A mid-air collision warning system: Vision-based estimation of collision threats for aircraft

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Abstract
This paper describes a vision-based technique for predicting whether non-cooperative moving objects are possible collision threats. The technique predicts the time to minimum separation (TMS), as well as the absolute minimum separation (AMS), to identify object(s) that pose a threat based on a predefined safe separation zone. Theory demonstrates how the TMS can be estimated by measuring changes in the target’s angular visual position as captured by the on-board vision sensor. Furthermore, we show how the AMS can be estimated from the calculated TMS and the size of the object’s image. The performance of the technique is demonstrated through simulations, as well as in outdoor field tests using a rotorcraft.

1 Introduction
Collision avoidance is a key factor in enabling the integration of Unmanned Aircraft (UA) into commercial airspace – be it in civilian or military applications [Pham et al., 2015]. When implementing collision avoidance, one must first establish an early warning system that determines potential conflicts in airspace – for example, Aircraft Warning System(s) (AWS). Given such a system, which could ideally rank surrounding obstacles (e.g. aircraft, people, trees, structures, etc.) based on collision threat, a template for avoidance theory can be established.

A review of mid-air collisions between 1961 and 2003 [ATSB, 2004] outlines that the probability of a near miss between aircraft substantially increases in high-density airspace. Therefore, strict rules and regulations have been introduced, and are being continuously updated, to minimise the risk of mid-air collisions [Mcfadyen and Mejias, 2016]. Given the larger scale application of AWS in manned airspace, such as the Traffic Alert and Collision Avoidance System (TCAS) and an Automatic Dependent Surveillance-Broadcast (ADS-B) [Griffith et al., 2008; Stark et al., 2013; Mcfadyen and Mejias, 2016], we can see the benefits of adapting such systems to handle the smaller, cluttered environments that are most likely to be occupied by small Unmanned Aircraft Systems (UAS). [Hobbs, 1991] states that without such systems, the risk of mid-air collisions would increase by factors of 34 and 80 for en-route and terminal areas, respectively. A system with the capability to predict and prevent collisions or near misses between aircraft is an important step towards ensuring equivalency with current aviation systems, enabling integration of UA into airspace.

UAS have demonstrated their strengths for applications such as scientific data gathering, surveillance, forest fire monitoring and military reconnaissance [Lee et al., 2004; Stark et al., 2013]. Many of these applications require low altitude flight, which introduces additional hazards such as pedestrians, trees, power lines etc. Therefore, traditional flight paths and collision warning systems are unreliable, and often unavailable.

While current regulations are well defined for light and commercial aircraft, working with small UAS will require further certification. Currently, there is limited trust in the operation of UAS, where remotely piloted aircraft rules, such as visual line of sight in flight, are imposed for safety reasons until we reach a level of true autonomy and trust in UAS. Consequently, the future of drone automation in civil airspace will be heavily dependent on the availability of aircraft warning and avoidance systems, and these systems must comply with the safety standards of current piloted aircraft.

Current safety standards for large commercial aircraft generally involve cooperative AWS (where all aircraft have knowledge about other aircraft in the vicinity – based on satellite Global Positioning Systems (GPS) and transponder communication). Some of the major cooperative methods currently used in manned airspace are TCAS and Traffic Advisory System (TAS), which rely on transponder communication between aircraft, and ADS-B (satellite-based GPS for aircraft location) [Hobbs, 1991; Griffith et al., 2008; Hottman et al., 2009].
Cooperative systems have demonstrated their safety and reliability through stringent regulations, and years of research and testing. However, they require all participating aircraft to have the same technology on-board. This is a significant disadvantage that prevents use on smaller, light-weight aircraft where size, weight, power and cost are key factors [Hottman et al., 2009]. Other disadvantages include inability to detect ground-based obstacles such as terrain and urban structures. Thus, in the context of UAS or light aircraft operating in residential or commercial airspace, it is desirable to implement reliable non-cooperative collision avoidance strategies – where aircraft act individually based on their own sensing mechanisms, without relying on information passed between nearby aircraft from any central infrastructure.

