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Optimal control of a diffusion process using networked unmanned aerial systems with smart health

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Abstract: In many future applications, such as pesticide spraying, unmanned aerial systems (UASs) are expected to operate cooperatively in a swarm configuration. A cyber-physical framework based on Centroidal Voronoi Tessellations (CVT) has been shown to provide optimal placement for sensors or actuators and can be used effectively for the control of a diffusion process such as a pathogen infection. However, previous work did not consider real-world constraints such as the effect of the UASs health on swarm utilization. While health degradation over time is inevitable, mismanaged swarms face expedited health degradation from over-utilization of one UAS over others. In this paper, a novel smart health balancing (SHB) system is implemented to extend the life of the most heavily taxed UASs and thus extending the life of the entire UAS swarm. The effectiveness of the proposed system is demonstrated with simulation results.

Keywords: Unmanned Aerial Systems, Precision Agriculture, Networked Swarms, UAS Applications, Cyber-Physical System, UAS Health Management

1. INTRODUCTION

Unmanned Aerial Systems (UASs) are increasingly being used for agricultural applications. These agricultural platforms are expected to fulfill two major roles: decision support and precision application of pesticides (AUVSI, 2013). While decision support applications rely on remote sensing strategies, precision application have traditionally been modeled after manned aircraft operations. Futurists envision that these 'smart' UASs will not only replace manned crop-dusting operations, but improve performance by providing intelligent targeted application, spraying only where it is needed and saving both money and time. This level of precision is envisioned to add up to significant economic benefits, especially in the U.S. with nearly 408 million acres of currently operated farmland (USDA, Economic Research Service, 2011).

The recent trend in the UAS industry has been towards the development of small unmanned aerial systems (SUASs). These small platforms are not only cheaper to manufacture and to operate, they are expected to be the most viable solution for the FAA to manage (Federal Aviation Administration, 2010). While these systems have a number of advantages such as portability and ease of use, they suffer from three major drawbacks: limited flight time, limited payload capacity and limited survivability. These platforms typically only operate for under an hour, are significantly limited in payload capacity, and can tolerate very little adversity before requiring repairs. The common solution to counter their limitations is to utilize them in swarms or cooperative operations. By using multiple UASs, a swarm can service a larger area in a shorter time than a single larger aircraft, but only if the proper optimization and control is applied. Unfortunately, while these cooperative control techniques are effective in countering the first two major drawbacks, they typically do not address the health and reliability issues posed by the third major drawback, the lack of survivability. The health of a UAS can have significant effects on overall mission performance and future reliability. In a swarm, a UAS that sees constant significant use may degrade faster than those that are used less frequently and may result in permanent failure reducing future performance. By balancing health in a cooperative control algorithm, the overall effectiveness of the swarm may be enhanced.

Coverage control problems have been addressed in literature for a number of applications including agriculture (Stark et al., 2013) as well as in many applications such as forest fire monitoring (Casbeer et al., 2006), nuclear radiation contour mapping (Han et al., 2013) and a multitude of military uses or persistent surveillance applications. In each of these scenarios, a single UAS is assumed to be constrained with limited sensing and communication ability, necessitating the use of a swarm of coordinated UASs to accomplish the mission. Cooperative control algorithms have taken a variety of forms in literature.

In many situations, UAS health degradation may severely effect both current overall mission performance and decrease the performance of future missions. Typically this issue has been addressed in literature for military applications or persistent surveillance operations where the objectives are simply to provide a presence at a location. In Geramifard et al. (2011), a cooperative control architecture is implemented with stochastic risk models to add intelligence to the UASs to avoid risky behaviors or locations. Previous work by Bethke et al. (2008) incorporated fuel usage into the architecture to develop a 'health-aware' mission planner with a dynamic programming approach. This architecture is well-poised for the discrete mission task orientated approach posed by those authors but is not well-suited for implementing diffusion process control such as found in agricultural applications. Other cooperative control approaches that include health management often appear in conjunction with enemy damage avoidance and balancing fuel consumption in those efforts, such as in Chen et al. (2013) where a model predictive control (MPC) was developed with a particle swarm optimization to incorporate fuel consumption with the potential of enemy damage.

