INFORMATION THEORY APPLIED TO A SELF-ORGANIZED, UNMANNED AERIAL SYSTEM

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Abstract

Cooperative teams of Unmanned Aerial Vehicles (UAVs) have applications for a number of civil and military missions. One active research area involves multiple UAV control strategy development and its application to self-organized systems. Compared with a centralized control system, self-organized systems demonstrate robustness, scalability, and better adaptation to environmental changes. This paper aims to report on a control strategy for a swarm of UAVs carrying out a mission that requires high level cooperation. Information measures are used to formulate information gain for sensing actions taken by each individual UAV. A simulation study has been carried out to evaluate the performance of a self-organizing UAV swarm against a centralized controlled swarm..

1 Introduction

The use of Unmanned Aerial Systems (UAS) for various civil and military missions has received significant attention in the last decade. The applications of UAS can be found in Search and Rescue (SAR), Intelligence, Surveillance and Reconnaissance (ISR) and ground target engagement missions. With recent technological advances in autonomous control and communication, multi-robotic systems are receiving a great deal of attention due to their increased ability to carry out complex tasks in a superior manner when compared to single-robotic systems. With effective cooperative control algorithms, multiple autonomous agents working in groups can be shown to exceed the sum of the performance of the individual UAVs.

The cooperative control of UAVs is a complex problem that is dominated by uncertainty, limited information, and task constraints. Centralized, hierarchical and decentralized, decision and control algorithms have been developed to address this complexity. In a centralized control system, the command and control centre receives information from each agent and generates task plans and decisions for individual agents based on global information. This approach optimises timing and task constraints but requires intensive computation, robust communication and must not be vulnerable to any degradation or destruction of the central infrastructure. The hierarchical controller decomposes the mission, and then assigns sub-teams to carry elements of the mission. The sub-team members have limited global information and receive assignments either from a sub-team leader or directly from the central control.

Decentralized control means a strategy in which agent independently receives local information and makes decisions. A Self-Organized (SO) system or swarm, is typically a decentralized control system made up of autonomous agents that are distributed in the environment and follow stimulus response behaviours [1]. Examples from social insects, such as foraging and the division of labour show that SO systems can generate useful emergent complex behaviours at the system level.

In this paper, we proposed a decentralized control strategy in which we use information theory to determine the control actions of multiple UAVs in a SO group. The scenario considered in this study is a group of UAVs tracking and attacking several ground based moving targets. Kingston & Schumacher in their paper solved this problem with a mixed integer linear program that addressed task timing constraints and agent dynamic constraints to generate a flyable path [2]. The assumption in their study was that each target is stationary with constant heading. In our study, we address this problem without this inbuilt assumption. Compared to centralized approaches, the SO based system has the potential to reduce communication cost and the amount of intelligence required in the control systems design. Moreover, SO based systems are usually much more adaptive, scalable and robust than those based on a single sophisticated agent or a number of agents under central control.

The remainder of this paper is structured as follows. The related work is reviewed in section 2. In section 3, the algorithm used for swarm control is described in detail. Simulation results are presented in section 4 and section 5 summarizes the study.

2 Related work

The study of information theory applied to sensor management is very active. Mutambara & Durrant-Whyte proposed a decentralized data fusion algorithm using information theoretic measures [3]. They later considered sensor management and control essentially as a means of maximising the information gain of the network as a whole [4] [5]. Their algorithms enabled information to be communicated and assimilated in a decentralized network, while a centralized objective function was computed redundantly by each of the vehicles to ensure coordination. Sinha, et al. applied this approach to generate a path for a group of UAVs tracking ground targets [6] [7]. The difference between their work and previous work is that they incorporated both target detection and UAV survival due to hostile action by potential targets and impacts with other vehicles and terrain probabilities into an objective function. They later solved this objective function with a combination of randomized and non-randomized search techniques.

