HUMAN VISUAL AVOIDANCE SYSTEMS “SEE and AVOID“

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Summary. This paper provides a comprehensive review of the vision-based See and Avoid problem for mainly manned aircraft. The unique problem environment and associated constraints are detailed, followed by an in depth analysis of visual sensing limitations. In light of such detection and estimation constraints, relevant human, aircraft and robot collision avoidance concepts are then compared from a decision and control perspective. Remarks on system evaluation and certification are also included to provide a holistic review approach. The intention of this work is to clarify common misconceptions, realistically bound feasible design expectations and offer new research directions.

Keywords: avoidence, conflict detection, flying object, positioning accuracy

1. INTRODUCTION

In the See and Avoid context, collision avoidance systems refer to the automated technology aimed at replicating the reactive collision avoidance function of pilots. Assuming that the object has been visually detected, the remaining collision avoidance functions involve the pilots decision making and control actions in response to the situation. This includes determining if the object is a collision threat (conflict detection), deciding what (if any) avoidance manoeuvre to take (avoidance decision or logic), and subsequently applying that action (avoidance control). The goal being to avoid a Near Mid-Air Collision (NMAC) and safely resolve the conflict._Importantly, the See and Avoid process does not include the pilots leverage of existing collision avoidance systems such as the Traffic Alert and Collision Avoidance System (TCAS I, TCAS II), Automatic Collision Avoidance System (ACAS), Air Traffic Controller (ATCO) directives or other cooperative communication devices (ADS-B, etc.). This is a common point of misunderstanding even in recently proposed See and Avoid systems [1]. Near MidAir Collision (NMAC) is defined as the incursion or breach of a cylindrical protection zone of height 200 ft and radius 500 ft about each aircraft.

This section provides an important background regarding relevant conflict detection, avoidance decision and avoidance control concepts used in human navigation, manned aviation. The term concept is used to describe a generic approach as opposed to specific details. The review aims to provide relevant information regarding how such concepts may be used or extended in the design of vision-based See and Avoid systems. The discussion is restricted to aircraft and obstacle avoidance, and does not include terrain (ground) and weather avoidance systems. An effort is made to identify both fundamental contributions and recent developments as applied to vision-based collision avoidance where possible

2. HUMAN AVOIDANCE SYSTEMS

The human visual navigation system is a key component for effective collision avoidance [2]. Given the requirement for equivalence, the human visual navigation system is then an important consideration in the subsequent design of automated See and Avoid systems. Although central to the See and Avoid discussion, human collision avoidance concepts are commonly ignored or by-passed, particularly in non-aerospacecommunities. This is typically under the assumption that machines (automated systems) can do better. This may be the case in some instances, but often coincides with complete negligence regarding the notion of predictability. In aviation, it is important that airspace users behave in a predictable manner where possible, given the airspace is shared with manned aircraft. A system that outperforms the human See and Avoid function, although useful, may degrade the overall airspace integrity (and safety). As such, human conflict detection, avoidance decision and avoidance control concepts are discussed below. Conflict detection: Humans can perform conflict detection using visually acquired measurements of angular position and rate. Specifically, a zero angular rate or constant angular position is used to infer a collision object [2]. The object may be stationary or moving in a linear or nonlinear manner (turning) [3], and is assumed to be in front of the observer such that the magnitude of the relative angular position is always less than 90°. This constant angle model offers a simple and useful conflict detection mechanism for objects moving in an arbitrary fashion. Additionally, the model verifies many assumptions often made in manned aviation. The conflict detection concept is shown in Fig. 1.

Considering practical limitations, such as sensor noise char- acteristics, the observed angular rate will rarely be zero in See and Avoid encounters. It is then necessary to place a small scalar threshold ϵ on the angular rate $\dot{\alpha}$ in an attempt to distinguish between collision and non-collision aircraft. This can be defined as

$$C(t > k) \Leftrightarrow \dot{\alpha}(k) \leq \epsilon \tag{1}$$

$$\bar{C}\ (t > k) \Leftrightarrow;\ \dot{\alpha}(k) > \epsilon \tag{2}$$

or, by considering some arbitrary time history τ of the angular observations

$$C(t > k) \Leftrightarrow \dot{\alpha}(k - \tau,\ \ldots,\ k) \leq \epsilon, \tag{3}$$

$$\bar{C}\ (t > k) \Leftrightarrow \dot{\alpha}(k - \tau,\ \ldots,\ k) > \epsilon \tag{4}$$

where C and $\bar{C}$ denote collision and non-collision respectively and k is the current time. This approach was empirically investigated in a number of See and Avoid flight trials [2c] with mixed outcomes. Results showed that collision objects can be correctly identified (>90%), but at the expense of multiple falsely classified non - collision objects. This suggests that additional information may be required to accurately discriminate between collision and non-collision objects. One drawback of the analysis is the assumption that a hard decision must be made regarding the status of the encounter. It is reasonable to assume that different actions may be taken for different angular rates or thresholds. By always acting, it may be possible to reduce false alarms whilst preserving a con- servative approach.