In Sharifi et al. (2013), a Centroidal Voronoi Tessellations (CVT) based framework was utilized for coverage control and introduced the use of multiplicatively weighted voronoi partitioning for addressing non-identical health conditions for sensors. In this work, each UAS was responsible for sensing and localizing some process. The use of the multiplicatively weighted regions allowed for region shaping depending on the health of each UAS's sensor. This effort was focused on the sensing of a process, however, when the objective is to provide control (such as the spraying of a pesticide) to diffuse an infection, this approach would not improve performance.

A framework for distributed control of a diffusion process was introduced in Chen et al. (2007). In that work, the authors utilized CVTs to solve the optimal actuator placement for a diffusion process of a partial differential equation (PDE). The optimality of the actuator placement provides the best use of control effort, reducing the use of spraying application and neutralizes the infection in the fastest time. This framework can be used in an agricultural application and provide a significant economic gain (Stark et al., 2013).

In this paper, a swarm of cooperative SUASs are set up within a cyber-physical framework to optimize spraying a neutralizing agent over a rapidly spreading diffusion process, while simultaneously balancing the health of the fleet to ensure the maximum life of the weakest UAS using a smart health balancing (SHB) system. In the following section, the problem statement and the CVT framework is introduced. The SHB system is described in Section 3. In Section 4, the proposed smart health system is evaluated through simulations. Finally, concluding remarks are found in Section 5.

2. PROBLEM STATEMENT

The problem of optimal coverage in the presence of degrading health can be framed in a cyber-physical system (Chao and Chen, 2012). In a setting where real-time sensing of an area is possible, an optimal cooperative control system for the eradication of an invasive and volatile pathogen is possible (Stark et al., 2013).

Suppose Ω represents a convex polytope such that $\Omega \in R^2$, where a diffusion process can occur. Within this region, suppose there exists a group of n UASs, denoted as the set $P = \{p_1, p_2, \cdots, p_n\}$ where $p_i = (x_i, y_i)$, representing the coordinates of each UASs.

The region with the pathogen within Ω can be described as $\rho(x, y) : \Omega \to R_+$. This diffusion process can be described by the following partial differential equation (PDE):

$$\frac{\delta\rho}{\delta t} = k\left(\frac{\delta^2\rho}{\delta x^2} + \frac{\delta^2\rho}{\delta y^2}\right) + f_d(\rho, x, y, t) + f_c(\tilde{\rho}, x, y, t) \quad (1)$$

where k is some positive constant system parameter, $f_d(x, y, t)$ represents the pathogen source, $f_c(\tilde{\rho}, x, y, t)$ represents the control application for neutralizing the pathogen, and $\tilde{\rho}$ is the measured sensor data. For convenience, ρ is used to represent $\rho(x, y)$.

The group of UASs behave as mobile actuators, each applying some application control force $f_c(t) = f_{c1} + f_{c2} + \cdots + f_{cn}$.

The region Ω can be partitioned into n Voronoi diagram regions such that $\mathcal{V} = \{\mathcal{V}_1, \mathcal{V}_2, \cdots, V_n\}, p_i \in \mathcal{V}_i, \mathcal{V}_i \cap \mathcal{V}_j = \emptyset$ for $i \neq k$

$$\mathcal{V}_i = \{q \in \Omega \| q - z_i| < |q - z_j| \text{ for } j = 1, 2, \ldots, n, j \neq i\} \quad (2)$$

where $|\cdot|$ is the Euclidean distance, z_i represents a set of points belonging to Ω and q is any arbitrary point. The members of the set $\{z_i\}_{i=1}^k$ are referred to as the generators of each cell $\mathcal{V}_i$.

Given a density function $\rho(\tilde{q}) \geq 0$ defined in Ω, then for each Voronoi cell, $\mathcal{V}_i$, the mass centroid z_i can be defined by:

$$z_i = \frac{\int_{V_i} q\rho(q)dq}{\int_{V_i} \rho(q)dq}. \quad (3)$$

For controlling a diffusion process, the following objectives are introduced:

- To control the diffusion of the pathogen
- To neutralize the pathogen as quickly as possible without over application of control force
- To balance the health and usage of the fleet

To meet the desired control objectives, the following evaluation equation is introduced:

$$\kappa(\rho, \mathcal{V}) = \sum_{i=1}^{n} \int_{\mathcal{V}_i} \rho(q)|q - p_i|^2 dq \text{ for } q \in \Omega \quad (4)$$

such that

$$|\dot{p}_i| < k_v, |\ddot{p}_i| < k_a, \sum_{i=1}^{n} \int u_{spray,i}(t)dt < k_s, |h_i - h^*| < k_h \quad (5)$$

where $\dot{p}_i$ and $\ddot{p}_i$ represent the first and second-order dynamics of the UAS, $u_{spray,i}$ represents the neutralizing control input of actuator i at time t, h_i is the health of the actuator, h^* is the average health of the all actuators, and constants k_v, k_a, k_s, k_h are strictly positive threshold constants.

