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An Evasive Maneuvering Algorithm for UAVs in See-and-Avoid Situations

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***Abstract*— In this paper, we present an collision avoidance algorithm for unmanned aerial vehicles (UAVs) based on model predictive control. When a UAV encounters other aircraft that is estimated to approach closer than the minimum safety margin, the vehicle must execute an emergency evasive maneuver to avoid the impending collision at all cost. During this procedure, the unmanned vehicle must compute in real time a safe and plausible trajectory based on the collected information on the predicted future path of other vehicles. During the evasive maneuver, the trajectory generation and control problem is very stringent since the conflict-free trajectory must be plausible with respect to the given vehicle dynamics with limited control input. Therefore, in this research, we propose a model predictive control-based trajectory planner to satisfy the requirements listed so far due to its capability to explicitly address the control problem of constrained nonlinear dynamic systems. We consider a few scenarios involving nearby flying objects with various velocity and incident angle conditions. The proposed algorithm is validated in a head-on collision scenario using unmanned aerial vehicles.**

I. INTRODUCTION

THE concept of a highly maneuverable, situation-aware UAV system demands a comprehensive flight control system that will actively sense the surrounding and make intelligent decisions to accomplish the given mission over an extended period of time, desirably with minimum intervention from remotely located human operators. In near future, it is expected that UAVs will be found as a ubiquitous surrogate for manned vehicles in the field of aerial sensing, ordnance delivery, and real-time battle damage assessment. In this context, the collision avoidance for UAVs becomes a crucial component technology since the vehicle is flying at low altitude where many obstacles such as terrain and buildings pose constraints in motion planning.

In order for a UAV to avoid any imminent collision with other vehicles or stationary objects on the ground, it should be capable of sensing, obstacle tracking, collision prediction, dynamic path planning and tracking control. For aerial collision avoidance, the vehicle should be equipped with active or passive sensing capability. In general, active sensing such as laser scanning or radar is more straightforward and accurate whereas, especially for covert missions, a passive method such as vision-based sensing will be more favored.

When the future trajectory based on the observation of nearby objects is identified, a safe trajectory free from collision should be computed and executed. There are a few available techniques for real-time path planning [1]-[4]. In the context of emergency evasive maneuver, one should expect that the vehicle may need to maneuver at its full dynamic capability, i.e., maximum turn rate, acceleration/deceleration, or climb/descent. In such case, the control inputs can be easily saturated or the vehicle states, such as roll angle or cruise velocity, may exceed the acceptable limits. In order to compute a trajectory that the vehicle can actually fly along without exceeding its dynamic range, the applied method should be capable of taking such limits into account. In this research, we favor a model predictive control (MPC) based approach due to their capability to explicitly address nonlinear dynamic systems with state constraints and input saturation, unlike most control theories available as now. One drawback of MPC is, as often pointed out, the heavy numerical load, which becomes reasonable with latest CPU technology as demonstrated in [4].

In this paper, we present an MPC-based collision avoidance algorithm for safe trajectory generation and control of constrained nonlinear dynamic system with input saturation in real-time. We also introduce realistic sensing range limit to the simulation. We consider a number of collision scenarios in one-on-one and one-to-many configuration optionally with surrounding terrain. A number of simulation results will be given and discussed. For validation, a flight test was performed using two helicopter UAVs in a head-on collision course.

II. REAL-TIME EVASIVE MANEUVERING USING MODEL PREDICTIVE CONTROL

In this section, we present the formulation of an MPC-based approach for real-time safe trajectory generation during an evasive maneuver for avoiding collision. We consider a scenario that, while a UAV flies to a given destination, a collision with nearby flying or stationary obstacles[1] is anticipated. We will not treat the theory of actual

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[1] In this paper, we sometimes refer the flying objects nearby that may impose any potential collision as *bogeys.*

detection of obstacles or tracking in this paper: the information is assumed to be acquired by onboard sensors or made available from other sources such as other cooperating vehicles or an eye-in- the-sky.