Significant research effort has been invested in recent years into the design of UAV cooperative control strategies. Schumacher, et al. developed a centralized task assignment algorithm, using a mixed integer linear program formulation. This algorithm can be used to assign multiple tasks, which involves applying timing and task order constrains, to the vehicles in an optimal manner [8-10]. Only for small sized scenarios with a few vehicles and targets can a solution be found in sufficient time using such methods. For large sized scenarios, Shima proposed a method using a generic algorithm to solve this task assignment problem [11]. A hierarchical controller was also investigated. Li, et al. in their paper presented a hierarchical control strategy that enabled multiple UAVs to carry out a Suppression of Enemy Air Defense (SEAD) mission [12]. This control strategy included a multi-layer path planner to generate feasible flight paths through enemy territory for the team leader. The position and input of the leader are passed to the formation control code of the followers to allow them to compute the control input to maintain formation.

Applying these concepts to a self-organised UAV swarm was first explored by Frelinger, et al [13]. They examined whether modern communication, sensors and technologies in robotic architecture would permit the development of decentralized control to command a swarm of low cost munitions. Gaudiano, et al. extended the work of Frelinger. In their paper, they adopted random, repulsion, pheromone and global decentralized control strategies. In Price's research, ten self-organization rules were implemented whose weight factors were collected into a single fitness function. This function was further refined using a genetic algorithm within the simulation [14]. A similar technique was also adopted by de Vries & Subbarao [15] who used a potential function to generate steering commands to control a swarm of quadrotors. Another widely adopted mechanism is digital pheromone maps that imitate the foraging behaviour of ants. Digital pheromones are modelled on the pheromone fields of the individual vehicles. By synchronizing these maps the UAVs avoid redundant searches [16].

3 Swarm Control Strategy

The mission scenario considered in this study is the cooperative moving target engagement scenario. This mission requires that two or more UAVs track a moving (ground) target with Ground Moving Target Indicator (GMTI) radar while an additional UAV launches a guided weapon. The information from the tracking vehicles is fused to form a precise target location for the weapon to follow. The GMTI sensors footprint is a sector-shape with minimum and maximum ranges. Moreover, the GMTI sensors are Doppler based. Thus a moving ground target can only be detected and tracked if the range rate relative to the vehicle is above some minimum detection velocity. Thus the trackers have to stay within some offset angle from the heading of the moving target. The estimation error in the position of the moving target can be reduced by multiple sensors with separated line-of-sight angles to the target. The detailed description of this mission scenario can be found in [17].

3.1 Information Measures Applied to Swarm Control

This moving target engagement scenario requires high level cooperation between team members. It is critical for the tracking vehicles to track the target simultaneously while maintain appropriate separation angles to reduce target position estimation error. We propose to use a decentralized extended information filter [18] [5] and information measures [19] to tackle this problem.

In this study, the UAVs are assumed to be equipped with GMTI sensors [20]. The measurement equation is given by:

$$\mathbf{z}(k) = h(\mathbf{x}(k), k) + \mathbf{w}(k) \tag{1}$$

The target state vector $\mathbf{x} = [\xi, \dot{\xi}, \eta, \dot{\eta}]$. ξ and η are the distances of the target in the x and y directions from the origin point. The corresponding velocities are thus $\dot{\xi}$ and $\dot{\eta}$. The discrete white noise acceleration model is used for the target kinematic model [21]. The measurement vector $z(k)$ comprises positions in the x and y directions and range rate $\dot{r}$ where:

$$\begin{aligned}\dot{r}(k) = \dot{\xi}(k) \cos\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big) + \\ \dot{\eta}(k) \sin\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)\end{aligned} \tag{2}$$

and where $\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)$ is the bearing angle of the target measured by the vehicle at time k. The sensor measurement matrix is given by:

$$h(\mathbf{x}(k), k) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 \quad \cos\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big) & 0 & \sin\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big) \end{bmatrix} \tag{3}$$

$\mathbf{w}(k)$ in equation (27) is the Gaussian measurement noise vector is denoted by $\mathbf{w}(k) \sim N\big(0, \mathbf{R}(k)\big)$, where:

$$\mathbf{R}(k) = \begin{bmatrix} \sigma^2{}_{\xi}(k) & \sigma^2{}_{\xi\eta}(k) & 0 \\ \sigma^2{}_{\eta\xi}(k) & \sigma^2{}_{\eta}(k) & 0 \\ 0 & 0 & \sigma^2{}_{\dot{r}} \end{bmatrix} \tag{4}$$