3. DISTRIBUTED COVERAGE CONTROL WITH SMART HEALTH BALANCING

Throughout the paper, the UAS is assumed to be a highly mobile vehicle, capable of moving in any direction and capable of hovering in place, such as a rotary-wing vehicle or a blimp. In this assumption, each UAS can be treated as a virtual particle with second order dynamics,

$$\ddot{p}_i = u_i, \tag{6}$$

where u_i is the control input of the i^{th} UAS.

The neutralizing spraying actuation force $f_c(\tilde{\rho}, x, y, t)$ can be any arbitrary function. In this paper, it is assumed to be in the form of a PDE, spraying an airborne neutralizing agent directly underneath the UAS.

The health for each UAS, i, can be represented by $h_i(t)$ at time t. The health function $h_i(t)$ can be formulated as:

$$h_i(t) = h_i(0) - d_i(t), \tag{7}$$

$$d_i(t) = \int_0^t k_d u_i^2 dt + f_{d,i}(t), \tag{8}$$

such that

$$\dot{h}_i(t) \leq 0, \dot{f}_{d,i}(t) \geq 0, h_i(t), f_{d,i}(t) \in [0, 1], \tag{9}$$

where $h_i(0)$ is the starting health of UAS i, k_d is a usage gain scalar, and $f_{d,i}(t)$ represents external negative effects on UAS health, for example in the event of a mid-air collision. In this paper, the health of each UAS degrades over time as a function of its control effort and any external damage it may encounter. A UAS directed to move quickly and change directions rapidly will encounter a faster health degradation than a UAS that is largely stationary. Physically speaking, this calculation can be a combination of remaining fuel and structural health, or amended to include UAS spraying usage.

The nominal health $h^*(t)$ of the UAS fleet is calculated as the current average health of all UASs,

$$h^*(t) = \frac{1}{n}\sum_{i=1}^{n} h_i(t), \tag{10}$$

such that

$$\dot{h}^*(t) < 0, h^*(t) \in [0, 1]. \tag{11}$$

It is assumed that each UAS can communicate globally with other UASs in the region to calculate their respective Voronoi regions and have access to the global average health $h^*(t)$. The control of each UAS is accomplished with a simple P controller modulated by the smart health balancing (SHB) system which utilizes a simple PD controller. The control $u_i(t)$ can be represented as:

$$u_i(t) = k_p \cdot [1 + k_{h,i}(t)] \cdot (p_i - z_i), \tag{12}$$

$$e_i(t) = h_i(t) - h^*(t), \tag{13}$$

$$k_{h,i}(t) = k_{h_p} e_i(t) + k_{h_d} \dot{e}_i(t), \tag{14}$$

where $k_{h,i}$ represents the SHB gain that changes the movement control of the UAS, e_i represents the health residual between UAS i and the global health average $h^*(t)$ and k_{h_p} and k_{h_d} represent the SHB gains.

The desired observation of the SHB system is to maximize the lifetime t of the vehicle with the lowest health, h_i. At each time step, UAS i calculates its Voronoi region and calculates its centroid z_i in order to construct its desired location. It then calculates its health and computes the residual to adjust its control input. The result is that the less healthy UASs are commanded to move more conservatively to maximize its flight endurance.

4. SIMULATION RESULTS

The performance of the smart health balancing system can be demonstrated by maximizing the minimum time till a UAS death for the swarm of UASs. With the implementation of the smart health balancing system, the goal is to keep all the UASs as healthy as possible and to mitigate disproportional health degradation. In this paper, four scenarios are presented and examined:

(1) No abnormal health behavior for any UAS in the swarm,
(2) One UAS suffers from an increase rate of health degradation,
(3) One UAS initializes at a lower health than the rest of the swarm,
(4) One UAS suffers from a sudden decrease in health.