Non-cooperative systems have the advantage that they do not require communication between the conflicting aircraft. Furthermore, they have the capacity to detect not only airborne threats, but also ground-based vehicles and structures. These non-cooperative systems can be classified into (i) active systems that use radar, laser, and sonar systems to detect obstacles [Lee et al., 2004; Griffith et al., 2008; Hottman et al., 2009], and (ii) systems that employ passive sensing, using Electro-Optical (EO) or Infra-red (IR) technology [Griffith et al., 2008; Hottman et al., 2009; Harmsen and Liu, 2016]. EO and IR sensors have the advantage of low power and weight [Griffith et al., 2008; Harmsen and Liu, 2016].

When considering AWS, the ability to judge the time to collision/contact (TTC) with sufficient Time For Evasion (TFE) is a desirable trait [Lee, 1980], especially in autonomous systems that navigate in cluttered environments. TTC has been used to assess conflict scenarios in many vision-based approaches. The time to contact an object that is on a direct collision course can be estimated by computing the ratio of the angular size of the objects’ image to the rate of expansion of the image (e.g. [Lee, 1980; Lee et al., 2004]). This calculation of TTC does not require information about the absolute size of the object, or the velocities of the aircraft and the object.

The key variables being measured for this computation are the angular size of the object’s image, and the rate of its expansion. While these variables can be used to predict the TTC accurately when the angular size of the object’s image is large, they become imprecise and impractical when the image is initially small for a long time, and then begins to expand rapidly when sufficiently close to the time at which collision occurs. This is dangerous, as looming cues allow little TFE. Furthermore, it does not provide information on whether the encounter will actually result in a collision or a near miss, and if it is a near miss, what the minimum separation will be. The method we propose here addresses these problems, and provides an estimate of the Time to Minimum Separation (TMS), as well as the Absolute Minimum Separation (AMS). The technique also allows us to rank threat levels during flight in the vicinity of several UAS, based on calculations of the TMS and the AMS for each of the aircraft in the vicinity.

The performance of our system is validated through simulations (both in MATLAB and our realistic virtual environment), as well as through field tests using a ground and an airborne vehicle (in this case, a rotorcraft). We use a vision system as the primary sensor, due to its low cost, weight, and multi-functionality (e.g. egomotion computation and target detection).

The paper presents the problem definition in section 2. The theory, and the implementations in simulations and field tests are then discussed in sections 3, 4, 5 and 6. Finally, sections 7, 8, 9 and 10 discuss the limitations, applications and advantages, and future scope of the method.

2 Problem Definition

We develop a method, which uses a vision-based geometrical approach, to compute the Time to Minimum Separation (TMS) and the Absolute Minimum Separation (AMS). TMS and AMS provide valuable information that can be used to predict scenarios including near misses, i.e. for trajectories that produce a near miss but not a collision, as well as safe, distant fly-bys. Furthermore, this approach enables a UAS to theoretically estimate in advance the AMS between itself and all of the aircraft operating in its vicinity. Using this information, we can determine collision avoidance strategies by ranking levels of threat. One strategy to obtain a quantitative threat measure would be to rank the various aircraft – first by TMS, and then by AMS – once the AMS has been estimated reliably. The focus of this paper is the theoretical derivation of TMS and AMS, and the testing of the feasibility of this approach for early warning of near-misses.

Our analysis makes the following assumptions:

1. The velocity of the UAS and the conflicting targets are constant. This is reasonable given that, at least for relatively small time scales, most aircraft will maintain a constant heading and velocity when flying along pre-defined trajectories.

2. It is assumed that the target has been detected, and that its bearing can be computed – only the bearing to the target is required for our algorithm to compute TMS.

3. The instantaneous absolute range to the target can be directly sensed, or inferred.
3 Theory

The following sections describe the derivation of the theory for TMS, as well as the calculation of AMS using instantaneous range information.

3.1 Time to Minimum Separation (TMS)

The theory is based on a geometrical approach, similar to a method conducted by [Han and Bang, 2004] and [Park et al., 2008]. However, both of those approaches assume prior knowledge about the state of the conflict (near-miss) UAS, including its position and velocity. For example, [Park et al., 2008] assume the availability of a system such as ADS-B. Our approach uses only on-board vision, and does not rely on ADS-B. Additionally, our approach takes into account scenarios where (i) both the target and the aircraft are moving; (ii) the target is stationary and the aircraft is moving; and (iii) the aircraft is stationary and the target is moving. We first develop our algorithm for flight in a 2D plane, and show that TMS can be determined by non-cooperative means. We then extend the algorithm to provide a full 3D solution.