Avoidance decision: Humans demonstrate a variety of behaviours with respect to avoidance decisions [4]. This includes whether to pass in front of or behind a moving obstacle. The decision is often ambiguous, so it is difficult to derive an explicit model for the avoidance behaviour. From a See and Avoid perspective however, this ambiguity may be resolved by considering the current right-of-way rules. The rules define the conditions in which to give way to nearby aircraft, and how to manage (near) head on collision encounters using lateral separation. Using vertical separation however, and except for the overtaking case, the rules-of-the air do not provide any explicit guidelines. To this end, recent pilot centric studies suggest that a decision to descend is preferable [5]. The avoidance decision is qualitative for both vertical and lateral separation such that direction (up, down, left, right) is used and not a specific heading, velocity, altitude, etc. [6].

Applying the right-of-way rules, it can also be assumed that precautionary avoidance manoeuvres may be prevalent in manned aircraft for ambiguous collision objects. This of course can result in suboptimal behaviour, but embedding such rules within an autonomous system may help demonstrate the required level of safety for certification [7].

Avoidance control: Considering the qualitative nature of human avoidance decisions, the subsequent control uses a direct visual feedback loop. Initial models, derived from object interception (reciprocal of avoidance), suggest that the object is visually steered in such a way that a non-zero angular rate is maintained [8]. This is demonstrated for both static and constant velocity objects and results in smooth control. Importantly, no specific non-zero reference position or velocity in the eye is used for control. This means explicit path planning or other waypoint based navigation is not used, and instead a reactive control input u is employed such that

$$\mathbf{u} = f(\dot{\alpha}(k)) \tag{5}$$

Extensions to the control strategy include the consideration of small object velocity changes over the encounter [9]. An inter- mediate anticipatory strategy was observed whereby a predictive control strategy aims to command a non-zero angular rate for a short time into the future (time horizon) Tp such that

$$\mathbf{u} = f(\dot{\alpha}(k), \ldots, \dot{\alpha}(k + Tp)),\ Tp \in P+ \tag{6}$$

Further research has showed that short prediction times ($0.5\ \text{s} \leq Tp \leq 3.5\ \text{s}$) result in more robust and accurate control [10]. This means predictive avoidance control strategies using relative angular observations may be representative of actual human avoidance behaviour.

2.1. Aircraft avoidance systems

Many automated collision avoidance approaches have been derived for manned aircraft [11] and since suggested for un- manned aircraft , including the well known Traffic Alert and Collision Avoidance System (TCAS) [12]. However, most of the methods are aimed at planned separation assurance and not reactive collision avoidance, as required for See and Avoid. The time at which the conflict is detected and resolved differs such that separation assurance occurs prior (minutes) to See and Avoid (seconds).

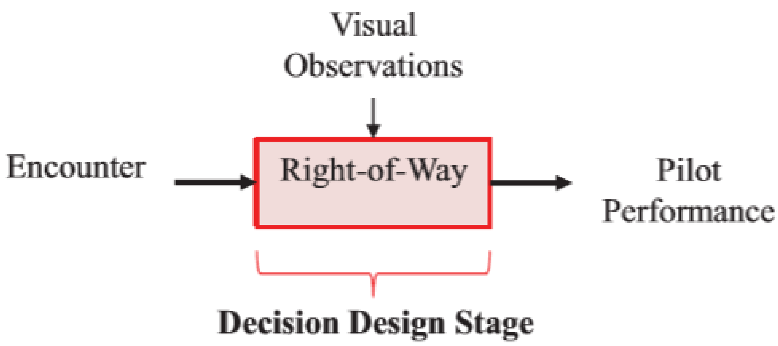

Fig. 1. Example avoidance decision (logic) design for human collision avoidance systems. [5]

Nonetheless, it is important to consider existing separation assurance concepts from a See and Avoid perspective. This is for a number of reasons. First, the basic separation assur- ance functions are very similar to those required for See and Avoid. After all, they are both essentially aimed at separating aircraft. This means some principles and concepts may be adapted or scaled to fit the See and Avoid constraints. Second, many existing concepts were derived with a particular focus on subsequent certification. Given See and Avoid systems will also require certification, it may be wiser to adopt similar concepts and better align with regulatory expectations and standards. As such, existing aircraft conflict detection, avoidance decision and avoidance control concepts are discussed below.

