A FUZZY-BASED HEALTH MONITORING MECHANISM FOR ENERGY MANAGEMENT OF SWARM INTELLIGENCE COORDINATED UNMANNED AERIAL VEHICLES

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Abstract— We propose a health monitoring mechanism based on fuzzy logics in order to mitigate the number of dead UAVs due to the lack of energy in Swarm of UAVs coordinated by a Particle Swarm Optimization (PSO) based algorithm. The proposed mechanism depends on the energy level of the UAV, the distance to the neighbor and energy level of the neighbor. We also propose a metrics named Death by lack of Energy (DE) which measures the percentage of dead UAVs due to the lack of energy in the swarm of UAVs during the mission. We analyzed the influence of the proposed mechanism in a PSO-based model designed to automatically coordinate a swarm of UAVs in order to avoid collisions, to track multiple targets and to perform environmental patrolling. We performed simulations varying the size of environment, the number of UAVs within the swarm and the fuzzy membership rules. We observed that the proposed fuzzy-based mechanism can mitigate DE without compromising the other swarm capabilities.

1 Introduction

The interest in Unmanned Aerial Vehicles (UAVs) has grown in the last years. UAVs have been applied to perform complex and sophisticated tasks, such as for agricultural applications and surveillance (Varela et al., 2011)

Swarm intelligence have appeared in the 1990's inspired by swarms of simple creatures, such as ants, bees, birds, fireflies and fish (Bastos-Filho et al., 2008)(Kennedy and Eberhart, 1995). In the swarm intelligence algorithms, the reactive agents are quite simple, but the emergent behavior of the entire swarm can tackle complex problems. One of the most used swarm intelligence algorithms is the Particle Swarm Optimization (PSO), proposed by Kennedy and Eberhart in 1995 (Kennedy and Eberhart, 1995). The coordination tasks are mainly been tackled by means of multi-agent system (MAS) which is a top-down approach. In general, the MAS approach uses cognitive and rational agents with particular mental attitudes, for instance belief-desire-intention (BDI) agents. nevertheless, Swarm intelligence algorithms have been successfully applied for control and/or to coordinate mobile robots (Silva et al., 2012)(Wang et al., 2011) and is often referred as swarm robotics. The preliminary results of these approaches suggest that coordination of multiple robots does not necessarily need to be performed by means of MAS.

The concept of fuzzy logics was introduced by Lotfi Zadeh in 1965 (Zadeh, 1965). Besides, fuzzy logics have been applied to implement controllers for UAVs (Yeh et al., 2011). Recently, Silva *et al.* (Silva et al., 2012) proposed a coordination model for UAVs based on the PSO algorithm. Although the authors demonstrated that the coordination model can self-organize the swarm aiming at maintaining the communication and avoiding collisions, there is a need to establish a mechanism to define when the UAVs must return to the base for recharging purposes. This paper proposes a health monitoring mechanism for a swarm of UAVs managed by a PSO-based algorithm in which fuzzy logics is applied to mitigate the probability of death of the UAVs due to the lack of energy. The mechanism also defines dynamically which UAVs have the priority for the recharge process.

The remainder of the paper is organized as follows. Section II presents some related works. Section III describes the PSO-based coordination model for the swarm of UAVs. Section IV introduces our contribution regarding the application of fuzzy logics for the health monitoring mechanism. In Sections V and VI we present some results and the conclusions, respectively.

2 Related works

Some previous works proposed to tackle coordination issues in swarm robots by means of distributed models. In 2011, Wang *et al.* (Wang et al., 2011) used the PSO algorithm to coordinate multiple robots aiming to perform territorial exploration in a collaborative manner. Varela *et al.* (Varela et al., 2011) used the PSO to coordinate multiple UAVs equipped with sensors aiming to find pollutants in the atmosphere. Other works (Shaw and Mohseni, 2011) tackled UAVs coordination issues, but they considered a global positioning systems (GPS). Nascimento *et al.* (do Nascimento et al., 2012) proposed a prototype model for UAV designed for swarm of robots applications. Zhu *et al.* (Zhu et al., 2011) developed a multiple robots search algorithm independent of GPS signals to overcome this limitation. Qu and Zhang (Qu and Zhang, 2011) proposed a fault-tolerant collaborative algorithm to address GPS signal losses. Shames *et al.* (Shames et al., 2011) proposed a self-localization mechanism for mobile agents in a cooperative manner. Other recent works that deal with swarm energy consumption and sensors signal error were recently proposed (Kim and Seo, 2012).