A. MPC Formulation

Suppose we are given a nonlinear time-invariant dynamic system such that

$$x(k+1) = f(x(k), u(k)) \tag{1}$$
$$y(k) = g(x(k)) \tag{2}$$

where $x \in X \subset \mathbb{R}^{n_x}, u \in U \subset \mathbb{R}^{n_u}$. The optimal control input sequence over the finite receding horizon N is obtained by solving the following nonlinear programming problem:

Find $u(k)$, $k = i, \ldots i+N-1$ such that

$$u(k) = \arg\min V(x,k,u) \tag{3}$$

where

$$V(x,k,u) = \sum_{i=k}^{k+N-1} L(x(i), u(i)) + F(x(k+N)) \tag{4}$$

where L is a positive definite cost function and F is the terminal cost. Suppose $u^*(k)$, $k = i, \ldots, i+N-1$ is the optimal control sequence that minimizes $V(x,k,u)$ such that $V^*(x,k) = V(x,k,u^*(x,k)) \le V(x,k,u)$, $\forall u(k) \in U$. The cost function term L is chosen such that

$$L(x,u) = \frac{1}{2}\left(x^r - x\right)^T Q\left(x^r - x\right) + \frac{1}{2}u^T R u + S(x) + \sum_{l=1}^{n_o} P(x, \eta_l) \tag{5}$$

The first term penalizes the deviation from the original course. The second term penalizes the control input. $S(x)$ is the term that penalizes any states not in X as suggested in [10]. Finally, $P(x_v, \eta_l)$ is to implement the collision avoidance capability in this MPC framework: $P(x_v, \eta_l)$ is a function that increases as $\| x_v - \eta_l \|_2 \to 0$, where $x_v \in \mathbb{R}^3$ is the position of the vehicle and η_l is the coordinates or l-th out of total n_o obstacles being simultaneously tracked. As well known, MPC-based approaches require online optimization. During this process, the control input can be enforced to meet the saturation requirement. It is done by enforcing

$$u_i(k) = \begin{cases} u_i^{\max} & if\ u_i > u_i^{\max} \\ u_i^{\min} & if\ u_i < u_i^{\min} \end{cases} \tag{6}$$

where $u \triangleq \left[u_1 \ \ldots \ u_{n_u}\right]^T$. In this manner, one can find the control input sequence that will be always within the physical limit of the given dynamic system. We use the optimization method based on indirect method of Lagrangian multiplier suggested in [9].

When an optimal control sequence is found at each epoch k, the control law is computed using

$$u(k) = u^*(k) + K\left(y^*(k) - y(k)\right) \tag{7}$$

where K is a explicit feedback control law, which can be found by approaches such as in [6]. With $u^*(k)$, $k = i, \ldots, i+N-1$, one can find $y^*(k)$, by solving recursively the given nonlinear dynamics with $x(i) = x_0(i)$ as the initial condition. Ideally, if the dynamic model used for solving the optimization problem perfectly matches the actual dynamics and the initial condition free from any disturbance, there should not be any tracking error. In real world, such assumption cannot be satisfied. Therefore, with a tracking feedback controller in the feedback loop, the system can track the given trajectory reliably in the presence of disturbance or modeling error. The architecture of the proposed flight control system is given in Fig. 1.

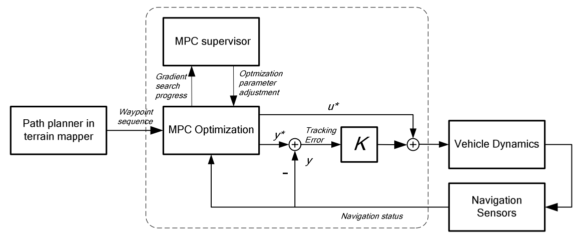


Fig. 1 Flight control system architecture with MPC and explicit feedback loop

B. Obstacle Sensing and Trajectory Prediction

Sensing for obstacle detection can be either active or passive and the choice depends on many factors such as operating condition, accuracy, and maximum detection range. Laser scanning method is very accurate and straightforward, so it is favored for short-range detection and three-dimensional mapping. However, as the detection range depends on the intensity of the light that radiates from the laser source, the range is usually no longer than a few hundreds of meters. Active radar has similar attributes since it operates in a similar principle: however, the resolution is much lower while the detection range is significantly longer. Both methods are not applicable when the mission should be a covert one. Therefore, vision-based methods have been favored as it is a passive sensing method. The ranging using 2-D cameras can be performed either by using stereo parallax or motion flow algorithms. In this work, we do not assume any coordination with other vehicles as such is not always available in realistic environment.

