required separation maintenance (more than 500 m) and also to prevent any mid-air collisions at all of the predicted time epochs. A typical case is that of multiple traffic performing cooperative and/or non-cooperative surveillance, as well as communicating with the ground ATM systems [25, 26]. In this scenario, potential conflicts are defined as close encounters in the 4D space-time domain. Close-encounters are typically evaluated as part of an intermediate step for pruning the full set of potential conflicts. Such 4D close-encounters are assumed to occur when the relative distance (i.e., the norm of the 3D relative position vector) between the nominal positions of a pair of traffic at a certain time is below a specified threshold. For all identified close-encounters, the uncertainty volume associated with host and intruder platforms are determined.

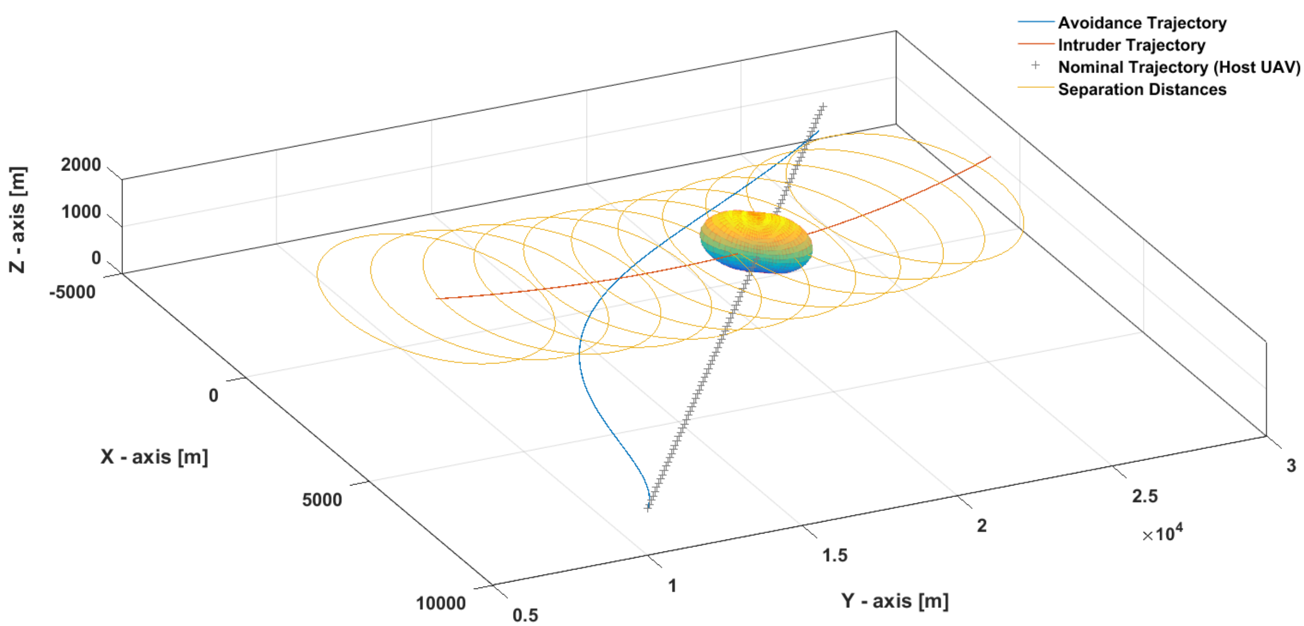


Fig. 9. Avoidance trajectory generation by host UAV platform.

Due to bandwidth limitations existing in current communication systems, a compact and versatile parameterisation of the uncertainty volume is highly desirable to extrapolate its actual shape and size at close encounter points with minimal data link and computational burden. In the second case, both host unmanned aircraft and intruder (Airbus A320 aircraft) platforms are assumed to have on board ADS-B systems. The host unmanned platform computes an avoidance trajectory as per the rules of flight while the other traffic performs a step descend phase to avoid the mid-air collision. The cost function use to obtain these avoidance trajectories are the same as defined in equation 4. As in the first case, in this scenario as well, the required horizontal and vertical separation distances were achieved. The simulations were performed on a Windows 7 Professional workstation (64-bit OS) supported by an Intel Core i7-4510 CPU with clock speed 2.6 GHz and 8.0 GB RAM. The execution time for uncertainty volume determination and avoidance trajectory optimisation algorithms was in the order of 8 sec. Such an implementation makes it possible to perform real-time separation maintenance tasks as well as avoidance of any identified collisions (emergency scenarios). The significance of the SUM is its focus towards addressing avionics and ATM certification requirements in the CNS+A context. In order to fulfil safety requirements for SAA system certification, performance monitoring and augmentation algorithms (including integrity) have to be implemented encompassing the entire CNS sensors/systems chains and the associated navigation and tracking loops. In the CNS+A context, this means that either a specified level of performance is available (with a specified maximum probability of failure) or, if not, a usable integrity flag is generated within a specified maximum Time-To-Alert (TTA). Using suitable data link and signal processing technologies on the ground, a certified SAA capability can thus become a core element of future network-centric ATM operations.