In 2012, Pinheiro Silva and Bastos-Filho (Silva et al., 2012) proposed a distributed coordination model for swarms of UAVs with local ad hoc communication based on the PSO algorithm. In their model, the swarm robots present the following objectives: (i) allow the locomotion through an environment; (ii) avoid obstacles and collisions; (iii) patrol the entire environment; and (iv) detect and track targets. They analyzed some communication issues and assessed the energy consumption (Silva et al., 2012).

In 2013, Monteiro, Silva and Bastos-Filho (Monteiro et al., 2013) proposed three specific scenarios in order to allow one to analyze the performance of swarm-intelligence based coordination models for swarm of robots: (i) contraction and expansion; (ii) self-segregation and self-aggregation; and (iii) the capacity to change abruptly the fly direction whenever it is necessary. However, although the energy of the swarm coordination model was assessed, the authors did not consider the need for recharging since they were not treating long-duration missions. In 2011, Arif (Faisul Arif et al., 2011) proposed a decentralized controller system inspired by artificial bees in order to manage the energy in mobile robotics. In 2012, Nigam *et al.* (Nigam et al., 2012) devised a health monitoring policy based on the crisp information in their decision making mechanism and evaluated it in a swarm of UAVs.

Although many previous works considered energy issues (Kernbach and Kernbach, 2011), to the best of our knowledge, none of them considered the coordination of multiples UAVs with a distributed control using an ad hoc communication network aiming to track mobile targets, while avoiding obstacles, performing energy health monitoring and performing recharging processes.

3 PSO-Based Coordination Model for swarms of UAVs

The previous PSO-based coordination model proposed in (Silva et al., 2012) presents the following features: (i) locomotion mechanism, in which the UAVs obtain their localization within the environment, $\vec{x}_{uav}(t)$. This information can be acquired by a GPS; (ii) perception mechanism, whereupon each UAV has a perception sensor in order to detect targets; (iii) anti-collision mechanism, whereupon each UAV has an anti-collision sensor to avoid obstacles and to ensure a safety locomotion; (iv) and communication mechanism, whereupon every UAV owns a wireless communication device and acts as a routing bridge in to build a 2-connected ad hoc communication network.

The locomotion mechanism is guided by physical dynamical variables and parameters, such as horizontal acceleration ($\vec{a}$), maximum horizontal acceleration (a_{max}), horizontal speed ($\vec{v}$), and maximum horizontal speed (v). The $\vec{a}$ vector is composed by other vectors: synchronism ($\vec{a}_{syn}$); avoiding collisions ($\vec{a}_{col}$); avoiding losing communication ($\vec{a}_{com}$); cognitive ($\vec{a}_{cog}$); and social ($\vec{a}_{soc}$).

The Synchronism vector is given by:

$$\vec{a}_{syn} = \vec{a}_{col} + \vec{a}_{com}, \tag{1}$$

in which $\vec{a}_{col}$ and $\vec{a}_{com}$ are calculated by using the information provided by the collision and the communication sensors, respectively.

The Cognitive (related to the UAV) and Social (related to the UAV neighbors) vectors compose the swarm vector, which is given by:

$$\vec{a}_{swm} = \vec{a}_{cog} + \vec{a}_{soc}, \tag{2}$$

where $\vec{a}_{cog}$ and $\vec{a}_{soc}$ are calculated by the PSO algorithm at each iteration. Since the PSO algorithm needs a fitness function, we adopted the euclidean distance to the detected target as the quality metric for the PSO, which is given by:

$$fitness_{uav}(t) = |\vec{x}_{tar}(t) - \vec{x}_{uav}(t)| \ , \tag{3}$$

in which the information about target position, $\vec{x}_{tar}(t)$, is provided by the perception sensor.