For collision avoidance, as validated in [5], we choose $P(x_v, \eta_l)$ in (5) such that

$$P(x_v, \eta_l) = \frac{1}{(x_v - \eta_l)^T G (x_v - \eta_l) + \varepsilon}, \tag{8}$$

where G is positive definite and $\varepsilon > 0$ is to prevent ill conditioning when $\| x_v - \eta_l \|_2 \to 0$. One can choose $G = diag\{g_x, g_y, g_z\}$, $g_i > 0$ for an orthogonal penalty function. The penalty function (8) serves as a repelling field and has nonzero value for entire state space even when the vehicle is far enough from obstacles. The crucial difference from the potential field approach here is that we optimize over a finite receding horizon, not only for the current time as in the potential field approach. For obstacle avoidance, we consider two types of scenarios: 1) a situation when the vehicle needs to stay as far as possible from the obstacles even if no direct collision is anticipated and 2) a situation when the vehicle can be arbitrarily close to the obstacle as long as no direct conflict is caused. For the second situation, one can choose to enable (8) only when $\| x_v - \eta_l \|_2 < \sigma_{\min}$, where $\sigma_{\min}$ is the minimum safety distance from other vehicles.

Since MPC algorithms optimize over the receding finite horizon into future, the predicted obstacles' trajectory over $k = i, \ldots, i + N - 1$ is needed in (8). It is anticipated that the inclusion of predicted obstacle locations in the optimization will produce more efficient evasion trajectory if the prediction is reasonably accurate. If the obstacle detection system is capable of estimating the current velocity in addition to the position of an obstacle, one can predict $\eta_l(k)$ by extrapolating it over N_p steps, namely *prediction Horizon*, using an equation such that

$$\eta_l(k+i) = \eta_l(k) + \Delta t v_l(k)(i-1), \tag{9}$$

It is noted that the prediction can be done in more elaborated way using a Kalman filter [7] if the dynamic characteristics is known at least partially in advance.

In this research, we propose a dual-mode strategy for the MPC-based flight control system. In normal flight, we choose a parameter set that achieves good stability and tracking performance. When the obstacle prediction algorithm using (9) predicts the trajectory of a bogey over next N steps approach the host vehicle's future trajectory within a cautionary margin σ_c where $\left\| \eta_l(k + N_p) - y(k + N_p) \right\| < \sigma_c$, the MPC-based controller is switched to the evasion mode, in which the parameter set in (5) tuned for effective evasive maneuver to generate a conflict-free trajectory, even at the expense of a large deviation from the original course or an aggressive maneuver with large control effort if necessary. The proximity penalty term is tuned to dominate the stability and tracking terms in L. The control effort is also less penalized to allow for more aggressive maneuver. This approach is illustrated in Fig. 2. Optionally, if the predicted future trajectories of the host vehicle and bogeys get closer within the absolute safety margin $\sigma_a < \sigma_c$, the proximity penalty gain can be increased to allow for more clearance margins. We will present the demonstration of the proposed idea so far in the following section.

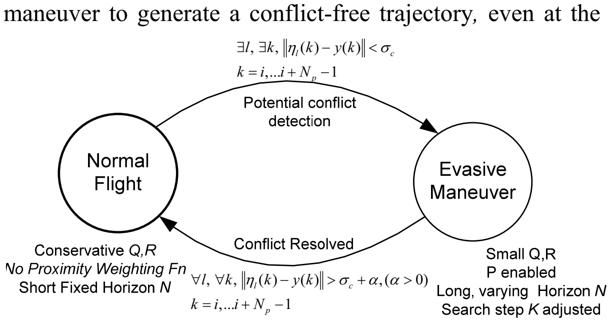


Fig. 2. State transition diagram for flight mode switching algorithm

III. Simulation and Experiments

In this section, we consider several exemplary scenarios that a UAV encounters another flying object. We take the following factors into consideration: approach speed, cruise speed of the UAV, angle, detection range, and MPC parameters, We will consider a case with multiple bogies with terrains in the subsequent research. In the second part of this section, we present an experiment result of two UAVs exercising identical evasion strategies to demonstrate the viability of the proposed algorithm in real situations.