## VII. Conclusions

State-of-the-art non-cooperative and cooperative technologies for SAA were identified and a reference system architecture was presented. The algorithms employed to achieve effective self-separation and collision avoidance functionalities were described. In particular, a unified SAA analytical framework was presented that allows computing the overall avoidance volume associated with single/multiple intruder tracks and computes the optimal avoidance trajectory when cooperative/non-cooperative detection is performed with avionics and ATM sensor/system inputs. Simulation case studies were presented to corroborate the effectiveness of the proposed approach. This method provides a clear pathway to certification of next generation SAA (and ACAS) systems for both manned and unmanned aircraft. Future research activities will address the full-scale development of the proposed SAA system in a variety of UAV platforms. Additionally, in order to meet the CNS+A integrity requirements, a suitable Avionics-Based Integrity Augmentation (ABIA) architecture will be employed [27, 28].

## References

[1] S.P. Cook A.R. Lacher, D.R. Maroney, and A.D. Zeitlin, "UAS Sense and Avoid Development - The Challenges of Technology, Standards, and Certification", 50th AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition, Nashville, TN, USA, 2012. DOI: abs/10.2514/6.2012-959

[2] K. Dalamagkidis, K.P. Valavanis, and L.A. Piegl, "On unmanned Aircraft Systems Issues, Challenges and Operational Restrictions Preventing Integration into the National Airspace System", Progress in Aerospace Sciences, vol. 44, issue 7, pp. 503-519, 2008. DOI: 10.1016/j.paerosci.2008.08.001

[3] The International Civil Aviation Organization (ICAO), Working Document for the Aviation System Block Upgrades - The Framework for Global Harmonization, Montreal, Canada, 2013.

[4] G. Amato, EUROCAE WG-73 on Unmanned Aircraft Systems, ed: EUROCAE.

[5] JAA, UAV TASK-FORCE, Final Report - A Concept for European Regulations for Civil Unmanned Aerial Vehicles (UAVs), 2004.

[6] A. Oztekinmet and R. Wever, "Development of a Regulatory Safety Baseline for UAS Sense and Avoid", Handbook of Unmanned Aerial Vehicles, pp. 1817-1839, Springer Verilag, Netherlands, 2015.

[7] X. Yu and Y. Zhang, "Sense and Avoid Technologies with Applications to Unmanned Aircraft Systems: Review and Prospects", Progress in Aerospace Sciences, vol. 74, pp. 152-166, 2015.

[8] J. Pellebergs and SAAB Aeronautics, The MIDCAS Project, SAAB Aeronautics, 2012.

[9] K.P. Valavanis and J.V. George, "UAV Sense, Detect and Avoid: Introduction", Handbook of Unmanned Aerial Vehicles, Springer Netherlands, pp. 1813-1816, 2014.

[10] Federal Aviation Administration, Pilot's Role in Collision Avoidance, AC90-48C, Washington DC, USA, 1983.

[11] DOT/FAA/CT-96-1, Human Factors Design Guide for Acquisition of Commercial-Off-the-Shelf subsystems, Non-Developmental Items, and Developmental Systems-Final Report and Guide, January 1996.

[12] R. Melnyk, et al. "Sense and Avoid Requirements for Unmanned Aircraft Systems Using a Target Level of Safety Approach", Risk Analysis, vol. 34, issue 10, pp. 1894-1906, 2014.

[13] L. Mejias, J. Lai, and T. Bruggemann, "Sensors for Missions", Handbook of Unmanned Aerial Vehicles, pp. 385-399, 2015.