The resultant acceleration is the sum of the Synchronism and the Swarm vectors. Finally, the new UAV resultant velocity is calculated by:

$$\vec{v}(t+1) = \vec{v}(t) \cdot \omega + \vec{a}(t+1), \tag{4}$$

in which $\vec{v}(t+1)$ is the new speed, $\vec{v}(t)$ is the current speed and ω is the inertia factor.

The total power consumption is the sum of all engine power consumption and communication sensor power consumption. In the case of a quadrotor, 4 (four) engines are used. Equation (5) presents the power consumption model:

$$P_{uav}(t) = 4 \cdot P_{uav-eng}(t) + P_{com} \ , \tag{5}$$

where $P_{uav-eng}(t)$ is the engine power consumption at time t and P_{com} is the communication sensor power consumption.

In this paper, we will assume that $P_{uav-eng}(t)$ is determined by Equation (6):

$$P_{uav-eng} = 12,4 \cdot |\vec{v}_{uav}(t)| + 11 \ , \tag{6}$$

where $\vec{v}_{uav}(t)$ is the speed of UAV in m/s at time t. P_{com} is determined by Equation (7):

$$P_{com} = 0.66 \cdot 10^3 \cdot r_{com} + 214.5 \cdot 10^{-3} \ , \tag{7}$$

where r_{com} is the communication sensor range in m.

4 Fuzzy Health monitoring mechanism

This section specify the health monitoring mechanism in details. This mechanism is responsible for monitoring the energy of the UAVs and determine when each UAV must leave the current tasks in order to recharge.

Basically, the health monitoring mechanism was modeled by using the following parameters:

1. Energy capacity ($W_{uav-cap}$): The maximum amount of energy that an UAV can have. This value is the average value of a gaussian distribution that is used to determine the energy capacity of each UAV;

2. Energy capacity standard deviation ($W_{uav-cap-std}$): it is related to the standard deviation of the gaussian distribution to define the energy capacity of each UAV;

3. Recharging area radius (r_{base}): Determines the recharging area;

4. Recharging power rate ($P_{uav-rch}$): Defines the amount of energy an UAV can be recharged at each iteration when it is in the recharge base.

Since the UAVs have a limited energy capacity ($W_{uav-cap}$), they will possibly need to recharge their battery during their operations. Ideally, when an UAV realizes that it needs to be recharged, this UAV should move to the recharging area which is localized in a r_{base} meters radius around the known base station position ($\vec{x}_{base}$). In our simulation setup, ($\vec{x}_{base}$) is in the center position of the environment. As soon the UAV reaches the recharging area, $|\vec{x}_{uav}(t) - \vec{x}_{base}| < r_{base}$, the UAV starts the recharge process with a $P_{uav-rch}$ recharging power rate. When the current energy ($W_{uav-crt}(t)$) reaches the energy capacity ($W_{uav-cap}$), the UAV battery is considered recharged and the UAV can return to the mission.

The current energy is initialized at the beginning, $W_{crt}(0) = W_{uav-cap}$. At each iteration, the energy is consumed according to Equation (8):

$$W_{crt}(t+1) = W_{uav-crt}(t) - P_{uav}(t) \ , \tag{8}$$

where $P_{uav}(t)$ is specified in Section 3.

We propose a health monitoring mechanism that uses fuzzy logics. Each UAV has information regarding the base position ($\vec{x}_{base}$) and the environment bounds (x_{lim}). The distance level at time t measures the distance from the base and is determined by Equation (9):

$$D_{lvl}(t) = \frac{|\vec{x}_{base} - \vec{x}_{uav}(t)|}{x_{lim}} \ . \tag{9}$$

The energy level at time t measures the energy level regarding the energy capacity and is determined by Equation (10):

$$W_{lvl}(t) = \frac{W_{uav-crt}(t)}{W_{lvl}} \ . \tag{10}$$

This value ranges in the interval [0,1].