A. Simulation Results

In this scenario, we consider a UV cruising at 3m/s at 10 meters above ground level (AGL). Without loss of generality, we use a dynamic model for a rotorcraft UAV based on Yamaha R-50 industrial helicopter, whose specification is given in [5]. The bogeys are staged to moves along a straight line at a constant altitude and speed at various incident angles. The detection range is simulated to be 50 meters based on a typical laser scanner and 100 meters for a hypothetic vision-based system. We investigate a fraction of these combinations of the factors mentioned above, which would highlight the performance of the proposed approach so that we may have the insight to the behavioral patterns and characteristics of the algorithm with a realistic detection.

1) One on One Situation

In this scenario, we consider the case when a UAV encounters a bogey at various speed and incident angle. The horizon N is set to 100 with 40 ms of sampling time, so the prediction horizon spans over 4 seconds. For fixed obstacles, stationary obstacles 12 meters away can be considered in the optimization when cruising at 3 m/s. As expected, the moving obstacles will impose more challenges in detection and finding a safe evasion trajectory in a short time.

First, we consider the following cases: a bogey cruising towards the UAV at 2 m/s, 5 m/s, 15 m/s and 30m/s. The cautionary margin $\sigma_c = 50$ m and the absolute safety margin $\sigma_a = 10$ m. We judge the vehicles collide when the distance from each other is less than 5 m.

In Fig. 3, an example when a bogey closes in at 10 m/s, with 0° incident angle (head-on collision course). As can be