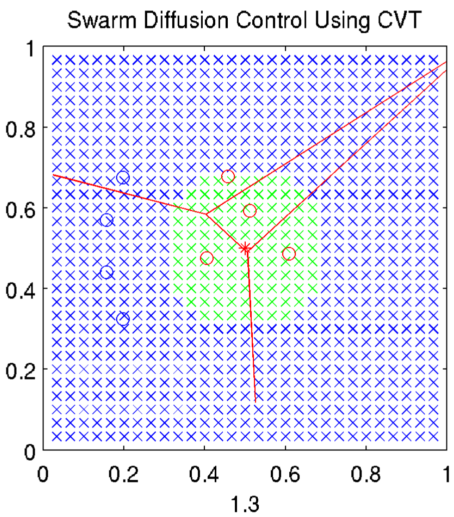

Fig. 1. Diffusion control using four UASs in a CVT framework

These scenarios represent some common expected health issues. Scenario (1) represents the best case scenario where no UAS suffers from abnormal health behavior and thus the SBH is utilized to balance the utilization of each UAS. Scenario (2) may occur during an engine malfunction that lowers fuel efficiency. Scenario (3) could represent a battery that was not fully charged before being used. Scenario (4) could be a minor component malfunction such as a structural fracture. In these scenarios, the health degradation or malfunction does not require an immediate recovery, but continued operation may impact future health and performance.

Each of these four scenarios were run with a swarm of four UASs sent to neutralize a diffusion process in the center of

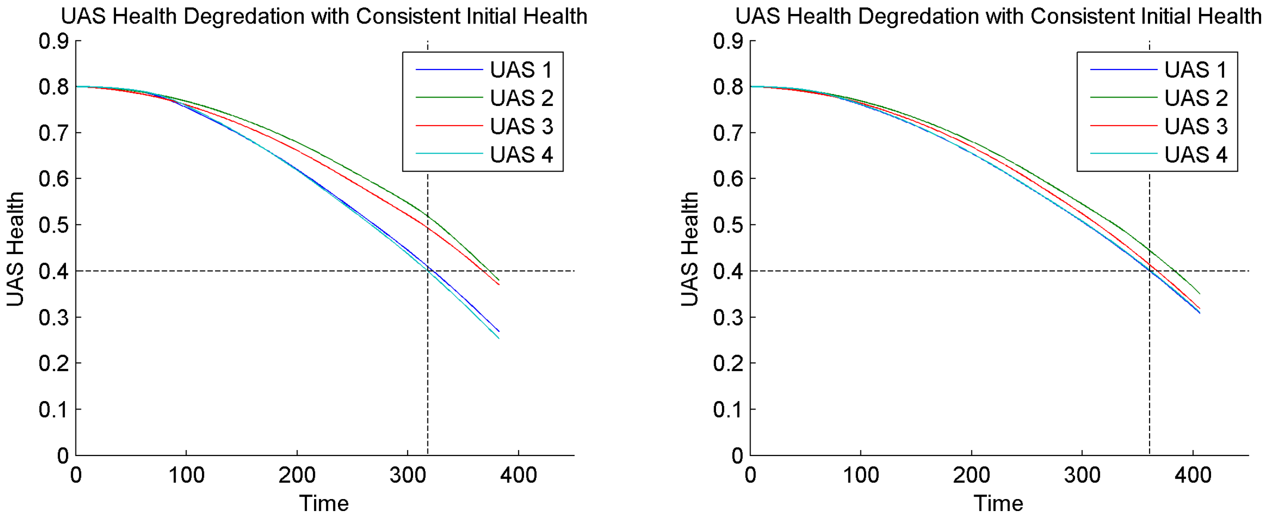

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Fig. 2. Plot of UAS Health for four UASs with an initial health of $h_i(0) = 0.80$ and normal degradation rate for (a) Nominal and (b) SHB.