We created three input fuzzy variables: Energy Level (EL), Distance Level (DL) and Neighbor Energy Level (NEL). These variables will map the energy of the UAV $W_{lvl}(t)$, the distance of the UAV to the recharge base $D_{lvl}(t)$ and the energy of the closest neighbor $W_{lvl}(t)$, to membership degrees related to the fuzzy sets.

The fuzzy variables EL and NEL are represented by three fuzzy sets: $Critical$, $Hungry$ and $Satisfied$; whereas the fuzzy variable DL is represented by three fuzzy sets: $Close$, $Middle$ and Far. The membership functions of EL and DL variables are depicted in Fig.1. The membership functions for NEL is similar to the one for EL.

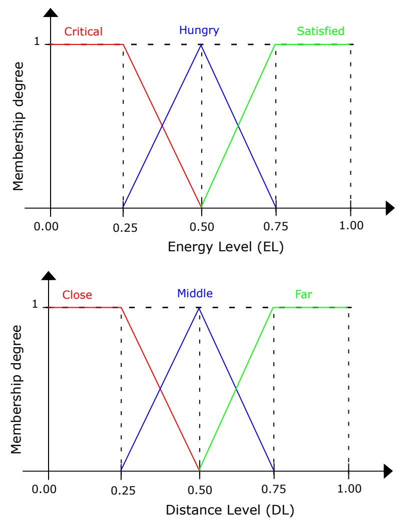

Figure 1: The upper chart presents the membership functions of the three fuzzy sets related to the fuzzy variable Energy Level (EL): Critical, Hungry and Satisfied; and the bottom chart presents the membership functions of the three fuzzy sets related to the fuzzy variable Distance Level (DL): Close, Middle and Far.

One can observe from Fig. 1 that the fuzzy sets Critical, Hungry and Satisfied are represented by the following mathematical functions, respectively: left triangular function with first threshold ($Critical_{x-1}$) equals 0.25 and sencond threshold ($Critical_{x-2}$) equals 0.50; a triangular function and with first threshold ($Hungry_{x-1}$) equals 0.25 and second threshold ($Hungry_{x-2}$) equals 0.75; and a right triangular function with first threshold ($Satisfied_{x-1}$) equals 0.50 and second threshold ($Satisfied_{x-2}$) equals 0.75.

In the same way, the fuzzy sets Close, Middle and Far are represented by the following mathematical functions, respectively: left triangular function with first threshold ($ClosW_{x-1}$) equals

0.25 and sencond threshold ($ClosW_{x-2}$) equals 0.50; a triangular function and with first threshold ($MiddlW_{x-1}$) equals 0.25 and second threshold ($MiddlW_{x-2}$) equals 0.75; and a right triangular function with first threshold (Far_{x-1}) equals 0.50 and second threshold (Far_{x-2}) equals 0.75. It is important to note that the output variable is the decision regarding to the following two fuzzy sets: recharge or not recharge.

The decision making is composed by the following three fuzzy rules:

Rule 1: IF EL is $Critical$ THEN $Recharge$;

Rule 2: IF EL is $Hungry$ AND DL is Far THEN $Recharge$;

Rule 3: IF EL is $Hungry$ AND NEL is $Satisfied$ THEN $Recharge$.

At each iteration, the health monitoring mechanism obtain the crisp values for the three values, transform then into membership degrees related to fuzzy sets, check the three aforementioned fuzzy rules and decide whether the UAV must recharge or not. If the *Recharge* membership degree is greater than 0.5, then the recharge decision is more representative.

It is important to note that in crisp set, the UAV is considered with Critical Energy if its energy level is less than or equal to 0.25; the UAV is considered with Hungry Energy if its energy level is less than or equal to 0.5; and the UAV distance is considered Far if its distance level is greater than or equal to 0.75. In other words, in the crisp set model there is no fuzziness or fuzzy uncertainty which is a type of uncertainty that arises from linguistic imprecision or vagueness.