[14] M. Strohmeier, M. Schäfer, V. Lenders, and I. Martinovic, "Realities and Challenges of NextGen Air Traffic Management: The Case of ADS-B", IEEE Communications Magazine, vol. 52, issue 5, pp. 111-118, 2014. DOI: 10.1109/MCOM.2014.6815901

[15] A. Moses, M.J. Rutherford, and K.P. Valavanis, "Scalable RADAR-Based Sense-and-Avoid System for Unmanned Aircraft", Handbook of Unmanned Aerial Vehicles, pp. 1895-1953, Springer, 2014.

[16] A. Finn and S. Franklin, "Acoustic Sense & Avoid for UAV's", Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), IEEE Seventh International Conference, 2011.

[17] S. Ramasamy, R. Sabatini, A. Gardi, "Avionics Sensor Fusion for Small Size Unmanned Aircraft Sense-and-Avoid", IEEE Workshop on Metrology for Aerospace, pp. 271-276, Benevento, Italy, May 2014. DOI: 10.1109/MetroAeroSpace.2014. 6865933

[18] C.K. Lai, M. Lone, P. Thomas, J. Whidborne, and A. Cooke, "On-Board Trajectory Generation for Collision Avoidance in Unmanned Aerial Vehicles", Proceedings of the IEEE Aerospace Conference, pp. 1-14, 2011. DOI: 10.1109/AERO.2011.5747526

[19] L. Rodriguez R. Sabatini, S. Ramasamy and A. Gardi, "A Novel System for Non-Cooperative UAV Sense-And-Avoid", European Navigation Conference (ENC 2013), Vienna, Austria, 2013.

[20] A. Gardi, R. Sabatini and S. Ramasamy, "Multi-objective Optimisation of Aircraft Flight Trajectories in the ATM and Avionics Context", Progress in Aerospace Sciences, vol. 83, pp. 1-36, 2016. DOI: http://dx.doi.org/10.1016/j.paerosci.2015.11.006

[21] R. Sabatini, A. Gardi and S. Ramasamy, "A Laser Obstacle Warning and Avoidance System for Unmanned Aircraft Sense-and-Avoid," Applied Mechanics and Materials, Trans Tech Publications, vol. 629, pp. 355-360, 2014. DOI: 10.4028/www.scientific.net/AMM.629.355

[22] R. Sabatini, M. A. Richardson, H. Jia and D. Zammit-Mangion, “Airborne Laser Systems for Atmospheric Sounding in the Near Infrared”, in SPIE Photonics Europe, 2012, pp. 843314-843314-40.

[23] R. Sabatini, “Cooperative and Non-Cooperative Decision Making for UAS Detect-and-Avoid: A Novel Unified Approach”, in Emerging Disruptive Technologies Assessment Symposium (EDTAS) 2015, Sydney, Australia, 2015.

[24] S. Ramasamy, R. Sabatini and A. Gardi, “Towards a Unified Approach to Cooperative and Non-Cooperative RPAS Detect-and-Avoid”, Fourth Australasian Unmanned Systems Conference 2014 (ACUS 2014), Melbourne, Australia. DOI: 10.13140/2.1.4841.3764

[25] A. Gardi, R. Sabatini, S. Ramasamy and T. Kistan, “Real-Time Trajectory Optimisation Models for Next Generation Air Traffic Management Systems”, Applied Mechanics and Materials, vol. 629, pp. 327-332, 2014. DOI: 10.4028/www.scientific.net/AMM.629.327

[26] S. Ramasamy, R. Sabatini, A. Gardi and T. Kistan, “Next Generation Flight Management System for Real-Time Trajectory Based Operations”, Applied Mechanics and Materials. vol. 629, Trans Tech Publications, pp. 344-349, 2014. DOI: 10.4028/www.scientific.net/AMM.629.344

[27] R. Sabatini, T. Moore and C. Hill, “Avionics Based GNSS Integrity Augmentation for Mission- and Safety-Critical Applications”, Paper presented at 25th International Technical Meeting of the Satellite Division of the Institute of Navigation: ION GNSS-2012, Nashville (Tennessee), September 2012.

[28] R. Sabatini, T. Moore, C. Hill and S. Ramasamy, “Assessing Avionics-Based GNSS Integrity Augmentation Performance in UAS Mission- and Safety-Critical Tasks”, 2015 IEEE International Conference on Unmanned Aircraft Systems (ICUAS), Denver, CO, USA, pp. 650 - 659, June 2015. DOI: 10.1109/ICUAS.2015.7152347