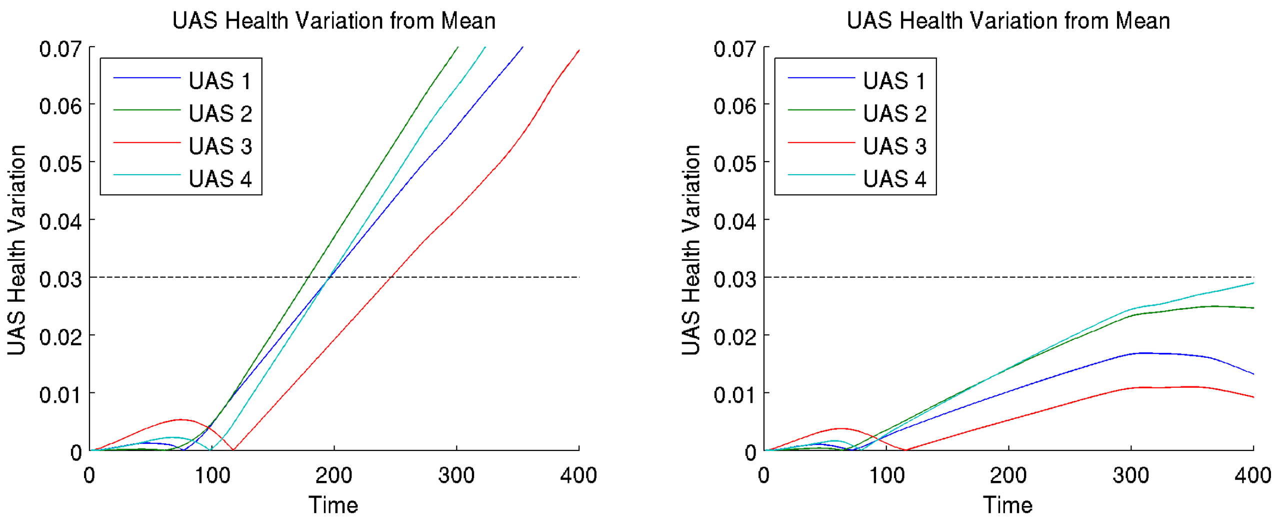

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Fig. 3. Plot of the difference between UAS health and mean health for (a) Nominal and (b) SHB.

the region (Figure 1). For each scenario, two simulations were performed, one without the smart health balancing system (Nominal) and one with the smart health balancing system (SHB). The green region in the center represents the diffusion source. The red circles represent the centroids of the voronoi regions and the desired UAS positions. The red lines represent the boundaries between voronoi regions. The blue circles represent the UAS.

Figures 2 and 3 depict results from the first scenario, where each UAS initializes at the same health level and the health of each UAS degrades normally with its motion. Figure 2a plots the health of each UAS during the neutralization swarm control without the smart health balancing. In this simulation, UAS 4 drops faster than the rest and hits an arbitrary health threshold at $h_i(t) = 0.4$ at time step 318. In Figure 2b with smart health balancing, the same UAS extends its life and does not reach the threshold until time step 361, representing a 13% increase in life.

It can be seen in Figure 3a that without the smart health balancing, the disparity in UAS health diverges over time, whereas in Figure 3b, the disparity is bounded and satisfies $|h_i - h^*| < k_h$ requirement set in eq. 5. Even though there is nothing wrong with any of the UASs, the addition of the smart health balancing extends the lifetime of the swarm.

The results are further pronounced in the remaining three scenarios. Figure 4 shows the health of each UAS under consistent initial health with UAS 4 having a degradation rate double that of the other UAS. In the Nominal scenario, the first UAS to degrade to $h_i(t) = 0.4$ health occurs after 210 time steps. After smart health balancing is applied the system requires 283 time steps. This is a represents a 35% increase in survival time for the mission.

Figure 5 shows the health of each UAS for scenario (3). While UASs 1-3 start at $h_i(0) = 0.8$, UAS 4 initializes at $h_4(0) = 0.6$. In the Nominal simulation (Figure 5a), UAS 4 degrades to $h_i(t) = 0.4$ after 211 time steps. After smart