Conflict detection: Conflict detection is primarily accomplished by either monitoring the current relative state (position, range) [8], or by predicting the future relative state (state propagation) and acquiring an appropriate estimate of the probability of collision. Although computational restrictive, state propagation is generally preferred, providing a relative measure of the probability of collision Pc(t) by considering future events. State propagation can be conducted in a nominal or probabilistic manner with respect to the predicted trajectories, and may consider one or more avoidance manoeuvres. This means multiple collision probability estimates given an action a was taken are estimated such that.

$$Pc(t) \in \{Pc|\ a0(t),\ \ldots,\ Pc|\ an(t)\},\ n \in Z+ \quad (7)$$

Multiple definitions for conflict probability exist including maximal , integrated and probability flow , along with multiple analytical , numerical and probabilistic (Monte- Carlo) approaches to approximate or calculate them. Conflict detection is then based on comparing the collision probability estimates. Considering only the current state or using nominal state propagation, then $Pc(t) = \{0, 1\}$. Considering probabilistic state propagation, then $0 \leq Pc(t) \leq 1$. Some simple examples of the differences in these conflict detection concepts are depicted in Fig. 2.

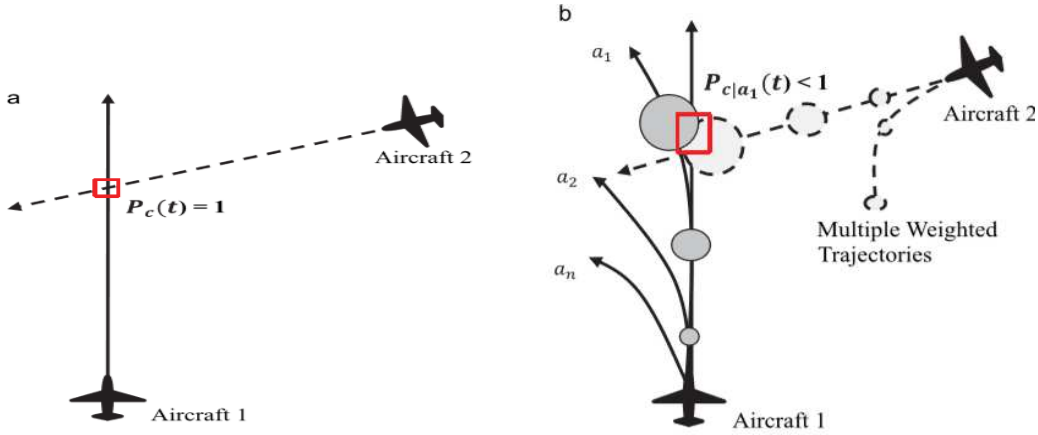

Fig. 2. Example conflict detection concepts using state propagation to estimate conflict probability Pc(t). [1c]

Applying conflict probability based approaches to vision-based systems is not straight forward, often leveraging additional sensors and filters (fusion) [6]. For vision-only systems that estimate relative state, the approach can be applied directly. Recent results demonstrate that the conflict of probability estimate is highly dependent on the filter performance. Additionally, calculating the conflict probability can take up to 3 s, reducing the available avoidance time [4]. For vision-based systems lacking relative state or intent information, the direct application of the conflict probability approach to the image space is not feasible. Essentially, a meaningless estimate for the conflict probability may be obtained. This is due to the generally unknown motion of the aircraft, sensitivity to state uncertainty, and the fact that multiple image positions (or the entire image) could have an equally likely collision probability. In an attempt to circumvent this issue, whilst retaining focus on using conflict probability metrics, the amount of time the object remains stationary in the image has been suggested as an alternate approach [12]. The collision probability is defined as

$$P_c(t) = \frac{1}{1 + \frac{1}{k-1} \sum_{i=k-N}^{k-1} (\alpha(k) - \alpha(i))^2}, \quad N \in Z^+ \quad (8)$$

where $\alpha(\cdot)$ is the relative azimuth and N is the number of past observations considered. The metric has shown marginal perfor- mance in simulation on a select set of encounters (head-on, overtaking). It is also unclear how to select N, and although robustness to measurement uncertainty is claimed, no analysis or evidence is provided. The approach does however explicitly
consider human navigation models in conjunction with aircraft collision avoidance design concepts.