The error statics for sensor measurements are given in terms of the range standard deviation σ_r, the range rate standard deviation $\sigma_{\dot{r}}$ and the bearing angle standard deviation σ_α, which are known. In this exercise, they are set to correspond to 15 feet, 3 feet per second and 0.001 radians. With these and the position variances, the covariance can be calculated as:

$$\begin{aligned}\sigma^2{}_{\xi}(k) = r\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)^2 \sigma_\alpha{}^2 \sin\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)^2 \\ + \sigma_r{}^2 \cos\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)^2\end{aligned} \tag{5}$$

$$\begin{aligned}\sigma^2{}_{\eta}(k) = r\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)^2 \sigma_\alpha{}^2 \cos\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)^2 \\ + \sigma_r{}^2 \sin\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)^2\end{aligned} \tag{6}$$

$$\begin{aligned}\sigma^2{}_{\eta\xi}(k) = \Big(\sigma_r{}^2 - r\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)^2 \sigma_\alpha{}^2\Big) \\ \cdot \sin\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big) \cos\alpha\big(\mathbf{x}(k), \mathbf{x}_v(k)\big)\end{aligned} \tag{7}$$

where range of the target $r\left(x(k), \mathbf{x}_v(k)\right)$ measured from each vehicle is evaluated at $\mathbf{x}(k) = \hat{\mathbf{x}}(k \mid k-1)$.

Since the measurement of equation (2) is a nonlinear function of the target states, the extended information filter is employed to estimate the states.

The information filter is derived from the Kalman filter in terms of the information states vector $\hat{\mathbf{y}}(i \mid j)$ and the information matrix $\mathbf{Y}(i \mid j)$. The information state vector and information matrix are defined as:

$$\hat{\mathbf{y}}(i \mid j) = \mathbf{P}^{-1}(i \mid j)\hat{\mathbf{x}}(i \mid j) \qquad (8)$$

$$\mathbf{Y}(i \mid j) = \mathbf{P}^{-1}(i \mid j) \qquad (9)$$

The prediction step of the extended information filter is written as:

$$\hat{\mathbf{y}}(k \mid k-1) = \mathbf{Y}(k \mid k-1) \cdot \mathbf{f}\left(k, \mathbf{x}(k-1), \mathbf{w}(k-1)\right) \qquad (10)$$

$$\mathbf{Y}(k \mid k-1) = [\nabla \mathbf{f}_x(k)\mathbf{Y}(k-1 \mid k-1)\nabla \mathbf{f}_x{}^{-1}(k) + \mathbf{Q}(k)]^{-1} \qquad (11)$$

where $\mathbf{Q}$ is the process noise covariance matrix of the target dynamic kinematic and the estimation step is:

$$\hat{\mathbf{y}}(k \mid k) = \hat{\mathbf{y}}(k \mid k-1) + \mathbf{i}(k) \qquad (12)$$

$$\mathbf{Y}(k \mid k) = \mathbf{Y}(k \mid k-1) + \mathbf{I}(k) \qquad (13)$$

The information state contribution $\mathbf{i}(k)$ and its associated information matrix $\mathbf{I}(k)$ are given, respectively, as:

$$\mathbf{i}(k) = \nabla \mathbf{h}_x(k)^T(k)\mathbf{R}^{-1}(k)\left(\mathbf{z}(k) - \mathbf{h}(\hat{\mathbf{x}}(k \mid k-1), k) + \nabla \mathbf{h}_x(k)\hat{\mathbf{x}}(k \mid k-1)\right) \qquad (14)$$

$$\mathbf{I}(k) = \nabla \mathbf{h}_x(k)^T(k)\mathbf{R}^{-1}(k)\nabla \mathbf{h}_x(k) \qquad (15)$$