![Figure 1: Illustration of the constant velocity trajectories of the rotorcraft and conflict UAS in the x-y plane.](image)

A typical scenario is illustrated in Figure 1 where we assume, for simplicity, that each aircraft can be represented by a point object. We can then define the following equations to determine the variation of the x and y separation between the rotorcraft and the conflict UAS as a function of time:

\[
x = (x_{R_o} - x_{C_o}) + (V_{x_C} - V_{x_R})t = x_o + V_xt \tag{1}
\]

\[
y = (y_{C_o} - y_{R_o}) + (V_{y_C} - V_{y_R})t = y_o + V_yt \tag{2}
\]

Where: \(x_{R_o}\) and \(x_{C_o}\) are the initial x positions of the rotorcraft and the conflict UAS at \(t = 0\), respectively; \(V_{x_R}\) and \(V_{x_C}\) are the x velocities of the rotorcraft and the conflict UAS, respectively; \(x_o\) is the initial x separation between the two aircraft at \(t = 0\); and \(V_x\) is the relative x velocity between the two aircraft. Equation (2) describes the corresponding relationships along the y axis. \(t = 0\) is considered to be the current time, where events in the past occurred at \(t < 0\) and those in the future, at \(t > 0\).

The instantaneous separation \(r\) between the two aircraft is given by:

\[r^2 = x^2 + y^2 = (x_o + V_xt)^2 + (y_o + V_yt)^2 \tag{3}\]

Which can also be expressed as

\[r^2 = x_o^2 + y_o^2 + 2t(x_oV_x + y_oV_y) + (V_x^2 + V_y^2)t^2 \tag{4}\]

The time to minimum separation (TMS) is obtained by setting \(\frac{d(r^2)}{dt} = 0\) in (4) and solving for \(t\). This gives

\[
TMS = -\frac{(x_oV_x + y_oV_y)}{(V_x^2 + V_y^2)} = -\frac{\left(\frac{y_o}{x_o}\right)\left(\frac{V_y}{V_x}\right)}{1 + \left(\frac{V_y}{V_x}\right)^2} \tag{5}
\]

Here we show that TMS can be estimated without prior knowledge of \((V_x, V_y)\), as follows. From Figure 1, we note that the slope \((\tau)\) of the line connecting the two aircraft is

\[
\tau = \tan(\theta) = \frac{y}{x} = \frac{y_o + V_yt}{x_o + V_xt} \tag{6}
\]

We use a rearranged version of equation 6, as shown below:

\[(x_o + V_xt)\tau = y_o + V_yt \tag{7}\]

which can be rewritten as

\[
\left(\frac{y_o}{x_o}\right) + \left(\frac{V_y}{x_o}\right)t - \left(\frac{V_x}{V_y}\right)t\tau = \tau \tag{8}\]

By sampling three consecutive bearing measurements of the conflict UAS at three points in time \((t_1, t_2, t_3)\), we can construct a system of linear equations from (8), as follows.

\[
\begin{bmatrix}
1 & t_1 & -t_1\tau_1 \\
1 & t_2 & -t_2\tau_2 \\
1 & t_3 & -t_3\tau_3
\end{bmatrix}
\begin{bmatrix}
\alpha_{xy} \\
\beta_{xy} \\
\gamma_{xy}
\end{bmatrix}
= \begin{bmatrix}
\tau_1 \\
\tau_2 \\
\tau_3
\end{bmatrix}
\]

where \(\tau_i \equiv \tan(\theta_i) \in [1, 2, 3]\);

\[
\alpha_{xy} = \frac{y_o}{x_o}; \beta_{xy} = \frac{V_y}{x_o}; \gamma_{xy} = \frac{V_x}{x_o} \tag{9}
\]