Avoidance decision: Many aircraft systems, including the certified Traffic Alert and Collision Avoidance System (TCAS), use discrete logic to make avoidance decisions [11]. The logic is derived by placing one or more thresholds on the collision probability estimates in a tree-like (nested) decision structure. Multiple prescribed avoidance actions are generally considered in the collision probability estimates, but often refined to a limited set of vertical climb, descend and level-off manoeuvres subject to aircraft performance limitations [7]. Some extensions including prescribed lateral (left and right) avoidance manoeuvres have also been considered .

The resulting decision policy is often complex with multiple stages, but can be designed to be conservative, delayed or delayconservative . The nomenclature stems from the differences in sensitively regarding the time at which the resulting avoidance decisions are issued. In any case, the decision policy is derived using an iterative process. The logic structure and associated thresholds are specified, evaluated on simulated encounters, and then further refined using a set of statistical performance metrics to visualise performance variations. In fact, the evaluation process is based on derivatives of Receiver Operating Curves (ROC), and include System Operating Curves (SOC) and System Performance Curves (SP). The curves capture a complete description of the decision threshold effects regardless of the system particulars, so may be extended to other avoidance decision frameworks.

More recently, Dynamical Programming (DP), Markov Decision Process (MDP) and Partially Observable Markov Decision Process (POMDP) techniques have been combined to better optimise the avoidance decision policy . The optimisation problem can be solved offline , online or in a hybrid approach . The result is an optimal logic table that maps the current state to an avoidance action (or lack thereof) [9]. Similar to traditional approaches, a discrete set of avoidance actions is considered. In contrast to traditional approaches, a reward structure (cost function) requires tuning instead of collision probability thresholds. Additionally, a comprehensive encounter model is required for logic optimisation. As with traditional conflict probability approaches, validation using statistical performance evaluation techniques such as System Operating curves would still be required for certification. Despite the optimality of recent approaches, the extensibility to vision-based See and Avoid systems is questionable. Computational complexity (and tractability) can be restrictive and com- prehensive encounter models for a mixed airspace environment are not readily available. Only recently have some approximations been derived using recorded radar data [10]. More importantly, they do not perform well when applied to angle-only sensors, inducing unwanted oscillatory avoidance behaviour. Given the limited avoidance time available in See and Avoid encounters, this may not be acceptable. Traditional conflict probability approaches do not suffer from these negative effects, and can still approximate the optimal logic reasonably well [3c]. The inherent overhead using an iterative approach to refine the logic can also be reduced, by minimising the number of variable design parameters and thresholds. As such logic designs and associated performance evaluation methods were used in the certification of current systems, they may offer an attractive framework in which to design avoidance logic for vision-based See and Avoid systems.

Avoidance control: Considering that an onboard pilot is usually assumed with many aircraft collision avoidance systems, the avoidance decision can be implemented either manually or automatically. At a high level, the avoidance control is implemented in an open-loop manner whereby a prescribed avoidance manoeuvre from a discrete set is implemented and maintained until a revised action is issued. The prescribed actions are quantitative in the sense they are made up of both direction (up, down, level-off, left, right) and magnitude defined by an achievable rate (i.e. ± 1500ft/s,
±6°/s, etc.) for common aircraft types [12]such that

$$\mathbf{u} \in \{\mathbf{u}1, \ldots, \mathbf{u}j\}, j \in Z+ \tag{9}$$

At a low-level, the specific action is implemented in a closed-loop manner to establish and maintain the required vertical rate. If automated, onboard autopilots are used. If manual, the pilot reg- ulates the corresponding rate using onboard instrumentation and available control inputs. Similar to human navigation, the avoidance control does not use path planning or other optimal control approaches. In contrast to human navigation, the localised controller regulates both the direction and the rate to move toward a specific reference value.

4. CONCLUSION

Designing and certifying vision-based See and Avoid systems is a challenging task that remains in the developmental stage worldwide. The review presented in this paper highlights design, implementation and performance evaluation considerations for automated systems in light of existing approaches, regulatory restrictions and realistic expectations regarding the operating environment. The structure of the review offers a unique perspective on See and Avoid systems for potential researchers and system designers, with the intention of providing a solid foundation in which to stem further research and development. The review represents a particularly useful contribution toward the progression of automated See and Avoid systems.

4. LITERATURE LIST

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