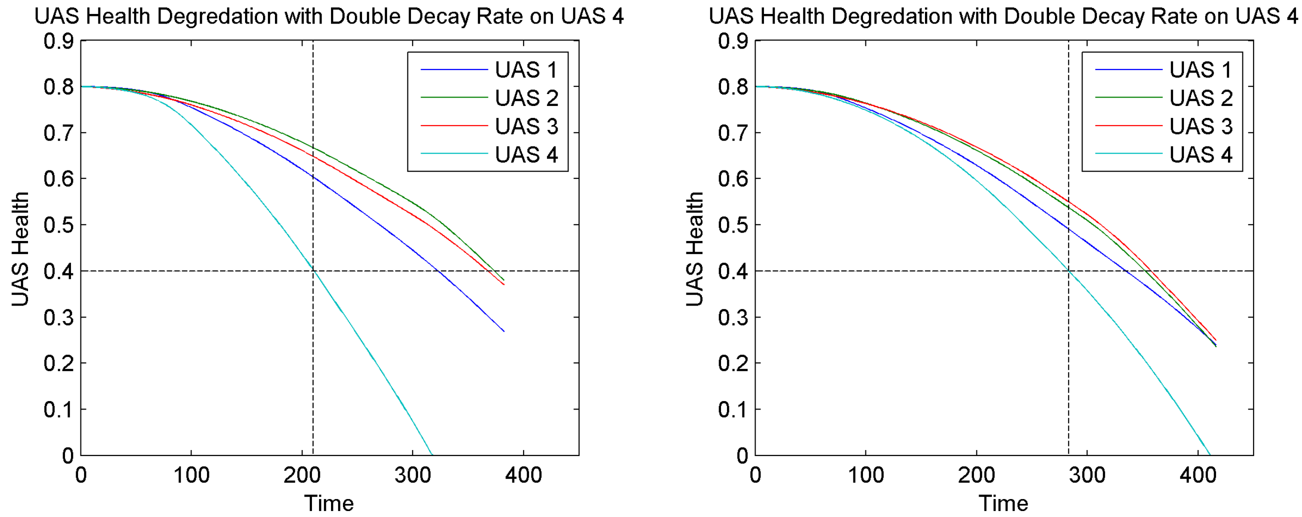

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Fig. 4. Plot of UAS Health for four UASs with an initial health of $h_i(0) = 0.80$ and double degradation rate for UAS 4 for (a) Nominal and (b) SHB.

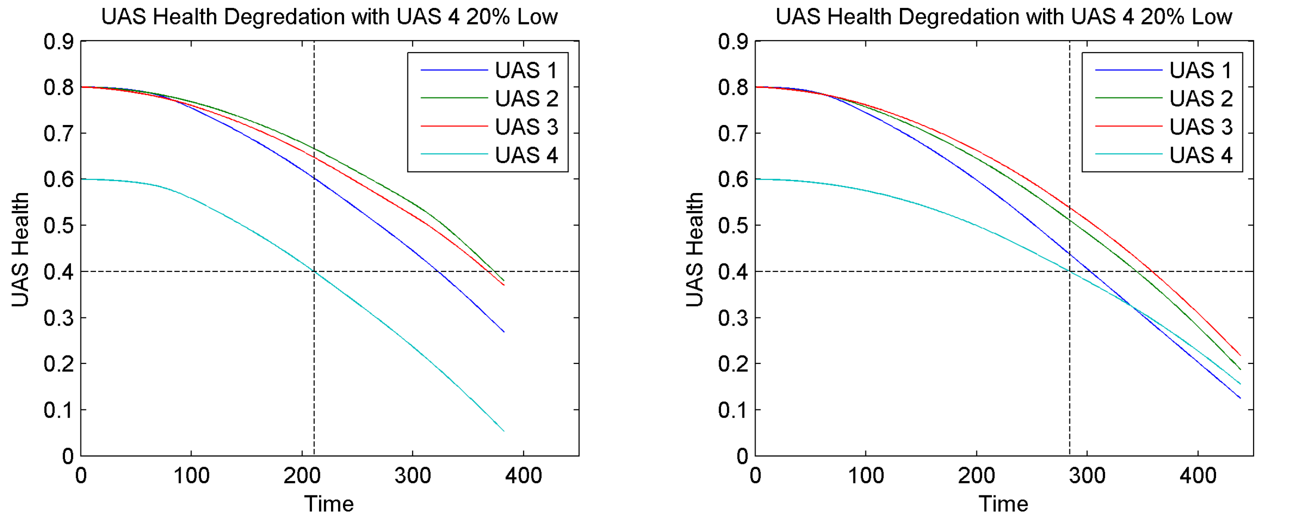

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Fig. 5. Plot of UAS Health for three UASs at $h_i(0) = 0.80$ and UAS 4 at $h_4(0) = 0.60$ for (a) Nominal and (b) SHB.

health balancing is applied the same system survives to 284 time steps before reaching the threshold (Figure 5b).