5 Simulation results of decision making with fuzzy information

This section reports the results for three scenarios. The first one analyzed the influence of environment size; The second simulation analyzed the effect of the number of UAVs; and the last analyzed the influence of each fuzzy rule. For each scenario we simulated 30 independent trials for the fuzzy approach and for the crisp approach.

5.1 Death by lack of Energy metrics

In the previous works (Silva et al., 2012) (Monteiro et al., 2013), the following metrics were already proposed: Collision (CL): measures the collision degree; Targets Tracking (TT): measures the swarm of UAVs tracking capability. We propose in this paper a new metrics named Death by lack of Energy (DE) in order to evaluate the percentage of UAVs that dies due to the lack of energy and is presented by Equation (11):

$$DE = \sum_{t=1}^{I_{max}} \frac{n_{uav-dth}(t)}{n_{uav}} \ , \qquad (11)$$

where I_{max} is the maximum number of iterations, $n_{uav-dth}$ is the number of dead UAVs by lack of energy and n_{uav} is the total number of UAVs at beginning. If the current energy is over, $W_{uav-crt}(t) = 0$, the UAV enters in a Death Energy state and becomes inoperative.

5.2 Analysis Regarding the Environment Size

We performed an analysis regarding DE as a function of the environment size. We compared the use of fuzzy decision making with crisp decision making. The boxplots for both cases are presented in Fig. 2. One can observe from Fig. 2 that DE increases as the size of environment also increases when a crisp decision making was deployed from 150 m^2 to 200 m^2. On the other hand, DE=0 when the fuzzy decision making mechanism was used for the entire range.

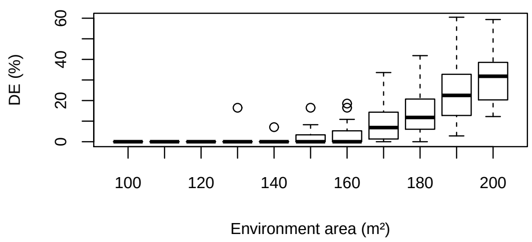

Figure 2: DE as a function of environment size varying from 100 m^2 to 200 m^2 with crisp decision making. DE was zero for all range with fuzzy decision making.

We performed the Wilcoxon non-parametric statistical test for the tracking capability (TT) and the Collision (CL) comparing the fuzzy and crisp approaches with a 5% significance level and there was no significative difference for TT and CL. These results suggest that a fuzzy decision making can avoid dead UAVs, while not affecting the collision avoidance and target tracking.

5.3 Analysis Regarding the Number of UAVs

We analyzed the influence of the number of UAVs in the Death Energy varying the number of UAVs from 3 to 20 for the crisp and the fuzzy approaches. Fig.3 presents the results.

One can observe that the average value for DE is around 30% regardless the number of UAVs for the Crisp approach. On the other hand, not even a single UAV died due to the lack of energy for the

Table 1: Default parameters.

Parameter	Description	Value
Env	Environment area	200 m^2
r_{base}	Recharging area radius	10 m
$W_{uav-cap}$	UAV energy capacity	1000 mAh
$W_{uav-cap-std}$	UAV energy capacity standard deviation	0 mAh
$P_{uav-rch}$	Recharging Power	23 mAh
n_{uav}	Total number of UAVs standard deviation	10
$v_{uav-max}$	UAV maximum speed	0.5 m/s
$a_{uav-max}$	UAV maximum acceleration	0.3 m/s^2
w	Inertia weight	1.0
$n_{nei-max}$	Maximum number of neighbors	2
a_{cog}	Cognitive acceleration	1.0
a_{soc}	Social acceleration	3.0
e_{uav}	UAV extension range	0.1 m
n_{tgt}	Number of targets	1
$v_{tgt-max}$	Target maximum acceleration	0.4 m/s
$a_{tgt-max}$	Target maximum acceleration	0.2 m/s^2