where the Jacobian $\nabla \mathbf{f}_x(k)$ is evaluated at $\mathbf{x}(k-1) = \hat{\mathbf{x}}(k-1 \mid k-1)$ and $\nabla \mathbf{h}_x(k)$ is evaluated at $\mathbf{x}(k) = \hat{\mathbf{x}}(k \mid k-1)$. For N sensor information sources, the posterior information state and information matrix are obtained from:

$$\hat{\mathbf{y}}\ (k \mid k) = \hat{\mathbf{y}}\ (k \mid k-1) + \sum_{i=1}^{N} \mathbf{i}_i(k) \qquad (16)$$

$$\mathbf{Y}(k \mid k) = \mathbf{Y}(k \mid k-1) + \sum_{i=1}^{N} \mathbf{I}_i(k) \qquad (17)$$

where $\mathbf{i}_i(k)$ and $\mathbf{I}_i(k)$ are the information matrix and information state contributions of the sensors $i = 1, \ldots, N$,

The mutual information gain $I_{Track}^{i,j}(k)$ for vehicle i tracking target j is calculated from:

$$I_{Track}^{i,j}(k) = \frac{1}{2}\log\left[\frac{|\mathbf{Y}^{i,j}(k \mid k-1) + \mathbf{I}^{i,j}(k)|}{|\mathbf{Y}^{i,j}(k \mid k-1)|}\right] \qquad (18)$$

Mutual information in information theory is considered as an *a priori* measure of the information about state $\boldsymbol{x}$ to be gained through an observation $\boldsymbol{z}$. The expectation is taken over $\boldsymbol{z}$ and $\boldsymbol{x}$, so the mutual information gives an average measure of the information gain to be expected before making the observation [22]. By calculating mutual information for the potential observation, the tracking vehicles could steer toward the location where the observation yields the highest mutual information gain. This technique causes the tracking vehicles to maintain a separation angle to the targets without negotiation or centralized control command.

3.2 Swarm Behaviours

A self-organizing swarm can be described as a decentralized system made of autonomous agents that are distributed throughout the environment following stimulus response behaviors [1]. The social insects show that complex collective behavior may emerge from interactions among individuals that exhibit simple individual behavior. In this study, three behavioral states are developed; they being search, loiter, track, and attack. In each state, the behavior of the UAVs is governed by local rules. In order to compare swarm control with centralized control strategy, we make the targets' original position available to the UAVs at the beginning of the mission, which is needed for the centralized controller to plan tasks for each vehicle. The actual strength of the swarm lies in its ability to operate in an unknown and dynamic environment.

Loitering

UAV loiters above the target with a predefined safe standoff distance and broadcast a request for tracking support before attempting to engage the target. The communication is constrained by maximum range, i.e., line of sight. This UAV will then receive targeting information from the tracking UAVs maintaining a global track on the target.

Tracking

UAV tracks the targets with onboard GMTI radar and sends local track information to the attacking UAV. Once the UAV is in tracking state, the most basic rule for the trackers to follow is to place the target within the sensor footprint while remaining within the detectable line-of-sight angle to the target heading. To enhance the track accuracy, individual trackers will request local track information (i.e. information states $\hat{y}\,(k \mid k)$ and the information matrix $Y(k \mid k)$) from the another tracker and then calculate the mutual information gain given by equation (39) for the potential observations. The rule then forces it to fly toward the location where the observation could yield the highest mutual information gain. This rule guaranties that the trackers maintain a sufficient separation angle while providing tracking support.

Attacking

Once the target track is defined accurately enough for the guided weapon, the UAV that made the original contact switches to attack state. This accuracy is measured by the entropic information on the target. The attack state is simply modeled as the UAV heading toward the target and launching the weapon at a fixed distance from the target. The UAVs tracking the target must continue to track the target for the duration of the weapon flight.

4 Simulation Study

In this section, we present both the simulation environment and results. In order to implement and evaluate swarm control strategy, we have developed a MATLAB/SIMULINK based tool that is capable of simulating multiple UAVs which cooperate to accomplish a predefined mission. This simulation tool includes a six-degree-of-freedom dynamic vehicle model, an autopilot and a flight management system from a simulator named MultiUAV. MultiUAV was originally developed by U.S. Air Force Research Laboratory (AFRL) [23].