Figure 6 shows the health of each UAS under equal initial health and health degradation rates under scenario (4). At time step 250, UAS 4 simulates receiving damage mid flight by applying $f_{d,i}(t) = 0.3$ at $t = 250$. In the Nominal simulation (Figure 6a), UAS 4 degrades to death ($h_i(t) = 0$) after 363 time steps. After smart health balancing is applied (Figure 6b) the UAS survives to 411 time steps.

	Nominal	SHB
Scenario (1)	318	361
Scenario (2)	210	283
Scenario (3)	211	284
Scenario (4)	363*	411*

Table 1. Time for first UAS to reach $h_i(t) = 0.4$. * denotes time till UAS death, $h_i(t) = 0$

The results from all four scenarios can be seen in Table 1. In all four scenarios, the addition of the smart health balancing increases the minimum time till death of the weakest UAS by a significant margin with only minimal adjustments to the existing framework. The SHB ensures that the swarm is capable of operation for a longer period of time and prevents prolonged disproportional wear.

5. CONCLUSION

Ensuring the reliability of UAS in the field is vital to promoting UAS as a viable option for autonomous diffusion control applications. In real-world applications, the UASs are likely to experience a wide variety of environments and conditions that will negatively affect performance and lifetime. In commercial operations, swarm robustness and reliability is a vital aspect, especially in agricultural environments where usage can be frequent in harsh conditions. It can be seen that through the application of smart health

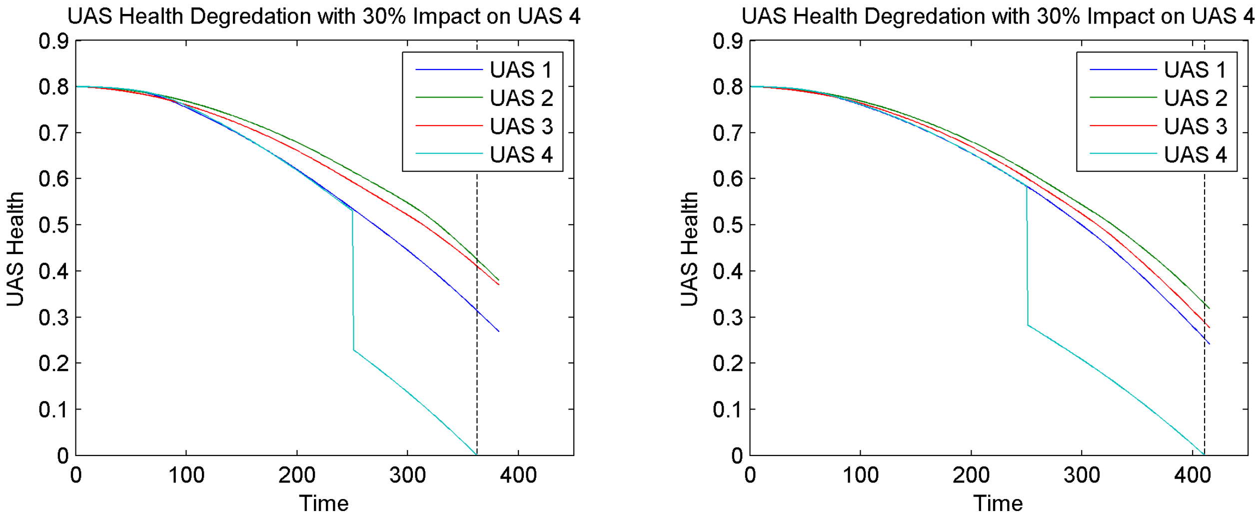

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Fig. 6. Plot of UAS Health for four UASs with an initial health of $h_i(0) = 0.8$ and a 0.3 health impact for UAS 4 for (a) Nominal and (b) SHB.

balancing to each UAS, the entire UAS swarm is more robust to variations in health, caused by any number of very plausible scenarios. The system can better react to unforeseen damage from collisions, mechanical failure, or insufficient maintenance. The method of team and individual health aware motion control can also be applied to systems of UAS with different performance capabilities, that is, the heterogeneous drone team, which cab be investigated in future research efforts.

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