The above \(3 \times 3\) system of linear equations can be solved to estimate \(\alpha_{xy}, \beta_{xy}\) and \(\gamma_{xy}\). These can then be inserted into (5) to obtain the estimated value of the time to minimum separation, \(TMS_{Est}\):

\[
TMS_{Est} = -\frac{\left(\frac{1}{\gamma_{xy}}\right)\left[1 + \alpha_{xy}\left(\frac{\beta_{xy}}{\gamma_{xy}}\right)\right]}{1 + \left(\frac{\beta_{xy}}{\gamma_{xy}}\right)^2} \tag{10}
\]
3.2 Absolute Minimum Separation (AMS)

Assuming that we know the current range to the conflict UAS (and therefore \( x_o \) and \( y_o \), from knowledge of the target bearing), we can insert these values into (4) to estimate the absolute minimum separation (AMS), as follows:

\[
\text{AMS}^2 = x_o^2 + y_o^2 + 2(\text{TMS}_{\text{Est}})
\]

\[
(x_o V_x + y_o V_y) + (V_x^2 + V_y^2)(\text{TMS}_{\text{Est}})^2
\]  

(11)

where:

- \( x_o \) & \( y_o \) are the x and y separations between the rotorcraft and the conflict UAS (current range);
- \( V_x = \gamma_{xy} \times x_o \);
- \( V_y = \beta_{xy} \times x_o \);

3.3 Extension of Theory to 3D

The derivation of TMS for the 3D situation is analogous to the 2D case. We note that:

\[
\text{AMS} \equiv \text{AMS}^2 = x_o^2 + y_o^2 + z_o^2 + 2(\text{TMS}_{\text{Est}})
\]

where:

\[
(x_o V_x + y_o V_y + z_o V_z) + (V_x^2 + V_y^2 + V_z^2)(\text{TMS}_{\text{Est}})^2
\]  

(12)

3.4 Special Cases

If the absolute bearing of the target is constant over time, the three equations in (9) will be identical, hence the matrix will be singular. This condition represents one of three possible situations: (i) If the angular size of the target is constant, the range of the target is constant. This implies that the target is moving in the same direction and at the same speed, which can be classified as non-threatening, requiring no further action. (ii) If the angular size of the target decreases steadily, the target is receding from the UAS – also classified as non-threatening. (iii) If the angular size of the target increases steadily, the target is approaching the UAS on a direct collision course. This is obviously a severe threat. The instantaneous distance to the target (and the rate of decrease of this distance) can be inferred from the rate of change of the target’s angular size. The TTC can then be inferred from this information, or even without knowledge of the object’s absolute size by using well established methods for estimating the TTC (e.g. [Lee, 1980]). Methods for dealing with these special cases are well established. Our study focuses instead on near-miss scenarios, where it is important to assess the threat level by estimating the TMS and the AMS.

4 Implementation

This section describes the implementation of our method for estimation of TMS and AMS for the virtual environment and outdoor field tests. To estimate TMS and AMS the following information is required: the aircraft’s egomotion, location of the target in the image and the distance to the target.

Our vision system computes the egomotion of the rotorcraft using an optic flow and stereo technique, as detailed in [Strydom et al., 2014; Thurrowgood et al., 2014]. Object detection (and visual bearing computation) is based on a colour detector, utilised for its simplicity in the same manner as step (ii) and (iii) in section 3 of [Strydom et al., 2015]. We assume that the physical size of the object is known, which allows us to compute the instantaneous range to the target from the angular size of the object in the image – similar to [Molloy et al., 2014]. This computation is important for the estimation of AMS. Alternative methods such as radar can also be used, if available, for range and bearing estimation. Note that the focus of this research is not target detection per se, but rather to demonstrate the validity of our theory to compute TMS and AMS.

5 Validation

In this section, we describe the validation of the theoretical derivations through simulations, initially in a MATLAB environment (important for estimating TMS (14),...
and AMS (15) in a real time setting and with simulated noise) and then in a flight simulator (incorporation of the rotorcraft’s dynamics, and visual detection of a conflict UAS (represented by a red ball), including realistic simulations of noise at various levels of the system). These tests provide a comprehensive understanding of the prediction of these parameters at distances larger than 20m – in comparison to the field tests where the ball is detected at approximately 5m.

5.1 MATLAB Implementation
For the system to effectively rank threats from multiple aircraft, an initial simulation in real-time was conducted in MATLAB, as a proof of concept. The simulation used a single-point representation of the rotorcraft and 3 different conflict UAS (Figure 2). For each trial, the (constant) 3D velocity of the rotorcraft and the conflict UAS' were specified by a random number generator. As the purpose of this exercise was to validate the basic theory, the aircraft dynamics were omitted.