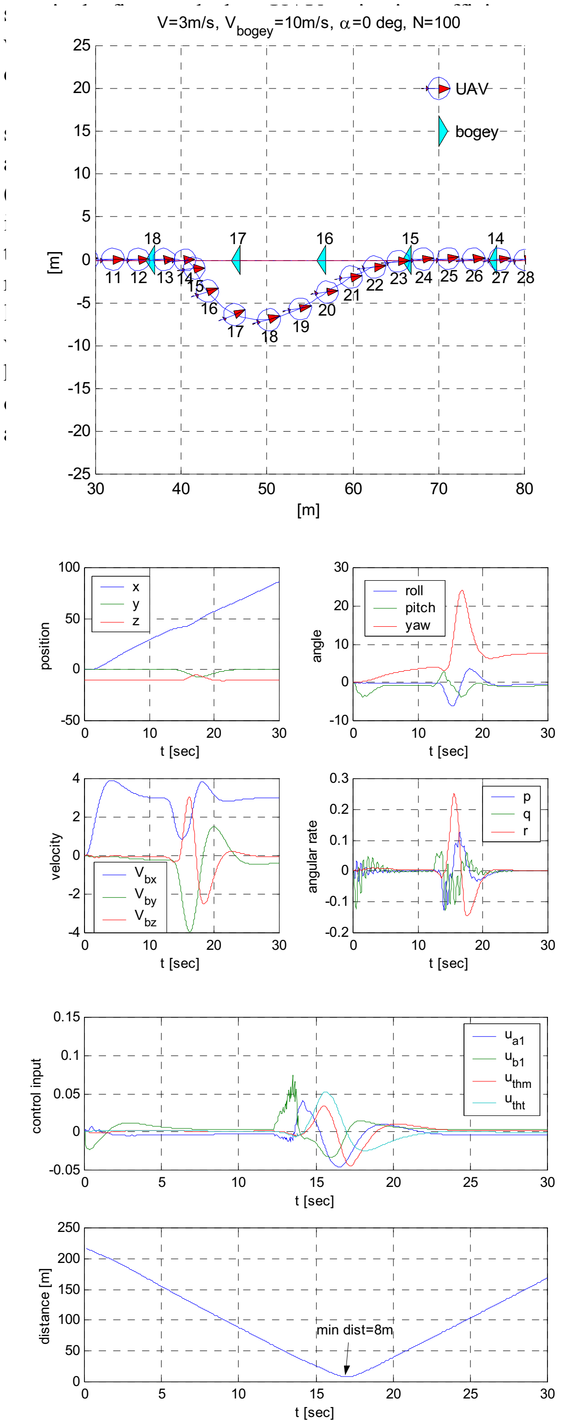


Fig. 3. A head-on collision scenario ($V_{cruise} = 3$m/s, $V_{bogey} = 10$m/s, $\alpha = 0^{\circ}$)