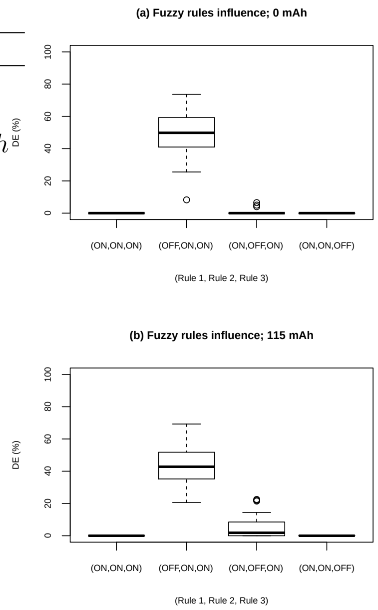

Figure 4: DE as a function of the activation of fuzzy rules.

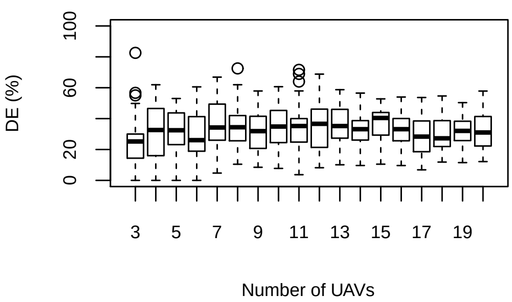

Figure 3: DE as a function of the number of UAVs varying from 3 to 20 with crisp decision making. DE was zero for all range with fuzzy decision making.

fuzzy approach. We performed the Wilcoxon non-parametric statistical test for TT and CL comparing the fuzzy and crisp approaches with a 5% significance level. For all situations there is no significative difference for TT and CL. Table 1 presents the default values for the parameters used in the following simulations.

5.4 Influence of the Membership Rules

We analyzed the influence of the three fuzzy rules individually in the DE metrics. Fig. 4 presents the DE as a function of activation of the three fuzzy rules for $W_{uav-cap-std}$ equals (a) 0 and (b) 115 mAh. The elements of the 3-tuple represents whether the fuzzy rule was activated (ON) or not (OFF).

One can observe in Fig. 4 that the deactivation of Rule 1 implied in a DE increasement from zero to approximately 40% in both cases. This could be expected since the Rule 1 is only related to *Critical* fuzzy set and probably should be the most used rule. The initialization of the $W_{uav-cap}$ by a normal distribution, $N(W_{uav-cap}, W_{uav-cap-std})$, caused different influences of Rule 2. DE presented some outliers when the Rule 2 was deactivated and $W_{uav-cap}$ was not normally distributed. However, when $W_{uav-cap}$ is normally distributed, the deactivation of Rule 2 implied in a DE increasement from zero to 5%. Finally, the deactivation of Rule 3 did not affected DE, but our hypothesis is that Rule 3 could support an alternation behavior when tracking targets.

6 Conclusions

We proposed a fuzzy health monitoring to tackle the management of energy in swarms of UAV. The fuzzy system is composed by 3 fuzzy variables, 9 fuzzy sets and three fuzzy rules. We also proposed the membership functions for all fuzzy sets. We also developed a new metrics named Death by lack of Energy (DE) in order to measure the percentage of dead UAVs due to the lack of energy and analyzed the proposed metrics, DE, regarding the environment size, the number of UAVs and the influence of the three fuzzy rules.

The proposed fuzzy mechanism mitigated the DE problem which occurs when crisp sets are deployed. Although the preliminary results indicate a good performance, it is still necessary to assess the mechanism with different number of targets, heterogeneous swarms and distributed recharging spots in large areas.

For future work, we intend to use type-II fuzzy sets to evolve the proposed mechanism, evolve the current coordination model by including some collaborative skills in the UAVs in order to improve the tracking capability and include mechanisms to diminish the energy consumption.

Acknowledgment

The authors would like to thank to UPE and CAPES.

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