Figure 2: Illustration of trajectories of a rotorcraft (red) and 3 conflicting UAS (blue): T1, T2 and T3. T2 has a negative TMS, and therefore poses no threat. T1 is positive and thus represents a potential threat. However, the threat level (as defined by the minimum acceptable separation) is negative and does not require action. T3 has a positive TMS and exhibits a positive threat level, and therefore requires an evasive manoeuvre.

Calculation and Plotting of TMS and AMS
First, an initial moving window is defined to sample the bearing information of visible targets. In theory, three bearings, sampled at three different times, are required for estimating the TMS (See Theory Section). We set a window size larger than the minimum 3 bearing window, and solve for the TMS using a pseudo-inverse approach. In this example, a window size of 9 was selected as a 3 × 9 pseudo-inverse demonstrated reliable results. Figure 3(a) compares the theoretical calculation of TMS (14) and AMS (15) with the running real-time TMS and AMS for the target posing the highest threat – the smallest AMS – (T3) from Figure 2 under no simulated noise. Note the delay in estimation of 9 frames (0.4 sec) due to the selected window size.

Figure 3: Comparison of running estimate of TMS and AMS under (a) no noise and (b) with noise against the theoretically expected values for T3. The dashed red lines denote the point of minimum separation. Note that the AMS value remains constant, as expected. Shaded region represents a possible reliable detection zone.

It is clear from Figure 3(a) that the technique correctly predicts the theoretical TMS and AMS – the theoretically expected values of TMS (magenta) and AMS (red) are overlaid perfectly by the estimated TMS (blue) and AMS (green). Following this initial proof of concept, simulated noise is added to the measurements of the bearings and ranges. Figure 3(b) illustrates the results obtained for flight trajectory T3 when noise of ±0.05° and ±0.5m is added to the bearing and range measurements, respectively.

Refinement of Technique
While the initial results are promising, they also reveal a sensitivity to noise, particularly in situations where the initial target bearing varies slowly with time. It is evident that the estimated TMS and AMS begin to show good agreement with the theoretically expected values just a few seconds prior to the instant of minimum separation, as shown by the shaded section in Figure 3(b). The reason for this is that when the target is far away,
its angular bearing slowly changes and is buried in the noise, leading to noisy and unreliable computations of the pseudo-inverse. The time at which the running estimates of TMS and AMS first become reliable (as shown by the left boundary of the grey section) defines the instant at which a reliable alert can be issued, and an evasive response undertaken. We call the temporal width of the grey box the Time for Evasion (TFE). The TFE specifies the time that is available for the execution of an evasive response.

Fortunately, as we shall show below in the flight simulator tests (section 5.2), pre and post filtering methods can be used effectively to reduce some of the compounded error in the estimates of TMS and AMS. To improve the efficacy of pre and post filtering, (i) The temporal separation between the sampled bearings is increased from 1 to 6, in order to register larger changes of the target bearing. The 9 bearings required for the pseudo-inverse computation are now sampled at frames [1, 7, 13, 19, 25, 31, 37, 43, 49], resulting in a window size of 49. (ii) A second order polynomial fit is performed on the 9 target bearings measured over this window, to obtain more reliable bearing estimates. (iii) A running 49-point median filter is used to post-filter the pseudo-inverse results to obtain the TMS and AMS estimates. While these operations reduce the noise, they also introduce a delay in the calculation of TMS and AMS. The selected window size of 49 is the smallest optimal window given a test from 9 through to 99 frames. It was evident that a larger TFE was determinable at 49 frames and above, thus this window size was selected to induce the smallest delay (1.96 sec before the first pseudo-inverse result becomes available). Furthermore, the post-filtering introduces another 1.96 second delay before the first median values of TMS and AMS are generated. Thus, there is a 3.92 sec delay between the acquisition of the first target bearing sample, and the generation of the first filtered values of TMS and AMS.