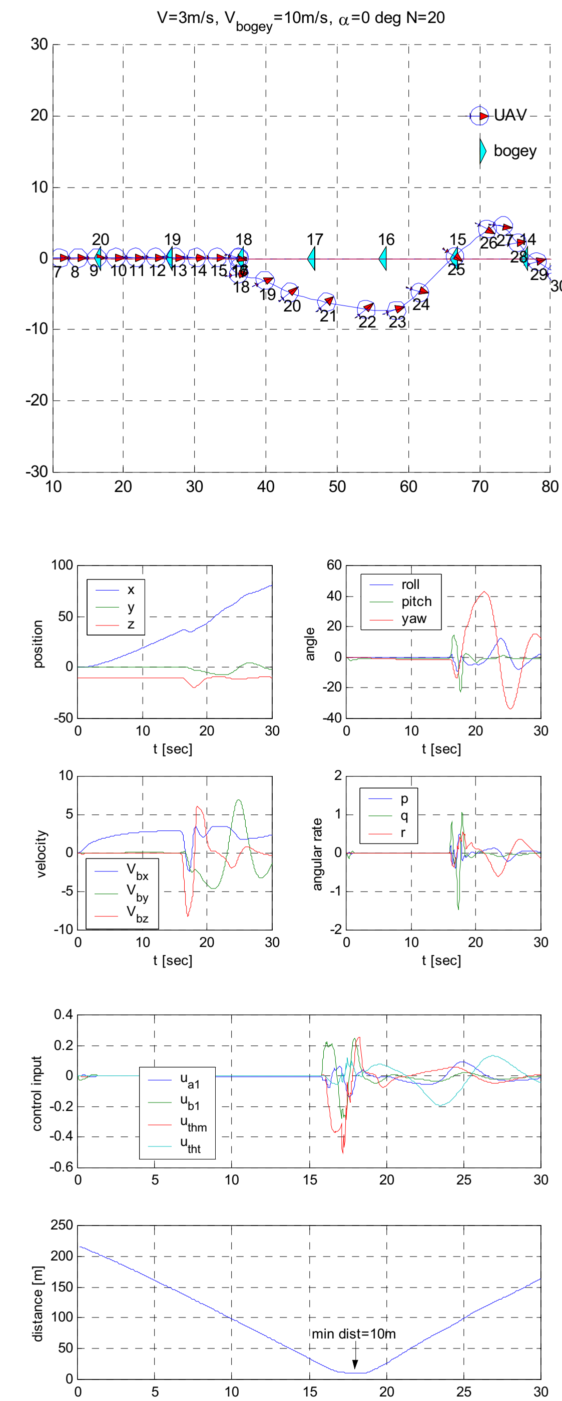
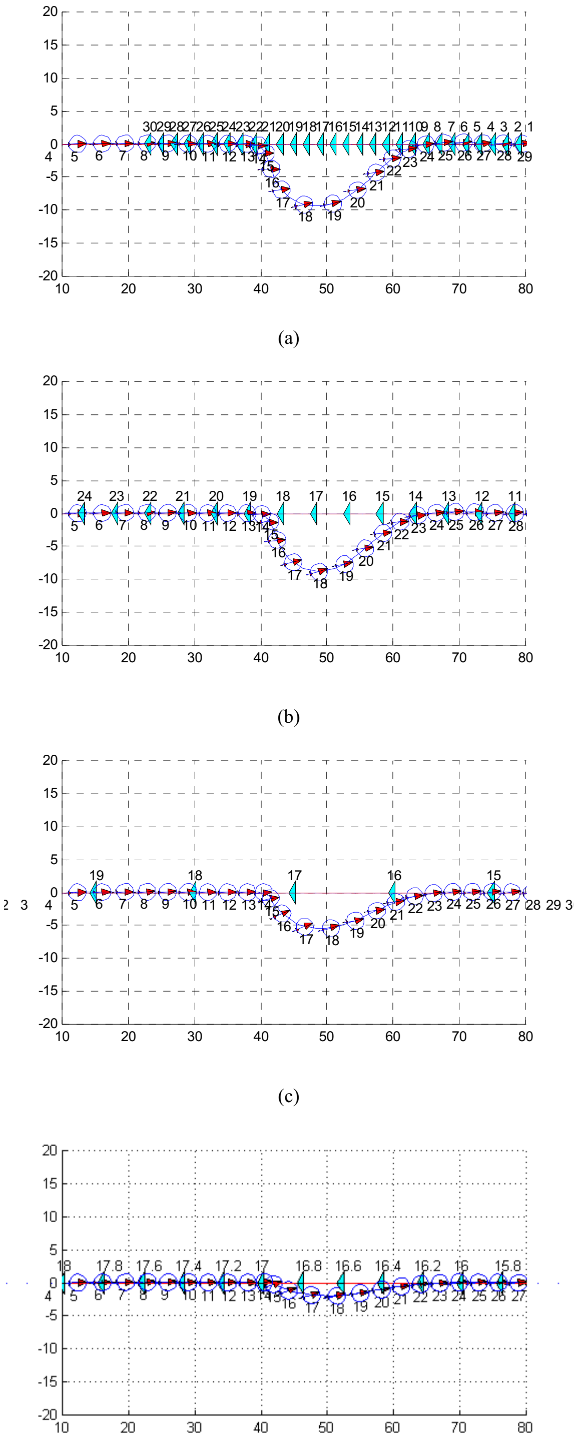
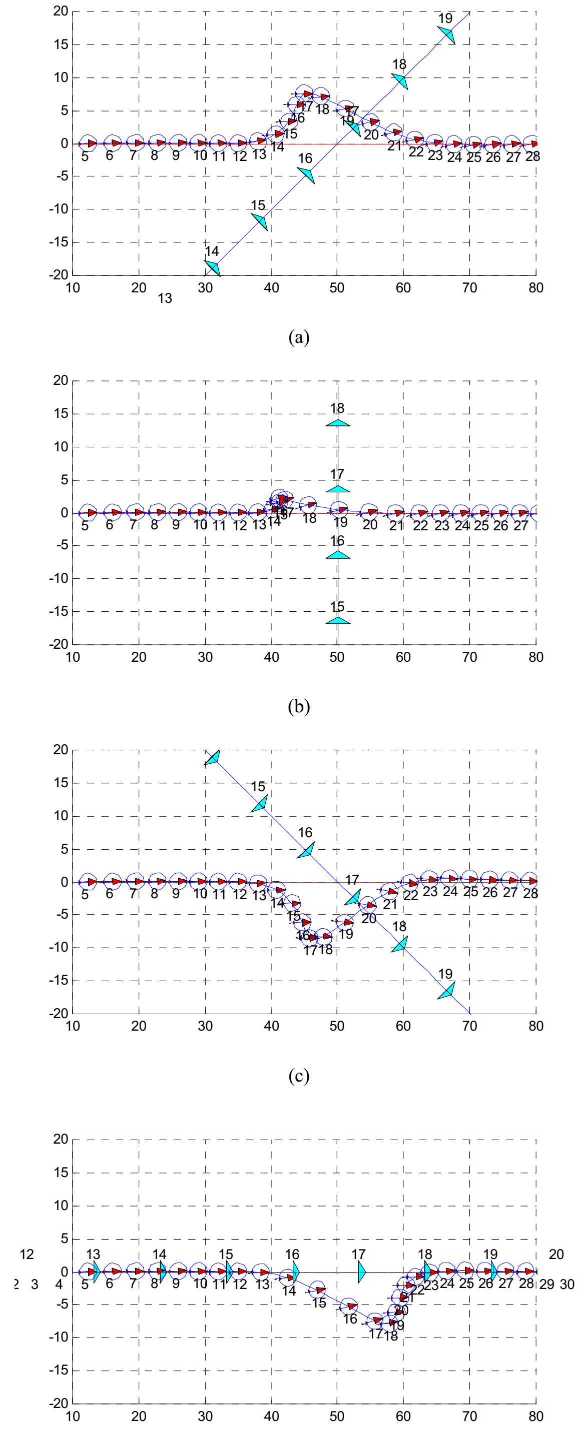