A Monte Carlo study, consisting of 100 runs for each scenario, was used to evaluate the proposed methodology compared with centralized control strategy used in [2]. In [2], this problem of assigning multiple agents to cooperative tasks was formulated with mixed integer linear programming and solved by using an open-source linear programming package, GLPK. The following assumptions were made in their study to reduce the complexity: 1. Targets have constant heading for targets travelling along known roads. 2. Targets were stationary since the sensor footprint is much larger than the distance travelled by the targets. In our study, we do not include these restrictions. The kinematics of the targets is modeled using the discrete white noise acceleration model which results in more time spent on target engagement.

The simulation study included six scenarios with different problem sizes. Each scenario involved three targets and a varying number of UAVs. Initially, the UAVs and targets were randomly distributed over a 100 km square mission area. At the end of the simulation we recorded the time for eliminating all targets. The progression of the simulated scenario is shown in Appendix A. The results in Figure 1 are the average of the final task completion time for each simulated scenario in 100 runs. From the simulation results, it can be seen that the advantages of the centralized

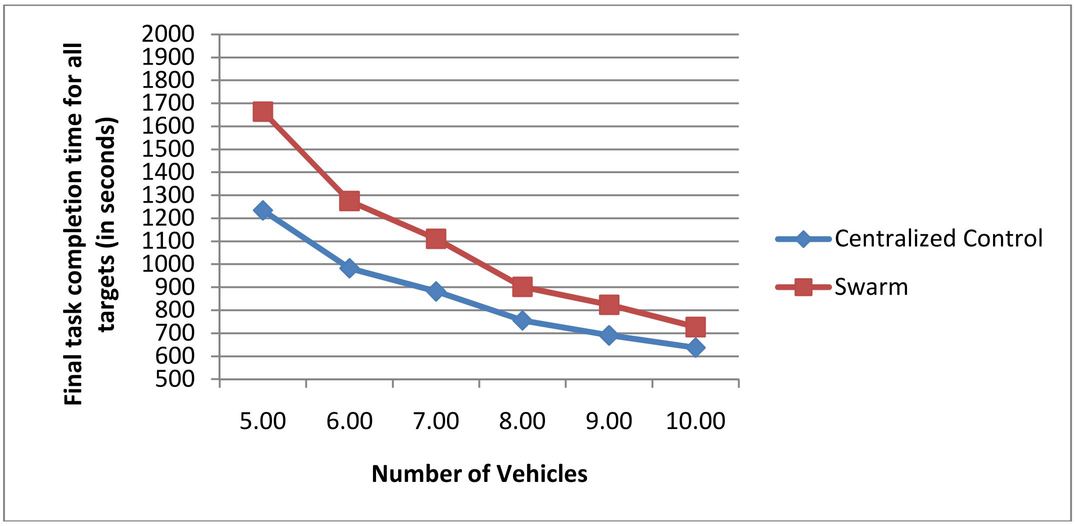

Figure 1: Comparison of swarm control and centralized control.

controller was becoming less significant with the number of UAVs increase. For a small size group of agents, the self-organised swarm is less efficient as centralized controller especially for mission scenarios with strong timing and coupling constrains. As the size of the group increase, the collective behaviour of the swarm emerges. As we can see, the curve representing the self-organised swarm descends faster than the centralized controlled swarm. As obtaining a solution to the mixed integer linear programming requires an extreme amounts of computation, this method would soon become non-solvable for a real time large problem sizes.

5 Conclusion

In this study, a swarm control strategy using an information theoretic approach is examined. This decentralized control strategy is applicable to missions requiring high level cooperation between team members. Different to a centralized task assignment algorithm, the cooperation of the agents is entirely implicit. The behaviour of the UAVs is governed by simple local rules which ultimately lead to cooperation at a system level and complex behaviour.