### Evaluation of Potential Threats

To determine the potential threat from a UAS, we first examine whether the computed TMS is positive or negative. If the TMS is negative, this implies that the minimum separation would have already occurred in the past, so that this UAS is no longer a threat (e.g. trajectory T2 in Figure 2). It is only the aircraft that generate positive TMS values that imply potential future threats; these are the only aircraft that need to be considered further. We can rank the threat level of these aircraft by computing a threat level parameter:

\[
\text{Threat Level} = (\text{Safety range} - \text{AMS})
\]

The safety range is the minimum allowable separation between the two aircraft, for a safe fly-by. Thus, a threat exists if TMS > 0, and the threat level is positive; the more positive the threat level, the greater the threat (e.g. trajectory T3 in Figure 2). A positive threat level close to (safety range) implies a near-direct collision, because the AMS is then very close to zero.

### 5.2 Virtual Environment

This section describes the implementation and results of our method for estimation of TMS and AMS in a virtual environment of a rotorcraft encountering a single moving target. The simulation incorporates the effects of realistic noise in the vision system, as well as the dynamics of the rotorcraft. The Open Scene Graph ¹ environment encapsulates the vision system of the rotorcraft.

#### Set-up and Testing

![Figure 4: (a) Panoramic image acquired by vision system in the virtual environment, showing the object (red sphere). (b) Illustration of virtual environment scenarios.

The target was a virtual red sphere of known size (radius 1.5m set large to facilitate visual detection at large distances) moving in the environment with a defined velocity vector. To simulate a real-life flight scenario the object was placed on the ground level, with its movement in the ground (x-y) plane. The rotorcraft’s height (z) can be set to any desired value, but was chosen to be 3 metres above ground to ensure reliable detection of the ball. The algorithm used in the MATLAB study described above was implemented in the virtual implementation. Figure 4(a) shows a view of the environment, as captured by the simulated vision system.

¹http://www.openscenegraph.org/
Following this, set trajectories for the movement of the red sphere (representing a conflicting UAS) were tested against the forward movement of the rotorcraft. These trajectories were selected to test a range of conflicting scenarios with the forward moving rotorcraft (Figure 4(b)). 10 virtual flights for 7 trajectories (70 trials) – with set constant velocities of 1.0 m·s\(^{-1}\) and 1.2 m·s\(^{-1}\) for the rotorcraft and conflict UAS, respectively – were conducted. It is clear that these trajectories would be equivalent, by symmetry, when they are reflected in the left-right and up-down quadrants (x-y and x-z planes). Hence, there is no need to examine target trajectories originating from all four quadrants.

**Results and Discussion**

Figure 5 shows an example of the evolution of the mean estimate of TMS (blue) and AMS (green) for Trajectory two, averaged over 10 flights. As time proceeds, the estimates of TMS and AMS approach the theoretical values (magenta and red, respectively), and the variability (standard deviation) is progressively reduced. The deviation of the estimated AMS during frames 350-500 is due to local warping in the centre of the stitched panoramic image, which introduces an error in the estimate of the size of the object’s image, and therefore of its range.

Figure 6(a) shows the time course of the RMS error in the estimate of the TMS for each of the 7 trajectories, averaged over 10 runs for each trajectory. For each trajectory, the mean RMS error at each time point is defined as the RMS deviation of the estimated TMS profile from the theoretically expected profile, averaged over a time window extending from the current frame to the frame at which the separation is a minimum. It is evident that the RMS error drops to a value below 1.0 sec at a time that is 183 frames (7.32 sec) ahead of the true TMS, for all trajectories except for Trajectory 1.

Figure 6(b) shows the time course of the RMS error in the estimate of the relative AMS (RMS error normalised to the true value of the AMS) for each of the 7 trajectories, measured over 10 runs for each trajectory. It is evident that the RMS error drops to a value below 0.5 at a time that is 194 frames (7.76 sec) ahead of the true TMS for all trajectories.