Fig.4. Evasive maneuver when a short horizon N is used (=20)



(a) (b) (c) (d)

Fig.5. Various approach velocity $V_{cruise} = 2, 5, 15, 30$m/s, respectively with $V_{bogey} = 10$m/s



(a) (b) (c) (d)

Fig.6. Various incident angles α=45°, 90°, 135°, 180°, $V_{cruise} = 3$m/s, with $V_{bogey} = 10$m/s

In Fig. 5-(d), the vehicle passes the bogey with 7m distance, which is considered as a bare minimum. It is expected that a longer horizon length will help to avoid the obstacle with a more sufficient margin. In Fig. 6, the trajectory planner shows a reliable performance in computing safe trajectories when the bogey flies in at various incident angles.

The proposed MPC algorithm is implemented in CMEX format to run in Simulink for faster simulation and also for porting to the flight control system. At typical setup given below, it takes about 0.23 seconds to run 1 second of simulation on a Pentium M 1.86GHz running Windows XP. Therefore, the proposed algorithm can be computed sufficiently fast for real applications.

B. Experiment Results

The proposed algorithm is implemented on MATAB Simulink and tested for two helicopter UAVs. The detailed specifications and architecture for are explained in [5]. The Simulink block used for simulation above is configured to run in soft real-time and send the trajectory commands over radio link so that the UAVs follow the designated path. The vehicles broadcast their location using GPS to the ground station, where the MPC-based trajectory is generated in a centralized manner. It is noted in [4] that a fully decentralized trajectory planner using the algorithm proposed in this paper has been successfully implemented and tested.

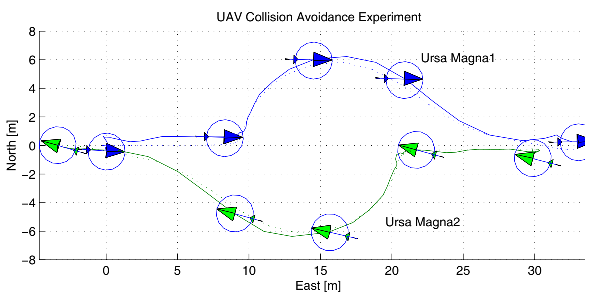


Fig.7. Trajectories of result of dynamic path planning for collision avoidance.

Fig. 8. Mid-air collision avoidance between two rotorcraft UAVs using real-time MPC

The experiment result is shown in Fig. 7 and 8. Two vehicles are configured to fly towards each other following a head-on collision course. In this particular case, the vehicles are constrained to make evasive moves in horizontal plane as a safety measure although the proposed algorithm is fully capable of vertical evasion as well. Both vehicles are also executing the same evasive algorithm. As can be seen from the figures, the vehicles were able to pass by each other with sufficient safety clearance. Therefore, the proposed algorithm is validated as a viable approach for conflict resolution of UAVs in real applications.

IV. Conclusion

This paper presented an emergency evasive maneuvering algorithm using model predictive control. The suggested approach is combined with a trajectory prediction algorithm and tested in various conditions. The previewing mechanism of receding horizon control is found ideal for such cases when the obstacles are moving at a fast speed. The proposed algorithm is tested on helicopter UAVs and showed a good performance. More tests will follow in various conditions to validate the proposed algorithm.

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