The simulation study evaluates the performance of the local control strategy against the centralized control strategy quantitatively. The results show that the size of the swarm has a significant impact on the viability of local against central control. Future work involves the investigation of the adaptive ability of swarms under uncertainties such as communication delay, maneuvering targets and threats.

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Appendix A

Figures 1(a), 1(b) and 1(c) display stages of the simulated scenario (3 targets and 7 UAVs) at 3 points in time. Local swarm control strategy was applied to this example run. The coloured area displayed the sensor footprint of the tracking UAVs. The UAVs' sensor footprints have the same colour as themselves.

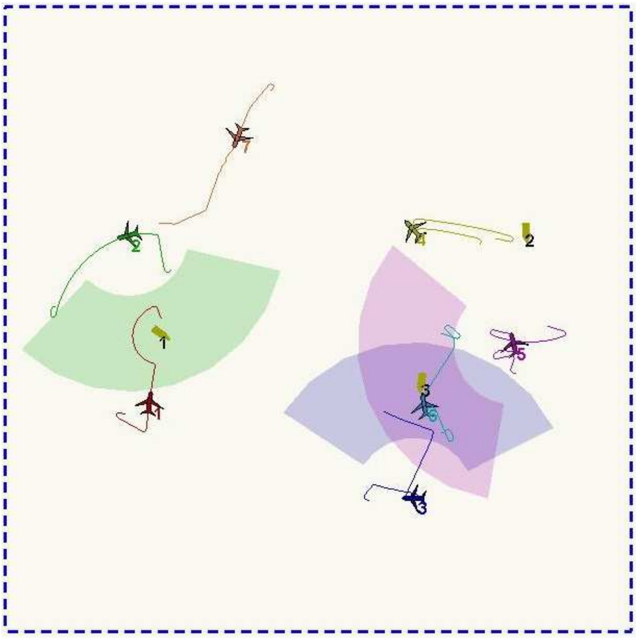

Figure 1(a): Simulated scenario at time 102 seconds. UAV 3 (blue) was tracking target 3 in cooperation with UAV 5 (purple). The fused track on target 3 was accurate enough for UAV 6 (cyan) to carry out attack. UAV 2 (green) was tracking target 1 and waiting for assistance from UAV 1 (red) and 7 (orange).

Figure 1(b): Simulated scenario at time 249 seconds. After destroyed target 3, UAV 5 (purple) and 6 (cyan) started tracking target 2 while UAV 4 (yellow) began to attack.

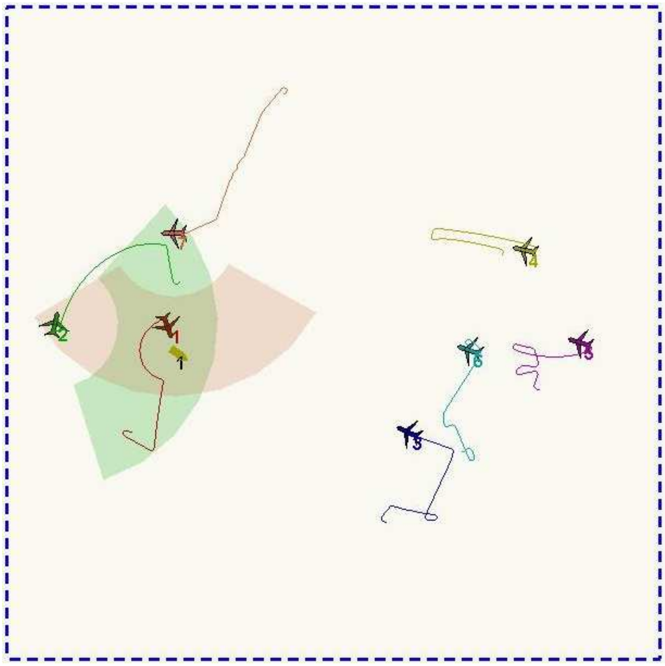

Figure 1(c): Simulated scenario at time 279 seconds. Target 1 was attacked by UAV 1 (red) with tracking support from UAV 2 (green) and UAV 7 (yellow).

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