These results indicate that the estimated TMS comes to within 1 sec of its true value, and the estimated AMS comes to within 50% of its true value, at about 7.3 and 7.8 sec, respectively, prior to the instant of minimum separation. In other words, the TFE is 7.3 sec – taking the worst case. We note that Trajectory 1 in Figure 6(a) displays a consistently high error. This can be attributed to a small change in the target’s bearing from frame-to-frame. Figure 6(c) shows the evolution of the frame-to-frame change in theta (\(\Delta \theta\)) for each of the 7 trajectories. It is evident that the reliabilities of the TMS & AMS estimates improve as the trajectories become

Figure 6: (a) Mean RMS error curves for each trajectory tested (TMS). Note, the lowest threshold value (1.0 sec) detected at 183 frames to minimum (approximate TFE of 7.32 sec). (b) Mean RMS error curves for each trajectory tested (relative AMS). Note, the threshold value (0.5) detected at 194 frames to minimum (approximate TFE of 7.76 sec). (c) Mean change in the dominant visual angle (Theta) per frame for the 7 scenarios.

Figure 5: Virtual environment mean evolution of TMS and AMS estimates for trajectory two after 10 flights.
more orthogonal. It is also shown that $\Delta \theta$ increases to a value above $0.1^\circ$ at about 200 frames prior to the time of minimum separation for trajectories 2, 4, 5, 6 and 7 (and at about 140 frames for trajectory 3). Thus, $0.1^\circ$ can reasonably be assumed to be the threshold value for reliable detection of $\Delta \theta$, and hence, for reliable computation of the TMS and AMS. In the case of trajectory 1, $\Delta \theta$ stays constant at a value close to or below $0.1^\circ$ throughout the trajectory – thus causing the motion of the target to be camouflaged, as the absolute bearing of the target is nearly constant [Srinivasan and Davey, 1995]. This explains the consistently high RMS error in the TMS estimates for this case (Figure 6(a)).

The results of Figures 6 (a) and (b) indicate a TFE of 7.3 sec, which is a reasonable window of time in which to execute an evasive action, given the low speed and high manoeuvrability of the rotorcraft.

6 Field Tests

This section describes preliminary field tests.

A custom built rotorcraft was used (see Figure 7(a)). The rotorcraft incorporates a MicroKopter flight controller, with supplied motor and speed controllers. An on-board Intel NUC – featuring an Intel i5 core 2.6GHz dual core processor, 8GB of RAM and a 120GB SSD (to save the on-board video stream) – is used to process the data obtained by the vision system and other sensors, including a MicroStrain 3DM-GX3-25 Attitude and Heading Reference System (AHRS), in real time.

The vision system consists of two cameras positioned back-to-back (Point Grey Firefly MV) with wide-angle lenses (Sunex DSL216), which endows it with a near-panoramic field of view (FOV). The synchronised cameras have a frame rate of 25 frames per second, and are calibrated as described in [Kannala and Brandt, 2006]. This calibration is then used to create a single stitched panoramic image with an approximate 360° by 150° (360 by 220 pixel resolution) FOV.

The conflicting target was a 0.8m diameter red sphere (Figure 7(b)) carried by an Unmanned Ground Vehicle (UGV) (Jackal, Clearpath Robotics), programmed to move along predefined trajectories at speeds ranging from 0.5 m·s$^{-1}$ to 2 m·s$^{-1}$.

![Figure 7: (a) The flight platform and (b) the ground vehicle used in the field tests.](image)

![Figure 8: Field test set-up and ground truth data.](image)

The target was set to move in a linear trajectory at a velocity of approximately 0.5 m·s$^{-1}$ in the $-x$ direction. The rotorcraft was set to a hover at position $x$: 4m, $y$: 3m and height: 3m from the starting location of the target (Figure 8). This scenario was selected because the theoretical minimum separation is easily calculated to be the perpendicular distance from the target’s trajectory to the rotorcraft, which is 3.6m in 3D. This also provides a quasi ground truth as image location of the target at the minimum point of separation is known – pixel (275, 152) of the 360 by 220 stitched image.

A theoretical TMS was calculated based on manual observation of the number of frames from the start to the time of minimum separation. Figure 9(a) compares this theoretical TMS with the TMS estimates obtained in the field test. A similar process was followed for the AMS, where the theoretical value was approximately 3.6m (Figure 9(b)).

Results and Discussion

As illustrated in Figure 9(a), the estimated TMS begins to match the theoretical expectation approximately 4 sec prior to the instant of minimum separation (shaded region). The initial noise can be attributed to the window size delay (discussed in Section 5.1) and the UGV ramping up to a constant velocity, where the initial acceleration, although small, can induce a small amount of error. It is evident that accurate estimates of AMS (Figure 9(b)) begin to appear at approximately the same time that TMS becomes reliable – approximately 4 sec prior to the instant of minimum separation. The system, therefore, delivers an advance warning that allows a TFE of 4 sec, under these experimental conditions, which would be sufficient for a UAS to react at the low speeds experienced in this scenario. Note that the estimated AMS deviates slightly from the theoretically expected value during frames 180-250. This is due to harsh environmental lighting conditions, which can occasionally cause errors in the precise localisation of the target and in the estimate of its image size, leading to errors in the estimates of target bearing and range.
Figure 9: Results of field test, comparing running estimates of TMS (a) and AMS (b) with the theoretical values (based on manual frame observation and ground truth measurement).

7 Limitations

While our approach shows promising results, we need to keep in mind the following limitations of the technique:

(i) Because the system relies on vision, it will not operate at night or in a white-out, unless the standard video camera is replaced by a low-light functioning camera, an infra-red camera or a completely different sensor, such as radar.

(ii) The process of estimating TMS and AMS can be commenced only after the target is detected visually, and is therefore, limited by the size of the target, the resolution of the vision system, and the noise level in the image.

(iii) The method relies on measuring changes of absolute bearing of the target over time. Typically, these changes will be small when the target is far away, so reliable estimates of TMS and AMS will start to be obtained only when $\Delta \theta$ between successive sampling instants can be reliably measured against the background visual noise. In our case, reliable estimates of $\Delta \theta$ (and hence of TMS and AMS) start to occur approximately 7.3 sec prior to the time of minimum separation. This is adequate for slow-moving, manoeuvrable aircraft (such as a rotorcraft), but can be problematic for high-speed commercial aircraft. Improvements to image stability (e.g. compensating for image motion by tracking pixel intensity changes between frames), and target detection [Mejias et al., 2016] can improve noise levels for better estimations at further distances.

8 Advantages and Applications

(i) Our system provides a means for evaluating collision threats that relies purely on vision, and therefore, does not require active sensing that can be heavy, bulky, expensive and not easily carried by small drones. Moreover, military applications that require stealth prefer to rely on passive sensing.

(ii) The system can be readily incorporated into any aircraft that already carries a vision system (e.g. for the purpose of surveillance or navigation).

(iii) Our method provides reliable estimates of the AMS when the target is not on a direct collision course. This information cannot be provided by methods that compute pure TTC.

(iv) The system is stand-alone, and does not rely on information from, or communication with, any external sources – such as GPS, other aircraft, or a centralised aircraft monitoring and control authority. Thus, it can be used in many low-cost private applications, such as light planes, gliders, and recreational aircraft.

(v) The approach is not restricted to vision sensors: other sensors if available, such as radar, can be used instead.

9 Future Work

Future work will include: (i) Extensive field testing to establish criteria for deciding when the estimates of TMS and AMS are sufficiently reliable, consistent with an adequate Time for Evasion (TFE). (ii) Utilising higher resolution image frames to enable target detection at larger distances, and reliable measurement of smaller changes in absolute bearing. (iii) Improvement of image stabilisation. (iv) Improved signal filtering, e.g. recursive Kalman filtering. (v) Extension of the theory to take into account accelerations of target and aircraft, as current work assumes constant speeds.

10 Conclusions

The key contribution of this paper is to provide a proof of concept and performance evaluation of a vision-based method for estimating the Time to Minimum Separation (TMS), using only the visual bearing, and the Absolute Minimum Separation (AMS) between two aircraft. The technique also allows the ranking of threat levels of several conflicts, based on calculations of the TMS and the AMS for each of the aircraft in the vicinity.

We have tested and evaluated the performance of the system in three ways: (i) MATLAB simulations; (ii) Tests in an Open Scene Graph environment, incorporating a realistic vision system and flight dynamics; and (iii) Initial field tests.

If we assume that the estimates of TMS and AMS are acceptable when they are within 1 second and 50% of their true values, respectively, our system delivers an advance warning that allows a Time for Evasion (TFE)
of 7.3 sec, which would, in general, provide the time required for a UAS to avoid a potential near-miss or collision — in particular for low-altitude/low-speed situations as demonstrated in this paper.

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**References**


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